8-23-2016

Farming Alone: Factors Influencing Farmland Conversion Along the Rural Urban Fringe

Andrew J. Huddy
University of Connecticut - Storrs, andrewhuddy@delta.edu

Farming Alone: Factors Influencing Farmland Conversion

Along the Rural Urban Fringe

Andrew J. Huddy, PhD

University of Connecticut, 2016

ABSTRACT

Urbanization is a complex process of converting urban fringe and rural land to urban land uses and has caused various impacts on ecosystem structure, function, and dynamics. Estimates of the agricultural land converted annually to low density non-agricultural uses vary from between 800,000 to more than 3 million acres nationwide—a rate of five times the rate of population growth, and in the process, fragmented the agricultural land base. Much of the land lost is prime or unique farmland, disproportionately located near cities. Classical land use theory asserts that a study of market forces and land value, defined in terms of inherent productivity and/or distance from urban centers, can explain this change.

This study is important in advancing geographic research on land use change in urban fringe areas, methodologically and theoretically. Data utilized were parcel-scale and remotely-sensed spatial data for a complete Michigan county in an attempt to better test the effects of economic and non-economic factors on land use change in a statistical model. An initial pilot study helped identify potential factor relationships in the research.

The research presented makes several advances over previous land use studies by combining several methods for modeling land use change. First, it uses non-economic variables based on land attachment and social capital, as well as traditional economic variables to explain land use change. Second, it develops a continuous parcel data set using existing ownership records. This better represents the decision-making unit at farm scale with respect to farm retention. Third, it combines modeling techniques, including ordinary least squares Geographic Weighted Regression (GWR), to analyze and visualize factors influencing land use in the rural fringe reduce residual spatial autocorrelation. Other spatial analyses were used to identify factor concentrations, patterns of rural networking, and clustering related to social capital.

Results show that prime farmland is significantly related to farm conversion and that the important social capital variable related to farm preservation participation also accounts, to a certain degree, for the change in land use for the study area. Strength of relationship and factor patterning factors related to land use change were successfully identified. Additionally, this research has illustrated the need to explore means to include non-economic variables in future research on the causes of urban sprawl and loss of farmland.

Farming Alone:
Factors Influencing Farmland Conversion
Along the Rural Urban Fringe

Andrew J. Huddy

B.S. Manhattan College, 1981

M.A. CUNY Hunter College, 1994

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2016

andrew.huddy@uconn.edu

andrewhuddy@delta.edu

APPROVAL PAGE

Doctor of Philosophy Dissertation

Farming Alone:
Factors Influencing Farmland Conversion
Along the Rural Urban Fringe

Presented by

Andrew J. Huddy, B.A., M.A.

Major Advisor ______________________________
Jeffrey P. Osleeb, Ph.D.

Associate Advisor ______________________________
Ken Foote, Ph.D.

Associate Advisor ______________________________
Carol Atkinson-Palombo, Ph.D.

University of Connecticut

2016

ACKNOWLEDGMENTS

Completing this dissertation later in life has led me down many paths. The guidance and support of my advisors, teachers, and fellow students in the Geography department at the University of Connecticut has been significant for the completion of this dissertation. I would like to thank Dr. Jeff Osleeb for overseeing the project; he has been generous with his time, knowledge, and friendship. Ever since we worked together on my Master's Thesis at Hunter College and now complete this research at UConn, he has provided expert advice and encouragement throughout this difficult project.

Thank you to Dr. Robison and Dr. Siles from Michigan State University for introducing me to social capital concepts that served as a basis for this research, and for providing subsequent assistance with my initial survey work.

At different times during this project, certain individuals really came through; Dr. Brent McCusker, Dr. James Biles, and Phyliss Peterson, and all provided helpful advice, comments and suggestions on different aspects of producing this manuscript and progressing with the project.

Thank you for the support of different local organizations for providing financial assistance as well as access to their data for analysis. Jon Cooper and Paul Hamilton of the Tri-County Regional Planning Commission, and Tim Vandermark at Eaton County Equalization all provided great assistance in accessing local materials. Thank you also to Richard Harlow at Michigan Department of Agriculture and Rural Development Office for his continued advice in the collection and interpretation of farmland preservation data.

This project would have been difficult without the support of Andrew Kilpatrick at City of Lansing. Sam Quon from the COL IT/GIS Administration provided patient technical support working with local data and GIS procedures.

At different critical moments during this project, Dr. Kevin Brooks and Dr. Jeff Stratton provided critical statistical support. Thank you to Richard Mrozinski at UConn for his continued support and friendship during challenging moments of the research. Also, thank you Patricia, my anonymous reviewer for the thorough and constructive comments which greatly improved the quality of the dissertation document.

Most of all, this work is dedicated to wife, Cathy. Through her patience and great sacrifice, Cathy has helped provide the structured environment, ideas and suggestions that I needed to complete this this project. Throughout these past years, she has been the compass for this research, working with me in the trenches during the good and difficult times of this project. Without her support, I would have given up long ago and settled for "good enough". Thank you for believing in me.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE
INTRODUCTION

1.1. Introduction

Taking a casual drive from the outskirts of most North American cities into the surrounding countryside, an observer would notice a landscape of highly uneven development. An exclusive subdivision is situated in an expanse dominated by row crops. Nearby, a farmer continues to till a field surrounded by several newer residential subdivisions and commercial development. As an observer of this juxtaposition of such unrelated uses, one could ask the farmer: Why continue to farm; since it can no longer be efficient or easy to farm in such a dramatically altered landscape, what factors drive farmers to maintain an agricultural way of life?

Over the past 50 years, metropolitan areas have developed outward into adjacent parcels; more recently, this expansion has included low-density residential development of rural land. This process, commonly referred to as urban sprawl, is fueled largely by market forces. However, in the past few decades, societal concern about the loss of productive farmland to development has developed into a countervailing force against market forces (Galbraith, 1952) that operate to promote sprawl. This countervailing force takes the form of an appeal to maintain a traditional farming culture.

In this dissertation, farmland-to-residential land use conversion is examined through analysis of market forces responsible for sprawl, as well as through the countervailing forces responsible for retention of land in agriculture. Land is arguably the most important productive asset owned by farmers. Anecdotal evidence suggests that farmers often have a strong attachment to their farmland. Levak (1956) identifies farmer attachment as an intense emotional involvement to land based on the long family connection with the land. An "attached" farmer regards their specific land as something more than a capital investment. Attachment value allows land to take on emotional value in addition to its existing economic or physical value. Because of the association with family, farmland is a physical asset with potential for significant attachment value.

Attachment value is embedded in the concept of social capital, defined as a person or group's sympathy or sense of obligation for another person or group (Robison and Siles, 2000). Land value based on social capital reflects an expression of connection to family and community. Therefore, farmland is not only regarded as an economic asset, but also as a family holding whose value is heavily influenced by non-economic emotional connections to the land. In this study, attachment value for each farmer is measured indirectly as the percentage of land holding in a farm preservation program.

Research work in social capital often focuses on the outcomes of social capital (Putnam, 1993). This study focuses on emotional attachment and how it can influence the outcome of sale or retention of agricultural land (Robison, et al., 2002).

1.2. Purpose of Study: Social Capital and Farmland Conversion

In this research, farmland conversion is defined as the process where land is transferred from agricultural use and sold for the purpose of non-agricultural (predominantly residential) use (Freshwater, 2009). The main findings of this research results indicated that:

1 - Social capital, as a set of relations between family and community, is reflected in a farmer's attachment to land. Farmer participation in farmland preservation was used as the key proxy variable representing the relationship between land use, social capital, and

land attachment. Specifically, this analysis will focus on the interaction of rural land use with spatial characteristics of farmer participation in farmland preservation programs associated with social capital. Participation in these programs characterized a pool of farmers that had high levels of social capital, land attachment, and a sense of dedication to a future in local farming. Social capital and land attachment were measured by the acres of land committed by each farm household to the statewide preservation program. Land value based on attachment to land can have significant negative influence on the conversion of agricultural land.

This research has also estimated other non-economic variables that accounted for land use including duration of farm ownership, and the effects of neighborhood landscape change.

2 - Prime farmland is defined by a combination of productivity and location. Prime farmland produces the highest yields with minimal inputs of energy and economic resources; farming it results in the least damage to the environment. Currently, in the rural and urban fringe areas, the distance to residential development is becoming an increasingly important spatial characteristic affecting production.

Prime farmland loss is an important component of farm conversion of agricultural land. Aside from agricultural use, prime farmland characteristics have also been found to be particularly suitable for residential development. This particular aspect of prime land is reflected in the study as an influential variable of overall agricultural land use change.

3 - Individual farmers did not respond to the effects of neighborhood landscape change. With an increased shift of farmland to non-agricultural uses in the farm neighborhood, it

was anticipated that the loss of local rural landscape would be reflected in a reduction in individual farm holding. Residential development change in farm neighborhood use was not a significant influence on individual farm conversion.

The conversion of agricultural land to urban uses at the *rural-urban fringe* (RUF) is particularly compelling. The rural-urban fringe, as identified by (Pryor, 1968), takes the form of an irregular, low-density pattern of growth that produces a mix of residential and agricultural properties. These margins have been characterized as transition zones between rural and urban areas and exhibit a great deal of land use heterogeneity (Audirac, 1999). In the past, urban structure has been conceptualized as a series of concentric zones surrounding the city with an implicit order of uses (Harris, 1945). Perhaps more accurately, it has been represented as a rural-urban continuum with imprecise and fluid boundaries (Sullivan, 1994). While these approaches provide some explanation for incremental growth at the margins, none of them satisfactorily explain the unintended consequences of growth and fragmented patterns of land that are emerging in these fringe areas.

Some observers view land use change at the rural-urban fringe as a significant threat not only to agriculture, but also to a way of life (Berry and Plaut, 1978; Daniels, 1999). However, others researchers limit the consideration of the effects of urban development on rural areas to "unimportant" changes in soil conservation and food production capacity (Fischel, 1982; Vesterby and Heimlich, 1991).

1.3. Importance of This Study

This study is important in advancing geographic research on land use change in urban fringe areas, methodologically and theoretically. This research advances previous methods for land use change modeling in several ways: 1) it combines modeling techniques, including Geographic Weighted Regression (GWR), to analyze and visualize factors of land use in the rural fringe; 2) it uses non-economic variables to explain land use change; and 3) it develops a farm parcel data set using existing parcel records and, 4) it uses geographic models to identify factor concentrations.

In addition to these methodological advances, this study aims to pinpoint the causes of farm conversion at the rural urban fringe. Land conversion is presented here at farm level as a gradual, incremental process, not a simple binary choice of complete change/no change. This level of detail requires an accurate representation of the farm household—the decision-making unit that makes the choices to retain land, sell land, or as in many cases, selectively reduce acreage in order to keep a farmstead operating. Agriculture is still the predominant land use in the study area and partial conversion of "farm parcels"—parcels combined into parcels based on ownership and observed patterns of land use— is more consistent with actual land use change. This has led to the selection of methods used here. A pilot survey was developed to identify potential relationships between farm attachment and land use change at farm scale. A spatial dataset was constructed using a Geographic Information System (GIS) to compile tabular data and spatial imagery for analysis. Multi-variate analyses were then used to model land use change and explain the relative importance of the variables. Geospatial analysis was applied to the data to reveal the spatial distribution of a single variable (clustering) and to analyze the spatial variability of the local coefficients of dependent variables (elasticities), and with mapping, determine how these relationships vary over space.

Spatial data documenting farmer enrollment in the Michigan farm preservation program was an important source. Because of the nature of these agreements, farmers attracted to the program tend to be more interested in protecting farmland (and the agrarian way of life) than to finding an economic advantage. For this reason, data extracted from the public record for PA116 were used as proxy for land attachment/social capital.

Lastly, the concept of a farm was important in developing the study observation units. Using the plat map record, parcels were combined into farm parcels; based on ownership and observed patterns of land use. This refinement better specified the decision-making unit for the study.

1.4. Organization of the Dissertation

Chapter Two of the dissertation provides a comprehensive background of previous literature. This chapter opens with a discussion of three important theoretical perspectives on agricultural land use change: 1) social capital theory, 2) land use theory, and 3) economic land value.

Chapter Three contains a description of the Eaton County study area.

Chapter Four contains a description of the research questions and hypotheses section of this research. The dataset used is a combination of digital farm parcel records and associated attributes developed using GIS that is a combination of map techniques using graphic elements and data bases in analysis. The method developed for the empirical analyses designed to test the expectations for the pattern of land use change is then explained.

Chapter Five contains the methods and data analysis sections. The methods section includes the development of an Ordinary Least Squares (OLS) regression model where the dependent variable measures agricultural land use change. Two time periods—Model I (1978-91) and Model II (1992-99) were analyzed using economic, distance, and non-economic independent variables for the respective time periods. A descriptive overview of the data leads into an explanation of the modelling approach used to analyze relationships between the independent variables and land use. A GWR model is also employed enabling a visualization of clusters, relationship of variables, and the strength of relationship of the model.

The Data Analysis portion of Chapter Five includes the derivation of the conceptual framework that guided the choice of observation units and variables, as well as explanation of the observation units and variables themselves. The conceptual framework provides the rationale for the study.

Chapter Six contains the results and analysis of the two models described in Chapter Five. These results from model analysis are then presented and the findings interpreted in the context of associated analyses of the data and past studies. Implications are derived for land use, subdivision policy, and research methods.

Chapter Seven concludes this research with a summary of previous chapters and provides insight for future research endeavors.

CHAPTER TWO
LITERATURE REVIEW

2.1. Introduction

Classical land use theory asserts that land value is defined in terms of inherent productivity and/or distance from urban centers (i.e., the central business district). The free market assumption that land, for a given location, residential preference (for lower-density housing), and environmental attributes, will be allocated by competitive bidding. In other words, market forces effectively create urban structure.

These economic structures are significant in areas of land use change, particularly at the rural periphery of large urban areas. During this dissertation's study period, agricultural land at the rural urban fringe was converted from agricultural use to urban uses at five times the rate of population growth, has fragmented the agricultural land base, and driven up land values. The following chapter provides some description and theoretical background on land use change with a particular emphasis on change occurring at the rural urban fringe.

Original economic land use change models are usually at aggregate scale and have failed to account for "market failures" such as rural amenities, place attachment, and agricultural landowner persistence. In opposition to the "inevitable" increase in urban land use, there are household decision characteristics that are not based on economic metrics (impermanence syndrome, "value of the view," farm longevity, etc.) as well as the agency of the farmland owner for decisions. The literature presented here is intended to provide a practical working knowledge of social capital concepts and suggest how it may operate with respect to land use change. The objective of this chapter is to provide an overview of the land use research and to perhaps highlight some of the weaknesses of the literature.

The first section reviews classical economic land use operating in a free market. This approach does not always account for the factors that drive land use allocation decisions. Salient studies in recent land use literature treat scale as an important element in analysis. Land use is regarded as the cumulative result of many individual decisions and is developed at disaggregate scale analysis. Farmland conversion, representing the result of household decision-making, is a set of disaggregate processes reviewed at a finer spatial resolution. Revealed preference research has recently been conducted for land use analysis at the rural-urban fringe incorporating socioeconomic and environmental factors on land use and residential preferences for land in the estimation of property values.

Agent-based, discrete choice, hedonic, and simulation models all apply modern concepts in land use studies that are mainly rooted in economic land valuation and spatial patterns and predict spatial extent of urban growth (Rosen, 1974). Landscape Ecology literature focuses on the processes and relationships that exist within a landscape based on its structural characteristics. Land use fragmentation, used in combination with parcel data, has been important in the examination of landscape pattern and location in the rural-urban fringe (RUF) but not in behavior driven by attachment value. GWR is used to discriminate between spatially constant processes emphasizing differences across space of local processes that influence rural land use.

Urban sprawl describes qualitative increases in urbanism in physically rural areas and is often depicted by its dimensions and effects. Urbanization is the complex process of converting urban fringe and rural land to urban land uses. Typically, the effect of expanding development in rural and urban-fringe areas takes the form of lower-density housing on larger land parcels located at the urban periphery. Direct conversion of farmland and the indirect effects of reducing agricultural potential for remaining neighboring farms have proven difficult to measure. In more recent research, impacts on the spatial nature of rural areas have been successfully measured in terms of impervious cover. Studies have also described how scattered residential development also increases the potential for nuisance and neighborhood social conflicts.

Some description of local processes that influence rural land use and the aspects of farmland preservation provide the context in which the research operates. "Farmland Preservation" refers to those institutional structures that account for some of the strategic response of the rural household to retain land characteristics of quality farmland. Zoning and market-based policy solutions, including preferential tax to retain land in agriculture, make agricultural use of the land relatively more attractive in the hopes of preventing or delaying development.

2.2. Theoretical Background

2.2.1. Market Forces

Much of the current land use literature follows from the basic insights of Ricardo (1817) and von Thünen (1826), in which land value is related to its inherent productivity and its proximity to urban markets. The von Thünen model takes account of market price, costs of production, and transportation to determine the economic rent for a given parcel of land. Central to the von Thünen model is the assumption that land, for a given location and its environmental attributes, will be allocated to the use that earns the highest profit or surplus with variability of agricultural rent dependent on climate, land quality, and socioeconomic factors (Polsky and Easterling, 2001). Competition for land leads to an allocation among different agricultural uses. The spatial pattern that emerges from this behavior creates the classic pattern of concentric rings around a central market. The land rent concept provides a basic framework to help characterize successive land changes and their relationship to potential economic forces and proximate causes.

Alonso (1964) introduced locational factors into the broader analysis of land use. By assuming that all non-agricultural economic activities were in the city, urban locations were defined in terms of proximity or distance from the central business district (CBD). Alonso developed a model that explains land use allocation, defines housing locations, and describes resulting densities. The land market allocates each piece of land to the highest bidder. Given an increase in income, it is asserted that households will increase their consumption of land (a normal good) at the expense of proximity to the CBD (Alonso, 1964; Brueckner, 1990; Fuguitt and Brown, 1990). Locational choice based on incremental changes of per capita income drives modifications in the composition and geographic extent of an urban area (Alonso, 1964). In short, market forces create urban structure.

Classical general equilibrium models and empirical studies also suggest that residential preferences are for lower-density housing on larger land parcels (Mieszkowski and Mills, 1993). Larger lots typically are located at the urban periphery, where residential land use tends to outbid agricultural uses. Theoretically, this "natural evolution" or allocation of land resources to residential land uses is a rational, efficient, orderly result of functioning free markets.

2.2.2. Market Failure

The free market does not always operate perfectly in driving land use allocation decisions (Cropper and Oates, 1992; Irwin and Bockstael, 2002). Where it occurs, market failure represents an inability of the market to account for unpriced goods or attributes present in land use. In the rural-urban fringe, low land prices and reduced transportation costs have made rural amenities more accessible to new residents (Fuguitt and Brown, 1990). Rural amenities (Lopez, 1994), in turn, have drawn rapid population growth and the resulting development has changed the spatial structure of landscapes (Cho et al., 2009).

Counter-urbanization is a demographic and social process whereby people move from urban areas to rural areas (Berry, 1980). Counter-urbanization is predominantly used to describe a process of quantitative de-urbanization that qualitatively increases urbanism in physically rural areas. For the farmer, this extension of urban use into rural areas represents the loss of the amenity-rich "traditional" local landscape and often results in a reduced quality of life.

In their analysis of scale-based measures of place attachment (Brown and Raymond, 2007) show that landscape importance values, especially spiritual values, are significant predictors of place attachment. Aesthetic, recreation, economic, spiritual, and therapeutic values spatially co-locate with special places and, thus, likely contribute to place attachment. During the process of land use change, markets can also undervalue this rural sense of place. Castle (2001) proposes an integrated framework of rural-urban space and asserts that the entire economic system cannot be understood unless there is reliable knowledge about both rural and urban sectors, including their interactions. Long-term trends in rural-urban relations cannot be rationalized satisfactorily by existing economic theory.

Revealed preference research has recently been conducted for land use analysis at the rural-urban fringe (Irwin and Bockstael, 2002). Land use models developed at disaggregate scale use residential preferences for land in the estimation of property values. An examination of endogenous processes is employed to predict spatial extent of urban growth. At this fine level of detail, land use is regarded as the cumulative result of many individual decisions, often modeled as a set of discrete (binary) choices (Carrion-Flores and Irwin, 2004). In this manner, analysis of the locational, dis-amenity, and environmental effects on residential property values within a metropolitan area incorporates market failure externalities.

Preference models incorporate socioeconomic and environmental factors on land use in the context of policy analysis, but in the main, fail to consider the agency of the farmland owner for decisions concerning land disposition in the rural-urban fringe (Massey, 1990).

In general, the source data for land use change analysis tends to be either spatially aggregated to a county level or greater (U.S. Department of Agriculture's agricultural census and the Natural Resources Conservation Service's National Resources Inventory) or limited in its temporal coverage (e.g., satellite or aerial imagery). While there is an established literature that examines farmland loss using county-level data (e.g., Lynch and Lovell, 2003), there has been less analysis of farmland conversion at a finer spatial resolution, such as at the individual parcel level.

The only consistent data that are available at a spatially disaggregate level, the National Land Cover Dataset (NLCD), are systematically biased against recording low-density residential development, particularly in nonurban areas. Although land cover, defined in terms of physical characteristics, can be observed with aerial photography and often interpreted successfully from satellite imagery, it is land use, defined in terms of human activity, that is, most relevant for the study of urban patterns.

Consistent, fine-scale data on land use are not available for the entire United States; instead, research has been done using more limited geographical areas for which land use/land cover data are available for two points in time. Describing and explaining landscape patterns are two separate endeavors, each posing their own difficulties. As alternative to the NLCD data, Irwin and Bockstael (2004) developed Maryland Department of Planning (MDP) land use/land cover data from 2000 through a combination of aerial photography and geocoded tax data. From this research, an important series of three papers examining land use change linked four "snapshots" of tax parcel data over an eight year period (Irwin and Bockstael, 2004; Irwin, et al., 2003; Irwin and Bockstael, 2002). This work is notable not only for their contributions to the literature, but also because they represent one of the few examples of land use change analyses at the individual tax parcel level.

2.2.3. Social Capital as a Countervailing Force

Several empirical studies have explored farmland retention based in rural communities, relating development of strong linkages (networks) between members, and the attachment that individuals have for land. This pattern of rural behavior is ascribed to the formation and presence of social capital (Tsoodle, et al., 2006; Cordes, et al., 2003; Siles, et al., 2000). Social capital, based on superior networks, provides group members with the means to access scarce resources and to pursue shared objectives; in this way formation of social capital serves as a precondition for economic development (Cramb, 2005; Putnam, 1993). Attachment value is defined by (Robison and Siles, 2000) as the “change in an object’s value because of the socio-emotional goods embedded in it.”

As Robison and Siles, (2000) write, “in relationships characterized by social capital, expressions of validation, caring, or information provision are produced and, as goods, are valued and can substitute for physical goods or money in exchange.” By extension, land value also has the potential of being altered by different levels of social capital. Land use choices that individuals make are guided by: decisions for or against land conversion on the part of neighboring farmers; information sharing about these decisions; and attachment to places "embedded" within social relationships that reflect family history and ownership (Granovetter, 1985).

Embeddedness in the land is evident when farmers agree to participate in farmland preservation programs (e.g., Michigan's *PA116*). In exchange for a property tax reduction, participants agree to retain their land in agriculture and not to sell their property for development for a designated period of time (Michigan Department of Agriculture, 2011). This tax reduction does not compensate owners for foregone economic opportunity (particularly for land located close to the CBD) or for the loss of flexibility in their farm operation. These agreements frequently extend for 20, 30, or more years—well beyond the expected life of the owner operator. Farm owners' willingness to commit to such stringent terms suggests that they are motivated by non-economic considerations that reflect strong attachment to the land and to the agrarian way of life. Although these programs do not provide institutional support, local networks of like-minded farmers usually develop informally. As social capital increases, networked landowners engage more actively in land preservation practices (Wagner, et al., 2007; Cramb, 2005).

With community economic development (CED), farmers (Fey et al., 2006) have learned to how to invest well in a community's capitals (assets). When CED efforts are participatory and inclusive, CED proves to have greater, more far-reaching impacts on a community. It is important to recognize that the reemergence of social engagement can only happen once people "better understand *how* social capital works." Small communities do come together when it is absolutely necessary. The difficulty does not lie in finding forms of capital within a community, it is in finding a way to measure how capital is invested to affect a community's capacity. In describing the variation of individual social capital (Nieminen et al., 2008) identified three dimensions of social capital: social support, social participation and networks, and trust and reciprocity.

The spatial density and distribution of social capital networks are modeled in this study using farmland preservation variables. In networking, farmers practice information-exchanging strategies with their colleagues (Hägerstrand, 1967). Social networks in rural areas tend to be small, dense, and homogenous (ibid.). On average, the density of contacts contained within an individual's private information field decreases rapidly with increasing distance from the home location. As a result, the local community diffusion associated with drivers of land use change can only be expected to operate across relaively small distances (Robison, Schmid, A., and Siles, 2002).

Regional variations in social capital indicate that "pockets of resistance," or clusters, tend to form where local social networks remain strong (Schmid, C., and Rounsevelle, 2006). Preliminary survey findings indicated that strong interaction between farmers is strongly correlated with *PA116* participation; farmers working in isolation, without benefit of social networks, are more likely to consider conversion of their farms. (Salamon, 1985) identified patterns of farming based on ethnic heritage had a potential underlying spatial component. When farmers' children begin operating their own farms, they tend to locate near each other, network, and create pockets of farmers with similar management styles.

(Putnam, 1993) and (Coleman, 1988) both see social capital beyond the individual level. (Coleman, 1988) noted that the interaction between people is imperative for social capital to thrive. (Onyx and Bullen, 2000) found the measurement of social capital has been difficult over time: "To date, several researchers have attempted to measure social capital with theoretically grounded instruments," "social capital's high level of abstraction" is difficult to "operationalize." (Flora, et al., 1997) developed a new concept that relates to community capacity, entrepreneurial social infrastructure (ESI). This is a particular format for directing or converting social capital into organizational forms that encourage collective action.

Pritchard, (2010) noted how spatial networking of economic relations amongst farm enterprises aids small town survival, consolidates farms into fewer and larger units, and shifts economic functions from smaller to larger population settlements. The research reported in this paper was undertaken with a view to shed empirical insights into how local towns are increasingly interacting with larger regional centers, and thus become decoupled from their proximate farm economies.

2.3. Applied Research

2.3.1. Urban Sprawl and the Rural Urban Fringe

Urban settlement accounts for only three percent of the Earth's land surface, however, over half of the world's population resides in cities (United Nations, 1996). "The driving factors (population or development), mediated by the socio-economic setting (market economy, resource institutions) and influenced by the existing environmental conditions or context, lead to changes in land use through the manipulation of the biophysical conditions of the land" (Turner et al., 1995).

High population density in urban areas has resulted in a large-scale modification of the environment in the urban fringe known as sprawl. Sprawl is defined as a pattern of land use in an urbanized area that exhibits low levels of some combination of eight distinct dimensions: density, continuity, concentration, clustering, centrality, nuclearity (that is, centrality of a particular region with respect to cultural development), mixed uses, and proximity (Glaeser and Kahn, 2003). Sprawl is often a "judgment" about one or more aspects of excessive urban development, e.g., cities that are too extensive have an urban or suburban area that is larger than it otherwise would be. Sprawl can be characterized as noncontiguous residential development with unplanned, relatively low-density growth often characterized by undeveloped tracts interspersed with idle land among developed parcels and subdivisions. These are often connected by commercial corridors along busy roads that rely on automobiles for transportation. In general, sprawl has taken two main forms: in the form of expanding urban areas that have pushed outward and scattered residential sprawl outside established settlements.

Urbanization is a complex process of converting urban fringe and rural land to urban land uses and has caused various impacts on ecosystem structure, function, and dynamics (Luck and Wu, 2002). Between 1992 and 1997, agricultural land was converted at five times the rate of population growth, has fragmented the agricultural land base, and driven up land values. The "market value" for such non-agricultural land-use is normally significantly higher than the value of the same land for agricultural production.

Irwin and Bockstael (2007) investigated the dynamics and spatial distribution of land use fragmentation in a rapidly urbanizing region of the United States to test key propositions regarding the evolution of sprawl. Estimated gradients described mean fragmentation as a function of distance from urban centers and confirmed the hypotheses that fragmentation rises and falls with distance. It was found that substantial and significant increases in mean fragmentation values along the entire urban–rural gradient. These findings were in contrast to the results of (Burchfield et al., 2006) who concluded that the extent of sprawl remained roughly unchanged in the Unites States between 1976 and 1992. Both the data and pattern measure used in their study were systematically biased against recording low-density residential development; the very land use that we find is most strongly associated with fragmentation.

An attraction effect associated with natural amenity in rural areas has concentrated development (Aydemir et al., 1993) and increased costs to society through the loss of natural habitat / landscape “pieces.” The transition of parcels from old farms to subdivided lots for high or low-density residential development affects tree canopy cover and greenspace with resulting effects on ecosystem function (Gobster and Rickenbach, 2004).

The impact of interstate highway system expansion has lowered transportation costs, opened large tracts of agricultural land for development (Mothorpe et al., 2013), and led to an extended period of land use conversion and suburbanization. (Alonso 1964; Mills 1969; Muth 1969) developed a theoretical link between transportation costs and land conversion on the urban fringe; Baum-Snow (2007a) continued this link and calculated that each additional mile of interstate highway corresponds to 468 acres of agricultural land.

Wassmer (2008) analyzed differences in the degree of urban decentralization in the U.S. by focusing on the relative comparison of the influence of auto reliance, “natural evolution,” and “flight from blight factors.” As modelled, the latter category exerted a far greater magnitude of influence. (Brueckner and Fansler, 1983) modeled urban sprawl in regressions using explanatory variables that included population, agricultural land price, income, and commuting cost. Castle (2001) regards population density, commuting distance, and personal space as a fundamentally important aspect of the land use debate. Acreage development is being driven by “personal desires” to escape the stressful, fast-paced city life and its associated traffic, noise, congestion, and crime.

For some researchers, urban decentralization has produced desirable outcomes that included the increased satisfaction of housing preferences, the accommodation of automobile travel, the benefits of later filling in of “leapfrogged” land, and the generation of an increased number of suburban local governments providing better schools and policing (Siegel, 1975)

Undesirable outcomes occurring in sprawling metropolitan areas include increased automobile travel and congestion (Ewing, 1994), the disappearance of open spaces (Burchell et al., 2002), the degradation of urban fringe ecological environments (Nuissl et al., 2009), air and water pollution, and loss of farmland (Gordon and Richardson, 1997; Glaeser and Kahn, 2003). Sprawl is also associated with the lack of contiguous residential development that increases public service costs, lack of employment accessibility, concentrated poverty, and racial and economic segregation (Ewing, 1994, 1997). Urban sprawl and the (in)efficiency of farmland conversion have been a focus of neo-classical economists and planners since the 1930s (Plaut, 1980). If the undesirables of decentralization outweigh the desirables (as many urban planners believe), then it is appropriate to consider the adoption of public policies designed to reduce sprawl.

Urbanization is also a major threat to biodiversity due to the direct destruction of natural and semi-natural habitats and to the indirect impacts caused by urban areas beyond their limits. Vimal et al. (2012) proposed a methodological framework to assess the potential impacts of current and future urbanization on rural sites. An adapted land-use change (LUC) model was developed to project future urbanization over a 20-year period using a 100-meter grid cell. A multi-level approach based on impacts of urban development correctly identified the direct consumption of high diversity sites, and indirect urban effects on the surrounding area over scales of 2 km and of 50 km.

Brueckner (2000), Mills (1999), and Gordon and Richardson (1997), made appropriate empirical measures of differences in the degree of sprawl. Economists have associated the degree of sprawl in an urban area with “excessive” decentralization, which imposes greater net costs upon society than would have been generated if the corresponding urban development had instead occurred in the area’s central places and/or at a higher overall density. Urban planners often identify sprawl through the description of specific types of undesirable urban land uses. Ewing (1994) measured the characteristics of sprawl’s occurrence including: (1) low-density (also Galster et al., 2001), scattered, and/or dispersed development; (2) separation of where people live from where they work; and (3) a lack of functional open space.

The traditional monocentric urban model of Alonso (1964), Mills (1969), and Muth (1969) structured regression analyses that explained differences but does not account for other household characteristics due to the assumption that, with the exception of income, households are identical in the characteristics that influence their land use preferences.

With the “congestion effect”, Carrion-Flores and Irwin (2004) used parcel level data, which corresponds best to the household economic decision. The findings indicated that higher population density decreases the attractiveness of areas that are already substantially developed; new urban development is less likely to be located in densely developed areas. Sancar (2009) studied employment that is too dispersed and urban areas that are “not sufficiently dense” but lacked fine-scale land use data to quantify spatially explicit urban land use patterns beyond the extent of a single county or urban area. Yet it is precisely this fine-scale pattern with which the debate over sprawl and its impacts is principally concerned.

Urbanization is rapidly moving beyond the suburbs. As a result, competition has developed for incompatible uses of agricultural land. Land allocated to farming provides a flow of both market and nonmarket benefits to society (crop production and open space). Developers, on the other hand, seek these same lands for profitable building sites. The effects of expanding development in rural and urban-fringe areas can be divided into two primary categories: direct conversion of farmland (satisfying the demand for residential, commercial, and industrial land uses) and the indirect effects (reduction of the agricultural potential of the remaining farms).

Estimates of the agricultural land converted annually to non-agricultural uses vary between 800,000 acres to more than 3 million nationwide. More important than the exact rate of conversion is the location of rapidly changing land use. Much of the land being lost is prime or unique farmland, disproportionately located near cities. Fifty eight percent of the total U.S. agricultural production comes from counties that the Census Bureau classifies as metropolitan and their adjoining counties. Converting a tract of agricultural land to a non-farm use in these areas has long-term consequences. First, development immediately exhausts the agricultural productivity of the reallocated tract; unfortunately, often causing the preferential conversion of highly productive land. The characteristics of quality farmland (flat or well drained soils, level terrain) that make farmland advantageous for agricultural production also makes these lands attractive for housing and commercial uses (Barnard, 2000). Second, loss in terms of the opportunity foregone from the agricultural, open space, and related amenity benefits would be experienced indefinitely. A decision to restore the agricultural viability of a residential subdivision would not be feasible.

Additionally, development indirectly reduces the productive potential of surrounding agricultural land by limiting its current or future use. Impacts on the converted tract itself may be small in comparison to the current and future consequences impacting adjacent farmland.

Restrictions are often imposed on typical farming activities (such as the application of pesticides or manure) that affect the health, safety, and welfare of the growing non-farming population.

Bukenya et al. (2005) identified that the negative impacts of the new land-use patterns are most readily felt on the farm in terms of: reduction in the number and size of farms; an increase in the average age of farmers, with fewer young people venturing into farming; a general weakening of resource-based rural economies; and numerous other economic and social problems (Workman and Allen, 2003; USDA-NASS, 2001).

As a spatial process, urban growth subtly erodes rural communities through the breakdown of both social and physical networks (Ilbery, 1985). Incompatible uses develop when non-farming populations move into areas of active agriculture, reducing the viability of agriculture and creating neighborhood social conflicts in the rural-urban fringe. With larger non-farming populations, the political and social influence of the farmer in rural areas is diminished as well.

Carver and J.E. Yahner (2004) investigated sprawl and neighborhood social conflicts between non-farm residents and farmers using probit and ordinal probit regression models in an analysis of census data from the multi-county survey of farmers in areas where sprawl has been identified to be a problem.

The amount of farmland in the United States reached a peak at slightly more than (1.2 billion acres) around the mid-point of the last century (Gardner, 2002). In the half-century since, farmland has declined by about a quarter, to slightly less than (937 million acres) (USDA-NASS, 2005). While the rate of loss has been relatively constant over time, it has not been uniformly distributed geographically. These localized losses of farmland have raised a variety of concerns among both farmers and others (AFT, 2003; Hellerstein et al., 2002; Libby and Stewart, 1999).

Agriculture as an employer also remains relatively important in the fringe, despite nonfarm growth and development. Farming remains relevant in the urban shadows, perhaps even an amenity attracting some of the population growth in these regions.

In the rural urban fringe, processes of growth, community capacity, questions about how "community" develops, the locational arrangement of housing, subdivisions, shopping, or social institutions do not conform to traditional patterns found in cities, villages, and suburbs. Substantial U.S. population growth in relatively rural areas adjacent to large urban areas is creating renewed interest in the rural-urban fringe. Fringe residents have many attributes that place them in a middle position between suburban and rural places and residents. Sharp and Clark (2008) determined the extent to which the fringe is similar to or dissimilar from the suburbs or more rural areas. Findings indicate that the fringe does deviate from the urban continuum, though, particularly in terms of where residents work and the distance they drive to their place of employment. Fringe settlement is possible due to proximity to urban/suburban agglomerations of jobs and services. Finally, an analysis of the inner and outer portions of the fringe suggests it might simply be evolving in accordance to urban proximity.

Despite demographers reporting dynamic U.S. population changes at the interface between large urban and relatively rural areas (Johnson, Nucci, and Long, 2005; Heimlich and Brooks, 1989), study of the rural-urban fringe has received only modest attention from urban and community sociologists in the past. While some scholars have systematically examined matters of land-use policy and growth management at the rural-urban fringe (Daniels, 1999; Nelson and Sanchez, 1997; Davis, Nelson, and Dueker, 1994; Nelson, 1992), this work masked much of the change and provides little knowledge of fringe residents and communities.

Many of the negative effects of land consumption can be attributed to the “sealing” of soils (Scalenghe and Marsan, 2009). The transformation of arable or natural land to impervious cover can thus be taken as a ‘key variable’ when it comes to mapping and evaluating land use change and its impacts along the urban-to-rural gradient (Arnold and Gibbons, 1996).

La Greca et al. (2010) studied the role that Non-Urbanized Areas (NUAs) play in being part of agricultural and green infrastructures that provide ecosystem services. Their role is fundamental for the minimization of urban pollution and adaptation to climate change. Like all natural ecosystems, NUAs are endangered by urban sprawl. As regulation of sprawl is a key issue for land-use planning, a land-use suitability strategy model to orient land uses of NUAs, based on integration of Land Cover Analysis (LCA) and Fragmentation Analysis (FA), needs to be researched. With LCA, the percentage of evapo-transpiring surface is defined for each land use, whereas dimensions and densities of NUAs patches are assessed in FA.

Various state and local governments have responded to these concerns by enacting a broad array of measures designed to protect farmland from development for more intensive uses (AFT, 1997). Some have suggested that the viability of individual agricultural producers may be adversely affected by the conversion of agricultural lands to other uses (e.g., Lynch and Carpenter, 2003; Heimlich and Anderson, 2001; Olson, 1999; Lockeretz, 1989). The loss of markets or input suppliers could have a roughly equivalent effect on all producers within a region, while at a more local scale, conversion could disproportionately increase the costs of neighboring producers by increasing the extent to which these producers come into contact and conflict with other land uses (Olson, 1999).

Scattered residential development also increases the potential for nuisance conflicts. As new neighbors voice opposition to the odor, noise, and dust, potential problems associated with typical agricultural operations increase (Barnard, 2003). Furthermore, even if an area's proportion of agricultural land area remains high, but available only in smaller scattered parcels, farmers may be prevented from employing newer technologies that require more land to achieve full economies of scale. Such restrictions reduce efficiency and increase production costs, perhaps even leading to premature idling of land. Neighborhood social conflicts between non-farm residents and farmers' agricultural operations can interfere with residential uses, while rural non-farm dwellers can hinder the use of land for agricultural purposes (Dowling, 2000; Roakes, 1996).

Local government officials and planners may want to explore ways of further building relationships between farmers and non-farmers. The generally positive sentiments of non-farmers toward farming may have social capital like resource potential for developing local food systems (Lyson, 2004) or managing conflicts that arise where farm and nonfarm interests clash. The conversion of farmland could also generate benefits for other agricultural producers, including creating markets for outputs such as specialty food products or creating a buffer zone between incompatible agricultural operations (Heimlich and Anderson, 2001).

In appraising the attack on sprawl, (Brueckner, 2000) argues that criticism of urban spatial expansion is "only justified in the presence of market failures or other distortions, which bias the normal expansionary effects of population and income growth in an upward direction." This includes a failure by developers to account for the amenity value and has led to excessive conversion of agricultural land and undesirable sacrifice of farmland along with a loss of amenity benefits from open space in the rural urban fringe.

Putnam (2000) argued that the low-density suburban lifestyle associated with sprawl weakens social capital and thus, the level of social interaction, leading to a less-healthy society.

In choosing space consumption, a household would consider the direct gains from having more room, along with the negative effect on the social interaction it enjoys and the external effects of consuming more space, which consists of less social interaction for all its neighbors. The result is a density externality, which makes space consumption inefficiently high for each household, an effect that translates into an inefficiently low level of population density for the neighborhood.

These constraints have influenced the farmer's pattern of response to external forces (Sharp and Smith, 2002; Lockeretz et al., 1987). The overall response of individual farmers to urban development pressure is highly asymmetrical. Land use decisions for many farmers are influenced by their unique relationship with the land as steward and by their attraction to the agrarian pattern of life. Yet for others, emotional and social factors associated with land attachment, farmer social networks, and even agricultural production itself become subordinate to economic objectives tied to speculation in urban land markets. Berry (1978) suggests that this malaise or "impermanence syndrome" develops with declining expectations of maintaining a viable living in agriculture.

A number of researchers have examined the impact of local low-density residential growth in the rural-urban fringe. Low-density growth has accounted for a 50% greater reduction of farmland near urban areas (Anstey, 2009; Levia, 2000). With a diminished visual landscape of residential sprawl and associated land fragmentation, the "value of the view," that is, the symbolic nature of farmland can also be compromised (Paterson and Boyle, 2002). This transformation of the rural landscape character diminishes attachment value for agricultural owners. New residents, assumed to have no previous association with the land, do not perceive any attachment value component or "occupier preference" (Anstey, 2009). Other researchers designate a "neighborhood" surrounding a landowner's property to measure household characteristics (Polimeni, 2005; Ready and Abdalla, 2005; Goovaerts and Jacquez, 2005; Paterson and Boyle, 2002).

2.3.2. Farmland Preservation and Land Use Policy

Farmland Preservation refers to policies that perpetuate a given land use through an enforceable legal restriction — mainly permanent easements restricting development. Providing preferential (i.e., reduced) land tax is one of the most common agricultural land protection strategies across North America (Stobbe et al., 2011). The goal of preferential land taxes is to make agricultural use of the land relatively more attractive in the hopes of preventing or delaying development. However, research indicates that taxation alone is not an effective method of preserving agricultural land (Anderson, 1993; Conklin and Lesker, 1977). Taxation distorts property values and subsidizes speculation on farmland allowing farmers to hold out for the highest price (Nelson, 1992; Blewett and Lane, 1988). Although tax policies might increase net farm income by reducing the tax rate, they do not encourage farmers to make their land more productive. The persistence and adaptation of farmers is obviously impacted by land-use change and the rate of farmland loss (Ilbery, 1985).

Duke and Lynch (2006) established a conceptual framework that distinguishes farmland retention by classifying 28 techniques into four types: regulatory, incentive-based, governmental participatory, and hybrid. The analysis reveals that techniques often perceived to be incentive-based, such as the purchase and transfer of development rights (PDR/PACE and TDR), are better understood as participatory and hybrid techniques. Likely fiscal impacts, stakeholder acceptability and implementation challenges were assessed. The framework suggests that when governments select multiple techniques, attention should be paid to the implied allocation of property rights to maintain coherent land-use policy and minimize property rights conflict. In contrast, conservation refers narrowly to policies that affect the types of permissible agricultural or other land uses, with a goal of reducing environmental degradation.

Access to farmland can be a major limitation at the RUF due to the competition between farm and non-farm development (Inwood et al., 2012); additionally, concern over intergenerational issues in the RUF is warranted due to the particular vulnerability of farmland being converted to non-farm uses during the phases of succession and inheritance (Sharp and Smith, 2004; Hirschl and Long, 1993). State agencies have been encouraging the development of different (rural or farm) enterprises. There are a number of factors that can influence adaptation of these enterprises (the ways farm families adjust their deployment of resources in response to changing and evolving conditions). Barbieri and Mahoney, (2009) used principal component factor analysis performed on the importance ratings of diversification goals, an attractive farm adjustment strategy, which resulted in six dimensions of entrepreneur and farm characteristics and goal pursuit dimensions. These included operator's age, number of generations the farm had been in the family, household income, number of farm employees, farm size, and distance to an urbanized area—that influenced types of goals pursued through diversification.

The maintenance of agricultural landscape integrity is an important factor in land use choices that many farmers make, suggesting that farmland should be protected (Conklin and Lesker, 1977). In general, farmland preservation policies modify land markets by removing speculative and consumptive components from agricultural land markets. Their intended effect—reducing farmland loss and keeping farmers solvent—has also had the unintended effect of inhibiting residential growth in the rural-urban fringe.

In some cases, policy makers have been able to stem the tide of development in the rural-urban fringe by using a limited set of planning tools including: agricultural zoning; purchase of development rights; and property tax credits, among these Michigan's Farmland Preservation program (Public Act 116, or *PA116*). However, these programs are costly, and incentives alone may be insufficient to encourage farmland retention under the pressure of even moderate urban development (Daniels, 2000).

Zoning was ruled constitutional by the U.S. Supreme Court in 1926 (see Euclid v. Amber Realty Co., 272 U.S. 365); zoning is justified under the police powers of the state to prevent land uses that "threaten the safety, health, morals, and general welfare of the public." Zoning ordinances influence urban land use primarily through the physical isolation of uses. While zoning is the primary method used to influence urban land use, relatively little zoning is practiced in rural and urban-fringe areas. Agricultural zoning is generally used by rural communities that are concerned about maintaining the economic viability of their agricultural industry (York and Munroe, 2009). This is typically accomplished by regulating the density of development and restricting non-farm uses of the land. In many agricultural zoning ordinances, the density is controlled by setting a large minimum lot size for a residential structure. Densities may vary depending upon the type of agricultural operation. Minimum lot size is the primary conventional zoning method used to insure low residential density in rural areas. However, two, five, or even 10-acre residential parcel size restrictions do little more than scatter development and consume or cripple prime farmland.

Agricultural zoning can protect farming communities from becoming fragmented by residential development. In many states, agricultural zoning is also necessary for federal voluntary incentive programs, subsidy programs, and programs that provide for additional tax abatements. Zoning is the most predominant land use policy in the U.S. used by most communities to implement their master plan, but is weakly significant in the protection and retention of agricultural land.

Another variant, open space zoning relies on the principal of cluster development, whereby new homes are clustered onto part of the development parcel. This clustering allows the parcel remainder to be preserved as productive farmland or unbuilt open space. Exclusive agricultural zoning is one technique used to implement the objectives of agricultural preservation within a master plan. Certified exclusive agricultural zoning ordinances, which are required for participation in zoning, regulates the type, intensity and location of development admissible in a rural community (Wyckoff, 1987). Exclusive agricultural zoning is less frequently used than open space zoning, because it prohibits nonagricultural use of the land within the entire district ensuring there will be no conflict between residential and agricultural uses.

There is great variation in the incentives and disincentives on landowners, particularly because of local councils and board of zoning appeals' willingness to grant variances, zoning amendments, and special exceptions. Land-use institutional decisions are not made in vacuum; changes in the regional economy, as well as loss of culturally and economically important rural lands, will affect zoning and planning decisions.

Kaplowitz et al. (2008) noted that urbanizing areas must contend with a host of land use challenges (agricultural land preservation, habitat fragmentation, historic preservation, affordable housing, and infrastructure planning) and seek market-based policy solutions. As indicated above, these take two basic forms, either purchase of development rights (PDR), or transfer of development rights (TDR). They result in an easement becoming attached to the agricultural land that restricts the right to convert the land to residential, commercial, and industrial uses. Preservation of natural resources is done at low public costs (e.g., Danner, 1997) as the landowner is provided with a cash payment and/or tax benefit for participation (Lynch and Lovell, 2003).

In (Duke et al., 2012), results of a "choice experiment" measured social benefits for sustainable management practices and agricultural land preservation. Sustainable management is conceptualized with three illustrative practices that impact water quality, carbon sequestration, and soil erosion. This research examined possibilities for subsidizing sustainable management practices in urban-influenced areas as a more cost-effective means of providing benefits similar to those realized through land preservation.

Land use conversion has resulted in subdivision of farms into large residential parcels. Some of these "residential" parcels retain sizeable areas of undeveloped prime agricultural soil, yet the land is effectively removed from agricultural production.

Using a discrete choice model, (Lynch and Lovell, 2003) found that both landowner and parcel characteristics affected the probability of participation. Generally, the likelihood of participation increases with farm size, growing crops, if a child plans to continue farming, eligibility, and the share of income from farming. Landowners located closer to the nearest city were less likely to join a preservation program. Probabilistic modeling of the effects of different alternative land use policies offers decision makers a variety of ways to envision the range of outcomes of their potential decisions and compare among these outcomes.

Erickson et al. (2011) explored landowner willingness to enroll a portion of their land in a cooperative land management (CLM) scheme. CLM refers to embedding production agriculture and other cooperative land use options in residential parcels. A cluster analysis partitioned the respondents into five clusters based on the following variables: percent of agricultural land on parcel, parcel size, years in residence, and the population density of the town where the parcel is located. A cluster containing a high percentage of agricultural land ("farms") had the highest support for production agriculture options, while a cluster of long-term residents (old timers) had the lowest. Farmers were seeking access to affordable farmland through planning efforts that increased regional landscape multi-functionality. The investigation revealed the willingness of suburban and exurban (an area beyond suburbs, inhabited by many who work in the city) landowners to participate in a variety of multifunctional land management options, particularly food production.

Nielsen-Pincus et al. (2009) evaluated the effects of predicted exurban development using three measures: 1) the number of housing units predicted on productive agricultural lands; 2) the number of housing units predicted on a groundwater resource area; 3) the social acceptability of residential development patterns given current development preferences. Findings demonstrate the importance of using multiple indicators to evaluate growth management and land protection policy tools for making land use planning decisions.

Choosing among alternative land use policies is a difficult challenge; planners use study results to determine which policy alternative provides the greatest benefit for the measures they consider most important and can plan to compensate for negative impacts indicated under each zoning option. Often environmental, social, and aesthetic effects of prime farmland loss are not readily quantifiable financial resources for current zoning policies. Voluntary creation of agricultural districts included differential assessment, protection against nuisance ordinances, and limits on public investments for nonfarm improvements.

Nielsen-Pincusa et al. (2009) also predicted the effects of residential development on a rural landscape under alternative growth management and land protection policies. One of the biggest differences observed was the level of policy development, which actually varies more within a region than between regions of the state. This result supports the notion that the *fringe* should be treated as a distinct form of settlement along the rural urban continuum, not simply the suburbs of the suburbs.

Munroe et al. (2005) also assessed the impact of zoning with the statistical relationship between landscape fragmentation and various socioeconomic, biophysical, and spatial variables associated with land use and land cover at the scale of individual, privately owned parcels. The diversity of land uses is much higher at the aggregate level and at the parcel level, particularly in areas that are zoned to allow for the highest density in housing and smallest lot sizes (van Oort, 1999).

Local government officials and planners may want to explore ways of further building relationships between farmers and non-farmers. Again, the generally positive sentiments of non-farmers toward farming may provide a social capital-like resource potential for developing local food systems (Lyson, 2004) or managing farmer and non-farm resident conflicts that occur with differing interests.

2.3.3. Farmland Value

During the 1980-90s, examination of economic impacts of urban development has been focused on how rural space becomes capitalized (Livanis, 1998; Capozza and Helsley, 1989). In the analysis of farmland conversion, land value is correlated with the future value of agricultural production and potential development. Agriculture continues at the urban fringe only as long as the returns from farming exceed potential returns from urban uses. Because these studies use data aggregated at the county level, they shed little light on household decision-making processes.

Revealed preference studies incorporated locational effects and the endogeneity impacts of surrounding land uses to model factors that influence land value (or housing price). Household land decisions are structured as binary choices; conversion of land is based strictly on land value. This approach fails to consider that, in many cases land conversion is a gradual process in which farmland owners sell off land parcels piecemeal over time. Previous analyses viewed conversion as the outcome of cumulative change measured at a given end-point in time, again in binary terms—either conversion occurred, or did not occur (Polimeni, 2005; Ready and Abdalla, 2005). An alternate approach makes use of continuous measurements of land use at the parcel scale over time, enabling the capture of subtle changes when modeled as a direct response to neighborhood factors.

Individual farmers' response to increased valuation of their own, and neighboring farmland holdings are important in shaping land use decisions (Polimeni, 2005). However, analysis of the *process* of farmland loss must also account for non-economic factors that describe farmers' attachment to farmland as it embodies community social capital. The influence of these *social capital variables* has not been specifically addressed in previous approaches. This work proposes to explore the empirical link between non-economic factors and land use change. The focus is placed on the importance of social capital in managing change at the individual and community levels in relation to land use at the rural-urban interface.

The potential agricultural production of parcels is a significant factor that can explain the pattern of conversion (Clouser, 2005). Parcels with higher expected incomes from agriculture are less likely to be converted to residential land use. However, land that is best suited for agriculture is also often the best for development. This study explores these possibilities by including prime farmland as a variable.

The generally accepted theoretical *definition of land value* is the present value of the expected future stream of income and benefits from the land (Mills and Hamilton, 1989; Barlowe, 1986). The value, *V*, of a rural parcel to an existing or prospective landowner can be expressed generically as:

$$V = \mathrm{PV} + \mathrm{CV} + \mathrm{AV} + \mathrm{SV}$$

where: PV is the productive value, i.e., the present value of expected net returns to the land as an input to agricultural production, assuming a commercial rate of return (Pope, 1987). CV is the consumptive value, which is derived from the utility of the land as a residence, recreational resource and base for access to urban employment, education and social opportunities (Barr, 2003; Nelson, 1990). SV is the potential future sale value, which primarily comprises the discounted present value of any expected future sale price of the land, taking into account any capital gains tax payments and other costs expected to be associated with that transaction (Smith, 1967) while AV is the attachment value. This was separately recognized for the purpose of the research, to support conceptual analysis of the land use choice. It is believed to derive from positive emotional associations with a particular area of land, such as might arise from having grown up or raised a family on the land (Anstey, 2009).

Other land value and cost components, including any difficult to measure attachment value and transaction costs for the existing landowner, may affect land use choices, particularly by preventing the sale of a parcel. However, non-economic cannot be measured directly. Previous research has established that there are a number of factors that contribute to agricultural conversion, including farm size, distance from CBD and land value (Levia, 2000). This research aims to specifically look at the non-economic aspects of agricultural land conversion. Attachment value can only be measured indirectly.

In the context of urban encroachment, land rents on the relative amounts of agricultural land rent and indicators of land productivity are the most important predictors of the proportion of agriculture and urban uses. Rural land rents are overshadowed by urban land rents that drive land-use conversion. Chicoine (1981) noted that soil productivity's influence on farmland prices at the urban fringe market appears to be overshadowed by the locational attributes of parcels. Clonts (1970), in an analysis of land values at the urban periphery, estimated that urban development explained 30 percent of the variation in the value of land and improvements. Location has long been recognized as an important factor in explaining rural land values need to consider spatial characteristics in conducting economic research.

York and Munroe (2009) indicated that land rents and land characteristics guide land-use decision-making, as well as evidence of structural changes in urbanization processes. Land use change driven by exurban development has led to dramatic alterations in the structure and function of landscapes. Residential development outside of urban and suburban zones can disrupt agricultural and often leads to social conflict. Drozd and Johnson (2004) identified components that contribute to farmland values in urban-influenced real estate markets that are experiencing land use transitions. A model based on farmland productivity determines a "crossover point" where it becomes economically justifiable to convert farmland into acreage tracts. The concept of a "crossover point", in terms of market value, is where rational sellers of farmland would be economically enticed to change the land use and subdivide farmland into acreage tracts.

The development of the landscape is seen as a consequence of infrastructure and household preferences where buyers having special motivations often pay premiums to obtain agricultural land. Population changes are driven by natural growth and job-related migration (Capozza and Helsley 1989). Because amenity-based growth is driven by seasonal and retirement housing, it can occur well beyond the commuter shed of a metropolitan area. Unlike traditional rural development models, the relative and absolute productive capacity of the land resource plays little part in the decision making of incoming residents (Dillman, 1979). Amenity-rich areas experience “life-cycles” of growth and change driven more by the overall popular perception of a region than by an individual’s preferences (Butler, 1980). In both cases, the growth in amenity-rich rural areas is externally driven and the well-being of such communities becomes more closely associated with the well-being of distant urban economies.

Parcel size is often a critical factor; a parcel too small is impractical to manage for farming, while parcels too large may be impractical for housing or other consumptive uses (Gobster and Rickenbach, 2004). Parcel sizes help determine market values; land has not only a per-acre value, but also a value that derives from the necessary parceling for purchase, also known as *plattage* (Chicoine, 1981). The per acre land value for agriculture is different when that land converts to development. The premium can be two or more times the agricultural value when subdivided. Thus, parcels too small for one use may be subdivided to smaller parcels for another use.

Jeanty, et al. (2010) identified local interactions between housing prices and population migration to estimate a spatial simultaneous equations model that jointly considers population change and housing values, while also explicitly modeling interactions within neighborhoods, spatial interactions across neighborhoods, and controlling for unobserved spatial correlations.

Donnelly and Evans (2008) attempted to quantify the landscape features that influence rural parcelization: the division of land into smaller parcels and their subsequent sale on the market. It is through parcelization that the relatively raw resource of land is refined and packaged for wholesale and retail consumption as real estate. The characteristics of parcels can have significant impacts on the uses available to a parcel owner.

Parcelization of land ownership is a complex process that has dramatic implications for how landscapes are managed and how socio-economic changes. The pattern of land ownership is highly dynamic in the fringe, complicating efforts to create a landowner-landscape linkage over time. This has presented obstacles to the understanding the relationship between household/landowner characteristics and land cover change outcomes. Land cover is shaped by a combination of individual decisions, macro-scale social factors, and biophysical conditions. Land ownership is the link between land management decisions and landscape outcomes.

The process of parcelization can provide insight into the spatial pattern of land cover, as parcel size itself is an indicator of land use. The relationship between parcelization and land use change is particularly apparent at the exurban fringe where the rate of land use and land cover change is typically more rapid than in rural areas (Evans et al., 2001a). The transition of parcels from old farms to lots subdivided for high or low-density residential development affects tree canopy cover and greenspace with resulting effects on ecosystem function (Gobster and Rickenbach, 2004) as the rate of parcelization in many rural areas of the United States is increasing.

It is accepted in the literature that expected net returns are the driving force behind land values. Land's capitalized value, using a net present value calculation, is a static valuation and does not fully represent true market value. Isgin, et al. (2007) suggest that an important component of urban fringe farmland values may be the option value arising from nearby urban development. The hedonic pricing approach was used to determine the relationship between farmland option values and parcel characteristics under urbanizing influences and predict the differences attributable to the in the levels of these urban characteristics. The option value (or premium) of a parcel under urbanization influences land values and incorporates both the uncertainty about the future net benefits of a land conversion decision and the irreversibility of the action taken. Option premiums play the key role in land price formation and tend to increase in value as the rural-urban fringe moves closer to the agricultural land, reflecting substantial increases in the net value of land in urban usage. The hedonic option-pricing model recognized that this option use varied explicitly with the understanding that urban fringe farmland option pricing determinants are derived from the decisions based on *unobserved* farmer appraisal.

Abelairas-Etxebarria and Astorkiza (2012) studied the factors that determine the prices of farmland that are close to densely populated urban areas and changes in land use experiences, as well as the additional control policies needed to curb this unsustainable trend. This research investigated land use bordering on non-protected rural area as a reference for comparison. A spatial hedonic farmland price model was estimated and the willingness of land purchasers to pay ("WTP") for different farmland characteristics. The main results were: (1) residential development is taking place in all categories of farmland, and (2) aside from neighboring land prices, farmland prices depend on different factors depending on whether the marketed plots stand available.

2.3.4. Land Use Modeling

Land use refers to the purpose the land serves for human beings, for example, recreation, wildlife habitat, or agriculture. Remote sensing techniques usually relate to land cover from which land use can be inferred. A number of studies have analyzed land use or land use change, including conversion from agriculture to *rural* residential land use, using discrete choice models (Newburn and Berck, 2006; Carrion-Flores and Irwin, 2004; Irwin et al., 2003; Irwin and Bockstael, 2002; Kline and Alig, 2001; Bockstael, 1996; McMillen, 1989). At highly disaggregate scales (i.e., individual land parcels or cells of the landscape) researchers were interested in explaining the *causal* relationships between individual choices and land use change outcomes, more fully articulated economic models of land use change are necessary.

However, conceptual models presented in those studies did not adequately recognize the importance of characteristics of the existing landowner in influencing the availability of land for land use change. Virtually every farm conversion study utilizes land value as the dependent variable; studying and acquiring accurate temporal land value data has proven to extremely problematic.

As a consequence, some empirical studies did not either:

(a) differentiate between the types of land use decisions made in association with the conversion of agricultural land, or

(b) directly represent attributes of the existing landowner that might influence land availability (Carrion-Flores and Irwin, 2004; Irwin et al., 2003; Irwin and Bockstael, 2002; Bockstael, 1996).

Agent-based, discrete choice, and hedonic land use models explain the choice between two categories of land use (typically binomial probit or logit models) or several categories of land use (multinomial logit or nested logit). (Bockstael, 1996; Hsu, 1996; Kline and Alig, 2001; Carrion-Flores and Irwin, 2004; Newburn and Berck, 2006; Braimoh and Onishi, 2007); Páez (2009); Bell and Irwin (2002); Irwin et al., (2003); and Lubowski et al., (2008) have all applied such approaches. Logit models generally give qualitatively similar results to probit models (Gourieroux, 2000) and are more widely used due logit's computational simplicity relative to probit models (Bierlaire, 1997; Gourieroux, 2000).

The logit model formulation for land use choice is specified as:

$$y = a + b_1x_1 + b_2x_2 + \ldots + b_mx_m$$

$$y = \log_e\left(\frac{P}{1-P}\right) = \log it(P)$$

$$P = \frac{e^y}{1+e^y}$$

However, in this research the logit model might have simplified calculation and interpretation of probabilities but would only capture an on/off condition. Fleming (2004) indicated that introducing spatial dependence would render discrete choice models analytically intractable, and require the use of complex simulation or Bayesian techniques. Lewis (2008) highlighted the fact that incorporating a more general spatial dependence structure when jointly estimating discrete choice still remained an econometric challenge. Most land use studies based on spatially explicit data models avoid spatial error (i.e., autocorrelation) by using a spatial sampling technique to build a sample of non-nearest neighbors and, thereby, purge the data of spatial autocorrelation (Irwin et al., 2003; Carrion-Flores and Irwin, 2004; Irwin and Bockstael 2004; Lubowski et al., 2008; and Lewis and Plantinga, 2007). Land use choice research can also be categorized into *discrete choice* and *duration studies*. While the former examines the factors affecting choices among alternative land uses, the latter focuses on the factors affecting the timing of particular land use decisions (Bell and Irwin, 2002).

Agent-based computational models of urban land use change currently lack economic fundamentals, but provide a flexible means of linking micro-level behavior and interactions with macro-level land use dynamics. Agent-based computational models are at the forefront of the most recent wave of simulation-based modeling and have increasingly been adapted by every discipline save economics as the land use modeling method of choice. Economists have been slow to embrace this approach, perhaps because these models typically have omitted explicit representation of land markets (Irwin, 2009).

Economists have focused on development decisions by landowners or location decisions of households and firms at an individual level within an aspatial or highly stylized spatial setting. This approach has permitted consideration of key dimensions of constrained decision making, e.g., durability of capital (Anas, 1978; Harrison and Kain, 1974), intertemporal decisions (Capozza and Helsley, 1989; Fujita, 1982), and uncertainty (ibid.), land use (Plantinga et al.,1999) and how these features influence the resulting price gradient and land use pattern. The term "structural" is used in the economic sense of a model with structural parameters that correspond to a microeconomic process that determines macroscale outcomes, (e.g., the parameters of a land developer's cost function or of a household's demand function that influence the resulting market prices).

In gravity models, regional transportation accessibility is core to the spatial allocation of jobs (by type) and households (by category). Forecasts across all zones, and have been found to perform less well with disaggregate zone systems and/or sparse zone activity. Spatial input-output models are used to anticipate the spatial and economic interactions of employment and household sectors across zones, using discrete choice models for mode and input-origin choices.

These economic models are distinguished from “pattern-based” models that describe meso- or macroscale correlations between observed patterns and other observable variables. Patterns, either static or evolving over time, are the outcomes of processes. Patterns are revealed by spatial land use/land cover data “process-based” models focuses on the structural micro-foundations of the observed outcomes that in aggregate generate the observed land use pattern. Using a GIS-based model of the actual landscape, (Cunningham, 2008) developed option value models that account for the influence of uncertainty over future prices. This permits the role of individual-level factors in generating regional land use patterns, including land use policies and other spatially heterogeneous features of the landscape, to be investigated. Results can then be compared using spatial statistics or landscape metrics to draw conclusions regarding the predicted influence of these factors on the concentration, fragmentation, or other spatial dimensions of land use.

A “dynamic” process is one that transitions over time, individual as “forward-looking behavior.” Decisions are dynamic if they consider future expected benefits and costs. Dynamic decision is made at an individual scale (e.g., choice of land development over time) reaching static spatial equilibrium at an aggregate level.

Various dimensions of heterogeneity are important in land use modeling: “spatial heterogeneity” refers to spatial variations at local scales, e.g., land parcel or a local neighborhood around a given location, and “agent heterogeneity” refers to key differences among individual households, firms or other agents, each with differences in preferences, wealth, technology, or expectations. Focus is mainly on models that incorporate multiple sources of spatial heterogeneity, but acknowledge that agent heterogeneity is likely just as important for modeling spatial land use dynamics.

The term “spatial dynamics” refers to a spatially dependent dynamic process in which a change over time at one location is dependent on the state or changes in the state at other locations. This type of endogenous spatial dependence may arise, for example, from local interactions among spatially distributed agents or cumulative spatial feedbacks generated by the landscape decisions urban and rural. Economic urban land use change models that generate predictions of land use pattern are derived from structural economic models of land development decisions or residential location choice.

A variety of land use models now exist, driven by theoretical advances, data availability, enhanced computation, and new policy-making needs which simulate the subdivision and land use change of parcels, and the spatial allocation of households and employment across zones. Modeling methods vary dramatically across disciplines. Differences across disciplines are most evident between economics and quantitative geography (or GIScience). A large percentage of recent papers published in geography were simulation models, specifically either cellular automata or agent-based models.

Cellular automata (CA) models are used to simulate and/or optimize land use change (Balling et al., 1999). The CA based SLEUTH model (Slope, Land use, Exclusion, Urban extent, Transportation, and Hill shade) is the most widely applied (Syphard et al., 2005). Each of these models operates over a lattice of congruent cells. Cellular modeling methods underlie many land use land cover (LUCC) models. Tobler (1979) was one of the first to suggest the use of CA to model geographical processes. Cellular models have proven utility for modeling ecological aspects of LUCC, but lack behavioral foundations to explain the process. Moreover, they emphasize land-cover type, not land use intensity. Where cellular models are focused on landscapes and transitions, agent-based models focus on human actions and goals and can be grounded in one or more theories of behavior.

Wooldridge (1999) defines intelligent agents as being able to act with flexibility, which implies that agents are goal directed and capable of interaction with other agents and a common environment. Cellular automata and agent-based models often use statistical analysis to parameterize the model. This precludes much of literature in urban and regional economics on location and land use, including the canonical urban economic model. The monocentric model only allows for a single source of spatial heterogeneity-transportation costs to a central location and is of limited value in addressing ecological questions.

The dynamics of land-use and land-cover change are increasingly recognized as operating within a linked human-environment system that is shaped by the complex interactions of social, economic, climate, and biophysical factors (Turner et al., 2007; Global Land Project, 2005; Rindfuss et al., 2003a). In practice, the organization, function, and causes of land use activities are often not adequately considered in environmental change studies. As a result, the spatial and temporal complexity of human-environmental processes and feedbacks that operate at regional to global scales are not fully understood (Liu et al., 2007). Recent scientific thought emphasizes the longevity and sustainability of agricultural pursuits, while also recognizing the risks and vulnerability of the region to socioeconomic and environmental change and the opportunities to enable resilience (Parton et al., 2007). Wu and Hobbs (2002), and Grimm et al., (2008b) integrated socioeconomic and demographic models of human settlement, consumption, and land management dynamics with biophysical models. Because of the complexity in modeling land use and land cover changes over large areas, Drummond et al., (2012) found that analysis of agricultural regions is often hampered by change detection error and the tendency for land conversions to occur at the local scale. Pattern and magnitude of conversions are influenced by contextual conditions of land quality, and climate variability, plus economic and policy drivers.

In analyzing land use change at the local scale to forecast urban futures, Zhou and Kockelman (2007) developed a multinomial logit model of spatial relationships. Neighborhood impacts on land use change were derived from related processes of parcel subdivision and land development. Results indicated that local neighborhood conditions offer substantial predictive power, though these effects are inconsequential beyond two miles. Human interactions further strengthen or diminish the characteristics of local and regional-scale change through land use policies and economic opportunities, technological advances and agricultural inputs (Parton et al., 2007), and population and demographic shifts (Gutmann et al., 2005).

Econometric-based models of spatially heterogeneous land use patterns proceed in *two steps*. First, the econometric model is specified with a categorical variable representing land use as the dependent variable, which is hypothesized to depend on land rents from current and alternative land uses. Factors hypothesized to influence expected land rents are included as independent variables. These typically include heterogeneous landscape (soil and slope variables), location features (distance to CBD), presence of local amenities, neighborhood land uses), and policy constraints (zoning). Second, this model is then estimated using spatial, temporal land use at the scale of land ownership (land parcel).

This two-step approach has been used to model urbanization and sprawl (Carrion-Flores and Irwin, 2004; Irwin and Bockstael, 2002); the effects of land policies on urbanization patterns (Lewis, Provencher, and Butsic, 2009; Newburn and Berck, 2006; Irwin and Bockstael, 2004;

Irwin et al., 2003). In accounting for multiple sources of spatial heterogeneity, ecological features can be readily incorporated. Simulations are more appropriate for the analysis of marginal effects over shorter time periods (5–10 years).

As Glaeser (2008) notes in his book, *Cities, Agglomeration and Spatial Equilibrium*, the spatially heterogeneous models of urban land use patterns rely on spatial equilibrium assumption of urban economics upon which everything else stands. It can cost communities financial/technical resources to plan and address sprawl; often these surrounding rural areas do not have these resources as a way to measure urbanization patterns using freely available geospatial data with commonly found analysis software across an urban-rural continuum utilizing established political boundaries. Demographic data collected from census data and digital information derived through GIS were tabulated and ranked to form an index. This multi-indicator approach enabled (Glaeser, 2008) to measure how areas sprawled and to what degree.

2.3.5. Landscape Ecology

Urbanization is arguably the most significant form of land use change, as it has various impacts on the pattern, functionality, and dynamics of landscapes (Haase and Nuissl, 2009). The focus of landscape ecology is to investigate and understand spatial heterogeneity at multiple scales. Using the landscape ecology approach, DiBari (2007) applied landscape-level metrics to measure changes in landscape structure caused by urbanization over time.

If the costs of agricultural production play a relatively minor role in determining farmland conversion, there may be other spatial processes effectively driving land use change. There has been uncertainty over the relationship between farmland conversion and fragmentation of the agricultural landscape. DiBari (2007) compared the spatial distribution of agricultural lands before and after farmland conversion and examined the factors that influenced the spatial pattern of farmland conversion and the effect of the spatial pattern of conversion on continuing agricultural operations. Analysis at an individual parcel level over a relatively substantial time period was made possible by combining current data on individual tax parcels with historical data on withdrawal of land from differential assessment programs.

Landscape ecology has at its core the study of three landscape characteristics: structure, function, and change (Forman, 1995; Naveh and Lieberman, 1994; Turner and Gardner, 1991). Landscape structure refers to the spatial characteristics of landscape patches including their size, shape, composition, and spatial arrangement. The spatial landscape "patch", the basic building block for ecological landscape research, is defined as a relatively homogeneous area that differs from its surroundings in terms of key ecological features, including land use and land cover (Forman, 1995). Depending on the landscape and level of urbanization, patches with natural vegetation (e.g., forests, grasslands, wetlands), may vary from large contiguous blocks in more rural areas to smaller, more isolated patches in urban areas.

Landscape function refers to the ecological processes and relationships that exist within a landscape based on its structural characteristics. Landscape change refers to the dynamic nature of landscape structure and function over time, where changes are often the result of natural or anthropogenic disturbances. These disturbances can produce changes within and among patches, and in flows of energy and material.

A common source of data on individual parcels and a measure of landscape fragmentation was borrowed from the wildlife habitat literature. The fragmentation metric that seems best suited to capturing the relative extent of the interface between agricultural and other land uses is referred to as edge density, that is, "the total length of patch edge per unit area within each landscape," (Harris, Bissonette, and David, 1998).

Rank-size distribution is the distribution of size by rank, in decreasing order of size. The efficacy of rank-size distributions was tested with the other metrics and effectively described landscape structure including patch size, shape, or dispersion of specific land-cover types (Haase and Nuissl, 2009).

In areas of land use change, impervious cover effects become particularly obvious if observed and analyzed along an urban-to-rural gradient. Land consumption (i.e., the transformation of vegetated into built surface) is even more significant in that this interface is now often hardly perceptible; in many places the difference between urban, rural-urban fringe, and pure rural land use patterns has virtually disappeared due to the urbanization of 'the rural' (EEA, 2006). It is necessary to integrate historical data into a current land use change impact assessment and uncover effects of iterative and simultaneous phases of urban growth. In doing so, it provided evidence that what has been taking place at the interface 'between the urban and the rural' is not a linear and homogeneous process of urban expansion but rather a heterogeneous and often 'patchy business'.

Many rural counties have had net population loss, while there were substantial population gains in urban and fringe areas (Wilson, 2009). This is linked to decreases in farm numbers, larger farm sizes, and decreased labor needs of modern agricultural production (Hart, 2003). Public policies and subsidies that incentivize or delimit access to natural resources have a variable impact over time (Searchinger et al., 2008). Spatial ecological (landscape) information can be useful to development policy formulation, allowing diagnosis of rural ''health'' and sustainability.

Using parcel-level data, probit models were estimated to study residential land conversion. Studies of individual land-use conversion decisions have identified factors that drive changes at a disaggregate scale and involve the understanding of the factors that motivate an individual landowner to convert land. Individual land-use decisions aggregate over space and the extent to which they result in sprawl at a regional scale is not well understood. Certain parcel-level characteristics have been well-studied: high-quality soils are more likely to be converted. The probability of conversion is found to decrease with the size of the parcel, and the distance to large and small urban markets is significant—although not always in the expected direction. For those parcels located within the outer boundary of the urbanized area, the probability of conversion decreases at a decreasing rate with distance from CBD. For parcels located beyond this distance, the probability of conversion increases with distance from the urbanized boundary (Brueckner and Largey, 2006).

Local governments have adopted a wide range of anti-sprawl measures and price-based mechanisms such as impact fees that are designed to protect vacant land to slow the pace of development. Anstey (2009) examined the landscape pattern of unplanned rural living to assess whether its impacts are adverse enough to warrant land use policy change. A comprehensive conceptual framework was developed to inform empirical analyses based on data from individual sales as observation units. This approach provided the rationale for excluding the difficult to measure influences of a landowner's attachment to the land as explanatory variables. In order to avoid inappropriate conversion to unplanned rural living, Anstey's study focused on establishing the farm size (area required for a viable farm) and to set policy to establish the appropriate minimum parcel size.

Fragmentation of family-owned farms has been identified as the greatest single threat to nonagricultural value of rural land. Kjelland et al. (2006) examined the factors related to spatial patterns of rural land fragmentation. Trends in fragmentation was been found to be a reliable indicator of the "health" of agriculture but that fragmentation can vary depending upon land cover and prevailing land use. The effect of this increased fragmentation is to increase the extent to which the remaining agricultural lands come into contact with other land uses and, as a result, potentially increase the costs associated with production on these lands. One might expect that the most exposed parcels are also the ones that are most likely to be converted to another use.

While land-use/land-cover (LULC) changes in the rural-urban fringe (RUF) are often heterogeneous and fragmental in nature, detecting them in timely and accurate satellite imagery is essential for land-use planning and management. Although traditional spectral-based change-vector analysis (CVA) can effectively detect LULC change in many cases, it encounters difficulties in RUFs because of deficiencies in the spectral information of satellite images.

He et al. (2011) used an extended CVA approach by incorporating textural change information into the spectral-based CVA. By increasing overall accuracy of the extended CVA, more effective discrimination of LULC changes that are spectrally similar but texturally different in RUFs is needed. The dilemma of translating land cover data into meaningful estimates of sprawl continues. Land cover, in terms of physical characteristics, can be observed with aerial photography and is often interpreted successfully from satellite imagery, but it is land use, defined in terms of human activity, that is most relevant for the study of urban patterns.

Landscape ecologists (Wu and Hobbs, 2002) focus on the spatial heterogeneity of landscapes as a primary aspect of linking ecosystem processes and pattern ecology that highlight the importance of space and spatial dynamics. Ecologists' study of landscape processes and patterns emphasizes the critical role of space at all spatial scales. Multiple local sources of spatial heterogeneity create discrete differences in ecosystem function across the landscape. Multiple feedbacks occur between human and natural systems (Liu et al., 2007; Turner, Lambin, and Reenberg, 2007; Grimm et al., 2008a).

Abdullah and Hezri (2008) identified the link between changes in landscape patterns and land-related development policies. Spatial ecological information can be useful to development policy formulation, allowing diagnosis of the country's ''health'' and sustainability. Landscape analysis in the policy-making process is meant to prevent further fragmentation of the landscape and forest loss to larger, but highly fragmented patches, in suburban and exurban areas.

From an ecological perspective, urban development affects the patch structure of natural areas by altering its spatial pattern. Historical "legacy effects" were studied in which past states influence current functioning. This is an approach that accounts for spatial heterogeneity and spatial dynamics across multiple spatial and temporal scales. Likewise, an understanding of how individual decisions and actions can impact ecological processes requires a model that can account for the location of human activity and changes in these activities. Spatially disaggregate models of land use dynamics at the scale of land parcels are required. Urban economic models can be adapted to consider land use dynamics at these more spatially disaggregate scales by developing an empirical, analytical, or simulation models of urban land use change.

Levia (1998) examined the spatial pattern of sprawl and its change over time partially by measuring fragmentation. Distance to city center, nearby highways, and parcel size were all factors to consider in explaining a particular spatial configuration of land use. These were found to be related to the probability of conversion of farmland parcels at the rural urban fringe, known as hazard rate.

In a study of development and conservation policy, Irwin et al. (2003) build on other spatially explicit and disaggregate models of urban land use change, including the urban futures model by (Landis and Zhang (1998a, b), and work in the central Maryland region by (Irwin and Bockstael, 2002; Geoghegan and Bockstael, 2000; Bockstael and Bell, 1998). The rate of conversion zoning that affects the farmer decision is a binary discrete choice of converting the parcel to residential use value of the net expected returns from developing parcel $_j$, set of parcels that have "survived" in the undeveloped state until time T_n. This expression gives the ratio of the *n*th parcel's *hazard rate* to the sum over the hazards of all other parcels that have not yet been developed as of time period T_n. When multiplied by all other n –1 contributions, this forms the conditional probability that, given an event occurs in a particular time period, it occurs to a specific land parcel.

Using land use planning theory (Michigan Department of Agriculture, 2011), governments combat landscape fragmentation by controlling the type and location of land uses through planning land use patterns based on patch types (discrete and contiguous area of the same land use within a landscape). The hypotheses tested relates to the degree of landscape fragmentation as it varies across areas with different zoning policies, and that this relationship still holds when accounting for topographical and socioeconomic differences. Results show that a variety of factors influence a parcel's hazard rate, including several ‘‘smart growth’’ (sustainable development) policies as well as land use externalities from neighboring residential, commercial, and unpreserved open space lands.

2.3.6. Geospatial Analysis

Brunsdon, Fotheringham, and Charlton (1996) introduced the term Geographic Weighted Regression (GWR) to refer to a set of "spatially adjusted" regressions that operate by assigning a weight to each observation (*i*), which depends on its distance from a specific geographical location or focal point (*o*). This analysis has involved fitting as many regressions as there are observations, and was based on the concept of distance decay (where more weight is given to the closer observations than the farther ones). A local model calibrated with spatially limited sets of data (GWR) yielded local parameter estimates that assess local influences, allowed for a spatial shift in parameters and a more appropriate fit. By their nature, local statistics emphasize differences across space, whereas global statistics, such as Ordinary Least Squares (OLS), emphasize similarities across space (Fotheringham et al., 2002). GWR has the ability to discriminate between spatially constant processes and those with spatially varying relationships, and accurately retrieve spatially varying relationships. Since its introduction to the geographical and spatial econometric literature in 1996 (Brunsdon et al., 1996; McMillen, 1996), the non-parametric approach termed geographically (or locally) weighted regression (GWR) has become a popular tool for the study of geo-referenced data.

Shariff et al. (2010) applied the GWR approach to modeling urban land use changes. These changes took place during the period in which the study area experienced tremendous urban growth due to in-migration from adjacent areas. Land use change has potential impacts on the physical and social environment. Spatial variables describing environment, physical and socioeconomic factors were hypothesized to influence the change in the land use in the study area were identified to study sustainability in urban development. GWR extends the traditional regression framework by allowing regression coefficients to vary for individual locations (*spatial non-stationarity*). This is one method of utilizing spatial information to improve the predictive power of such models (Kupfer, and Farris, 2007). In geospatial research, it is also customary to compare the ability of GWR, a local model, with that of ordinary least squares (OLS) regression, a global model, to predict patterns of land use change. The GWR approach to spatial modeling dealt with spatial non-stationarity in multivariate regression and estimates regression coefficients locally using spatially dependent weights (Fotheringham et al., 2002).

Anselin (1995b) has noted that computer technology capable of providing spatial analysis has developed at a rapid rate. Henning et al. (2000) used Geographical Information Systems (GIS) procedures to provide a spatial view of rural land value data.

Hedonic model results indicate that tract location and whether the tract is located in a metropolitan statistical area (MSA) has a statistically significant effect on rural land values. Although these procedures provided much data, significant progress has been made in rural land modeling efforts using GWR.

Using survey data, Bocci et al. (2005) applied GWR methodology in order to estimate agricultural surface area (production for main cultivations of each area) at municipal level. The objective of the work was to evaluate if the knowledge of farm geographical location could be used in a GWR model and produce accurate estimations of production in sub-regional domains. After identifying non-stationarity of the data using the traditional OLS regression model, a local regression was derived and the phenomena specific model (allocation of agricultural area) was estimated.

Amara and Ayadi (2013) applied spatial analytical techniques in order to understand the geographic determinants of welfare in a study area. Exploratory Spatial Data Analysis, a set of dynamic tools based on a GIS, was conducted to visualize the local spatial structure of welfare. A GWR model was used to deal with both spatial autocorrelation (Griffith, 2001) and unobserved spatial heterogeneity of each household's behavior. Spatial and non-spatial models were compared according to their predictive performances. GWR spatial models are preferable to the traditional non-spatial regression model and provided a better approximation of the study welfare map.

''Global'' Moran's *I* can be decomposed into ''local indicators of spatial association'' (LISA) that identify local clusters of units with similar values (Anselin, 1995b). The local Moran's *I* map identifies clusters of counties with values that are statistically significantly similar. This indication of spatial clustering, along with other findings, leads to speculation about a few mechanisms by which the localized stability of farming was created during the 1980s farm crisis in the U.S. For example, a healthy farming infrastructure (financial institutions, supply stores, commodity sales outlets, etc.) was supported by the presence of a significant number of farms (regardless of size). In this circumstance, farms tended to be located near the infrastructure that best serves them (Lyson and Gillespie, 1995; DuPuis, 1993).

In a spatial analysis of water use patterns, Franczyk and Chang, (2009) used biophysical and socioeconomic factors to explain spatial patterns with Moran's *I* and the local index of spatial autocorrelation (LISA), a decomposition of global statistics into constituent local statistical components. There was a moderate positive spatial autocorrelation among counties that had similar irrigation withdrawals. LISA analysis was used to identify "hot" and "cold" spots, which are local clusters of spatially high or low values, or non-stationarity contained in a spatial dataset (Anselin, 1995b).

Cleveland and Devlin (1988) identified and illustrated three major uses of the local-fitting methodology: as an exploratory graphical tool; as a diagnostic tool to check the adequacy, or goodness-of-fit, of parametric models; and as a replacement for parametric regression, by using instead the estimated locally weighted surface. Farber and Páez (2007) suggest that volatility in the coefficient estimates may be due to the procedure used to select the bandwidth size required for estimation.

In general, global patterns are interesting, but they are simply spatial averages and often mask a great deal of regional variation that may result from a wide variety of possible sources. Luo and Wei (2009) modelled spatial variations of urban growth patterns. GWR was helpful in this situation because the maps displaying the parameter variation may offer clues as to why there was any patterning at all. GWR is helpful in identifying the nature of misspecification in individual-level effects, improving our understanding of the participatory behavior.

Logistic GWR (using binary values for dependent variables) significantly improves the global logistic regression model in terms of better model goodness-of-fit and lower level of spatial autocorrelation of residuals. Local estimates of parameters of spatial variables enable us to investigate spatial variations of the influence of each spatial variable on urban growth producing distinctive local patterns and effects of urban growth. GWR, not OLS technique, should be used for regional scale spatial analysis because it is able to account for local effects and shows geographical variation in the strength of the relationship.

Cho et al. (2009) studied the tradeoff between the values households' place on shared open space and parcel size, and the implications for housing development policy. Marginal implicit prices of shared open space and single-family housing parcel size were estimated using GWR corrected for spatial autocorrelation. A marginal rate of substitution (MRS) of shared open space for lot size was calculated for individual households. Defining target areas based on site-specific MRSs could provide policy makers with more accurate information for designing or updating location-specific land use policies in efforts to moderate urban sprawl.

"Global" dependence models, such as the classical regression model, assume the independence of the phenomenon from the data spatial location. For many agricultural phenomena, the application of one of these models could lead to incorrect conclusions and generate spatially auto-correlated residuals. GWR, a specific model that allows represent non-stationary local phenomena (Fotheringham et al., 2002) accounts for the spatial variability of the phenomenon.

2.4. Summary

The classical economic models hinge on the idea that market based variables related to productivity and location within an urbanizing area are key determinants of land value and land use. It follows that farmer decision making with respect to land is strictly determined by these economic variables. However, long- term trends in rural–urban relations cannot be rationalized satisfactorily by existing economic theory. Agent-based, discrete choice models, hedonic, and simulation land use models utilize parcel scale model to explain the process and predict future growth but lack behavioral foundations. Landscape ecology models are effective in the analysis of local patterns but stress land-cover type, not land use. All of these types of studies (including this one) are constrained by data for which land use/land cover data are available for two points in time and for limited geographical areas

By providing a parcel scale model this research can better explain localized losses of farmland and reflect key dimensions of constrained decision-making. Land use change at the fringe is characterized by "spatial heterogeneity" or spatial variation at local scales. Social capital emphasizes the importance of networks and "pockets of resistance"; spatial analysis is based on the "neighborhood". In addition, this research advances our knowledge of land use by incorporating a new set of variables intended to represent household decisions. In order to study more directly the *causal* relationships between individual choice, attachment, and social capital on land use change outcomes, participation in farmland preservation programs is used as a proxy explanatory factor for farm conversion.

The next chapters discuss precisely how this research attempts to uses conventional statistical analysis, geospatial techniques, and GWR procedures in order to test the effect of standard economic variables and non-economic variables on land use change in a local farm-based model. Conventional statistical analysis is used to understand the relationships between modeled variables. Geospatial techniques are used to analyze local variation that help identify the location of clusters (local clusters) and GWR procedures can also to reduce the effect of spatial autocorrelation on the model and enables visualization of the location of model significance (strength) as well as parameter patterns.

CHAPTER THREE
STUDY AREA

3.1. Introduction

Michigan is the only state in the U.S. that assesses farmland property at market value, resulting in the highest per-acre farmland property taxes nationwide (Clouser, 2005). Property tax assessment, as a result, has been an important issue for farmers in Michigan. In response, many farmers rely on agricultural preservation programs such as those established by Michigan Public Act 116 (PA116) to provide property tax relief. Over 30% of Michigan's 10 million acres of agricultural land are currently enrolled in and protected by PA116. In Eaton County, PA116 study period peak participation in 1992 accounted for 88,150 acres in 1,345 parcels, or 41% of agricultural land. State policy changes in property assessment in 1992 led to a reduction in property tax and with that, a reduced motivation for enrollment in the PA116. During the period 1992-99, PA116 program new enrollments were almost nonexistent and the overall program was in decline. In 2000, policy changes (State of Michigan MCL 36101) that have increased allowable tax credits for farmers enrolled in PA116 have driven a revival of this program. Therefore, an exploration of PA116 activity continues to be relevant for study.

3.2. Study Area Selection

The research on agricultural land use change was conducted on rural areas of Eaton County located adjacent to the urban core of Lansing and East Lansing, Michigan. The study area (Fig. 3.1) is centrally located in the main agricultural belt of Michigan's Lower Peninsula and is dominated by agricultural land use (57.6%). Eaton County was chosen as the study region because of its location in the rural urban fringe and the importance of its agricultural economy.

Eaton County is typical of many Lower Peninsula agricultural counties, with a strong farm tradition and an agricultural product base consisting of soy, corn, and winter wheat.

A preliminary pilot survey was conducted, collecting data from farm households located in three counties surrounding the city of Lansing, Michigan (Clinton, Eaton, and Ingham Counties). Reasonable access to farms was made possible by limiting the field survey range to these three nearby counties. The study area was eventually limited to Eaton County when it was concluded that all three counties were statistically similar in terms of agriculture and influence of Lansing. Of the three counties, only Eaton was currently showing significant urban fringe growth. Ingham County (Lansing) had completed much of its fringe development prior to the study period (during the 1970-80s) whereas Clinton County was experiencing only limited urban growth.

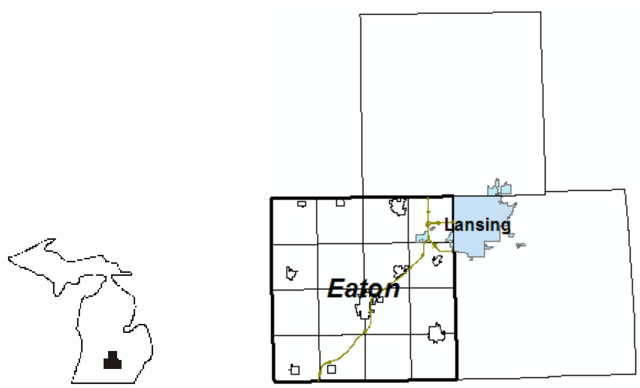


Figure 3.1 - Locator Map / Study Area: Eaton County town configuration and the City of Lansing. (Source: Tri-County Regional Planning Commission (TCRPC), 1999).

According to the 2000 census, Eaton County accounted for 103,655 of Lansing's metropolitan area population of 447,728. Most of Eaton's 15% population increase during the 1978-1999 study period was concentrated in Delta Township (in the county's northeast corner), with newly developed residential areas along the City of Lansing's western edge (TCRPC, 2001). Rural and suburban land, especially the areas located between 7 and 15 miles from Lansing, experienced population growth and rapid land development.

As a result of this redistribution from urban core to periphery, Eaton County lost approximately 300 farms (comprising 30,000 acres of farmland, or 11% of the total land area in agricultural use) to development (Census of Agriculture, 1997). In the decade from 2000-2010, Eaton County's population growth continued at a relatively modest at 3.96% to 107,759 (matching the slow growth for Lansing's metropolitan area at 3.64% to 464,036).

A number of different events have impacted development in Eaton County during the study period. Interstate I-69, an important transportation link running the entire north-south extent of the county, was completed in 1992. Perhaps in response to improved access, growth in local development was evident by a steady increase in the annual number of building permits issued in the county. Building permits are the public record of new construction for structures (associated with housing and commercial uses). The annual number of permits issued grew from 189 (1978) to 348 (1989), and 1,109 at period end (1999) indicating a trend of accelerating development in Eaton County. Growing employment opportunities and expanding industrial capacity along with rising farm prices saw Eaton County transition from a farm-based / rural residential economy to one more established and associated with the City of Lansing. Following a similar trajectory, assessed value for land ($ /acre) increased from $307 to $1,201 during (1978-91) to $3,491 (1992-99), more than a ten-fold increase during the study period.

To understand land use change, the effects of zoning typically must be accounted for. Properties in Eaton County that are designated as the study area are entirely located within the same zone. In Eaton County, exclusive agricultural zoning regulates the type, intensity, and location of development therein. For example, parcels cannot be split off from current agricultural land for the purpose (conditional use) of large parcel development for multi- unit housing (Eaton Zone Ordinance Article, 7.3). The agricultural district is intended for farming operations with allowance for very limited development of very low-density single-family dwellings and little provision for residential neighborhood development. Since there is no variation in zoning throughout Eaton County, this variable is effectively removed from study.

3.3. Summary

For this study, Eaton County met several criteria for selection as the study area. Outside of Detroit-Metro, many large cities in Michigan are separated by large areas and have discrete hinterlands surrounding them, Lansing being one of them. Eaton County's urban growth had only one real urban center with much of the county's population within reasonable commuting range of Lansing, the CBD. With the completion of the I-69 interstate link in Eaton during the 1978-99 study period, an opportunity emerged to analyze the effects of significant infrastructure change. Eaton is in many ways representative of Lower Peninsula agriculture with respect to the percentage of land in farming and types of crops produced. Finally, access to detailed temporal data was provided by local authorities and enabled the study of the unique relationship that Michigan farmers have with respect to farm preservation (PA116).

CHAPTER FOUR
RESEARCH QUESTIONS AND HYPOTHESES

4.1. Introduction - Research Questions

The primary objective for this study was to test the hypothesis whether changes in measures of social capital are associated with a meaningful change in land-use in the rural-urban fringe. At the broadest level, this undertaking demands an understanding of land use change as a function of economic, geographic, and non-economic factors. The models assessed which factors are significant in influencing land use conversion in the study area. While regional-scale factors may be important in driving land use change, spatial factors operating at a local neighborhood scale are also expected to provide a more complete explanation for land use change. Non-economic variables at farm parcel scale are also hypothesized to have a negative effect on the rate of land conversion.

4.2. Research Questions

4.2.1. Main Research Question (1)

For the major question, this research tests the hypothesis of whether changes in levels of social capital and other on-economic variables can be associated with significant change in land-use in the rural-urban fringe.

Non-economic variables (participation in PA116, time of ownership, and impermanence syndrome) may influence land prices and, it follows rural land use patterns. Neighborhood scale measures are used to capture a combination of factors that may relate directly to the individual land owner. Overall land values may differ among individual farm landholders, influenced in part by attachment value. Attachment value variation may influence some owners to convert and others to retain farm holdings, and were reflected in land use change measures (Evans, 2001a). If the null hypothesis is accepted, then it can be said that non-economic variable β's are not significantly different from zero in this farm parcel land use change hypothesis. Otherwise, there is support for the significance of non-economic variables in farm parcel land use change.

To test this association two basic hypotheses were used: the null and an alternative. The *null hypothesis* states that the independent variable (X) is not associated with the dependent variable (Y); therefore, the slope, beta (b_1) is zero. The alternative hypothesis states that X is associated with Y therefore this b_1 (the slope) is not zero.

These hypotheses are stated in statistical notation as follows:

H_0: $b_1 = 0$ (null hypothesis) dependent

H_A: $b_1 \neq 0$ (alternative hypothesis)

To test these hypotheses, an interval can be constructed around the slope estimate (b_1). The commonly used two-tailed 95% *confidence interval* was used for this analysis.

For the model for 1978-91 time period:

H_0: $b_o = b_{1,} = b_{2,} \ldots = b_{13} = 0$ (null hypothesis)

H_1: $b_o \neq b_{1,} \neq b_{2,} \ldots \neq b_{13}\ 0$ (alternative hypothesis)

Where at least one $b \neq 0$

For the model for the 1992-99 time period:

H_0: $b_o = b_{1,} = b_{2,} \ldots = b_{13} = 0$ (null hypothesis)

H_1: $b_o \neq b_{1,} \neq b_{2,} \ldots \neq b_{13}\ 0$ (alternative hypothesis)

Where at least one $b \neq 0$

4.2.2. Additional Research Questions

Research Question 2 – Does neighborhood land use change influence attachment value? Conversion of neighboring farmland to residential uses (neighborhood effect) can diminish rural character and reduce farmer land attachment (non-economic attributes). This effect is represented here by change in PA116 participation, proxy for attachment value. The agricultural buffer was designated to capture measurable change in the one-mile agricultural land neighborhood and its effect on attachment value. To test this association two pairs of basic null and alternative hypotheses were used. The second main research hypothesis (Hypothesis #2) for the 1978-91 and 1992-99 time periods takes the form:

H_0: $b_1 = 0$ (null hypothesis) the slope of *Agbdf7891* (agricultural buffer change)

H_1: $b_1 \neq 0$ (alternative hypothesis) the slope of *Agbdf7891*

H_0: $= 0$ (null hypothesis) the slope of *PAbdf7891* (PA116 buffer change)

H_1: $\neq 0$ (alternative hypothesis) the slope of *PAbdf7891*

H_0: $b_1 = 0$ (null hypothesis) the slope of *Agbdf9299* (agricultural buffer change)

H_1: $b_1 \neq 0$ (alternative hypothesis) the slope of *Agbdf9299*

H_0: $= 0$ (null hypothesis) the slope of *PAbdf9299* (PA116 buffer change)

H_1: $\neq 0$ (alternative hypothesis) the slope of *PAbdf 9299*

Research Question 3 – Does distance from the CBD impact neighborhood participation in the PA116 farmland preservation program, the variable of interest? Does PA116 program enrollment vary spatially within the study area? Beyond a certain distance from the CBD, economic factors are less likely to influence a farmer's decision to convert land (distance effect). It is therefore expected that the majority of PA116 parcels are concentrated within the most peripheral rural locations of the study area, where economic pressure to convert land is least and incentive to participate in PA116 is based more on attachment value. However, if PA116 parcels are evenly distributed throughout the study area - including parcels immediately adjacent to urban areas, does this provide evidence of other non-economic neighborhood effects?

The third research hypothesis (Hypothesis #3) for the 1978-91 and 1992-99 and time periods take the form:

H_0: = 0 (null hypothesis) the slope of *PAbdf7891* (PA116 buffer change)

H_1: ≠ 0 (alternative hypothesis) the slope of *PAbdf7891*

H_0: $b_1 = 0$ (null hypothesis) the slope of *LogCBD* (Distance to CBD)

H_1: $b_1 \neq 0$ (alternative hypothesis) the slope of *LogCBD*

H_0: = 0 (null hypothesis) the slope of *PAbdf9299*

H_1: ≠ 0 (alternative hypothesis) the slope of *PAbdf9299*

H_0: $b_1 = 0$ (null hypothesis) the slope of *LogCBD*

H_1: $b_1 \neq 0$ (alternative hypothesis) the slope of *LogCBD*

Research Question 4 – Do clusters of attachment value exert spatial influence on farm parcel land use change? The exchange of information among farmers is generally a function of diffusion across local community networks. Through geospatial analysis, mapping will be used to determine the existence of spatial concentration (clustering) of social networks and if they represent social capital variables (*PA116* participation, and other attachment values). By identifying spatial clusters it can be determined if these clusters are random or the result of processes involving diffusion and social networks.

The fourth research hypothesis (Hypothesis #4) for the 1978-91 and 1992-99 and time periods take the form:

H_0: = 0 Social capital variables do not cluster in the study area (null hypothesis).

H_1: ≠ 0 Social capital variables cluster in the study area (alternative hypothesis).

4.3. Summary

The four main research hypotheses are presented and tested using the basic null and alternative two hypotheses. The magnitude of the overall relationship between the dependent variable and the independent variables representing economic, distance, and non-economic change will be tested.

Questions that relate to the variable of interest (participation in PA116) will be tested to determine if the distance from the CBD has impact on participation in PA116 program and if program enrollment varies spatially within the study area.

The exchange of information among farmers is generally a function of diffusion across local community networks. For this reason, it is important to identify whether there is concentration (clustering) among the non-economic variables and if the appearance these variables is random or not. The next chapter provides the specific methods and analysis of the models that are discussed here.

CHAPTER FIVE
METHODS AND DATA ANALYSIS

5.1. Methods - Introduction

Chapter 5 reviews the methods used to determine the effect of social capital on farmland conversion, beginning with an in-depth discussion of the regression methods. The purpose of this analysis is to assess the relative importance and direction of association of the variables presented in the following model chapter in influencing farmer land use choice.

Farmers must choose between retaining their land and remaining active in agriculture or converting (selling) their property for non-agricultural use in land markets. In past empirical work, economic variables associated with individual rural parcel measures were regressed on agricultural land use change and fitted to a number of models (Polimeni, 2005; Ready and Abdalla, 2005). Results indicated the anticipated sign and strength of relationship between independent variables and farmland conversion, the dependent variable. For this research, an additional set of non-economic independent variables based on land attachment was regressed on land use change.

5.2. Statistical Analysis

Multicollinearity is used to describe the situation when a high correlation is detected between two or more independent variables. Such high correlations cause problems when trying to draw inferences about the relative contribution of each independent variable to the success of the model and can interfere with spatial modeling. As a first step in the statistical analysis, the group of variables was examined to detect the association (correlations) between variables (as tested by SPSS “Correlate/Bivariate” command). In the process, the correlation coefficient *r*, (Pearson correlation coefficient factor) was computed to obtain objective analysis that would uncover the magnitude and significance of the relationship between the variables. A degree and a direction of the relationship between two variables were measured. Correlations were useful because they can indicate if an explanatory relationship is present that could be exploited in analysis. (However, statistical dependence is not sufficient to demonstrate the presence of such a causal relationship i.e., correlation does not imply causation). The Pearson correlation coefficient indicated the strength of a linear relationship between two variables, but its value generally did not completely characterize their relationship.

5.2.1. Ordinary Least Squares (OLS)

The main research hypothesis (RQ1) was tested using a regression model that indicated the strength of a relationship. The model was specified to identify the presence of a relationship and to determine the strength of relationships between pairs of variables. For this research, OLS was used in study of the following questions:

a) What is the magnitude of the overall relationship between the dependent variable and the independent variables representing economic, distance, and non-economic change?

b) How much does each independent variable uniquely contribute to that relationship?

The beta value (standardized regression coefficient) is a measure of how strongly each independent variable influences the dependent variable, measured in units of standard deviation. Higher beta values indicated a greater impact for each independent variable on the dependent variable. R is a measure of the correlation between the observed value and the dependent value.

The multiple correlation coefficient (R^2), described the overall proportion of variance in the dependent variable that can be explained by the linear regression equation. This overall assessment of the regression equation has a more *global* sense than that provided by the individual beta-weights. Adjusted R^2 value (adj-R^2) gives the most useful measure of the success of this model. The adj-R^2 value is the total percent variation in the dependent variable that is explained by the independent variables together (the adj-R^2 accounts for the number of variables in the model and the number of observations that the model is based on). The OLS model is a global model in that the set of coefficients used in the linear equation represent an average and remain uniform in value over the extent of the study area.

The variance inflation factor (VIF) is another check on the severity of multicollinearity in an OLS regression analysis. It provided an index that measured how much the variance of an estimated regression coefficient is increased. A measure of redundancy among independent variables less than 2 suggests that there were no multicollinearity problems among the independent variables (VIFs of 10 or higher provided reason for concern).

5.2.2. Linear Regression: Null hypotheses

Two research hypotheses (RQ2 and RQ3) were tested with SPSS "Regression/Linear" command to perform a simple bivariate regression. In both cases, the relationship of one independent variable to another was explored to test if distance from CBD and neighborhood loss of agriculture (impermanence syndrome) had an impact on the location and strength of the social capital variable.

5.2.3. Stepwise Regression - Variable Reduction

The Stepwise variable-selection method was used for RQ1 to ensure that the smallest possible set of independent variables required to predict the dependent variable were included in a more parsimonious OLS model. The relative contribution of each independent variable was assessed to reduce the linear equation to the best combination of independent variables. These independent variables were entered into the regression equation one at a time based upon statistical criteria. At each step in the analysis, the independent variable that contributed the most to the equation in terms of increasing the multiple correlation, R, was entered first. The order in which the independent variables were entered into the model was based on the strength of their correlation with the dependent variable. This process was continued only if additional variables add anything statistically significant to the regression equation. When independent variables failed to add meaning to the linear equation, the analysis was stopped and non-contributing variables were removed. As a result, not all of the original full set of independent variables remained at the end. At the end of a stepwise regression, only variables that explained the distribution best remained in the model. Subsequently, variable reduction optimized the iterative processes of geospatial processing and mapping.

A standard multiple linear stepwise regression (OLS) was fitted to the model to estimate parameters representing land use change for the remaining stepwise-derived variables (OLS Reduced Set of Variables).

In the results, the direction of the sign and strength of relationship (beta coefficient) between each independent variable and dependent variable were used to assess and compare estimates of the underlying factors that contribute to farm conversion. The standard OLS model is widely used to model the global relationship between a dependent variable and one or more independent variables.

OLS assumes, among other things, that residuals are spatially independent. Residual autocorrelation captures unexplained similarities between neighboring districts, which can be a result of omitted variables or a misspecification of the regression model in general. Accounting for spatial effects reduces the magnitude of the prediction error, removes most of the systematic error, and leads to more reliable estimates. For this study, the OLS model using the reduced set of variables served as the reference model.

Akaike Information Criterion (AIC) was used as a measure of the relative quality of statistical models for a given set of data. With a statistical model of some data, let *L* be the maximized value of the likelihood function for the model; let *k* be the number of estimated parameters in the model. Then the AIC value of the model is the following:

$$\mathrm{AIC} = 2k - 2\ln(L)$$

With the AIC model selection technique coefficients are statistically significant by minimizing AIC value (preferred model). AIC offers a relative estimate of the information lost when a given model is used to represent the process that generates the data. In doing so, it deals with the trade-off between the goodness of fit of the model and the complexity of the model. This index rewards goodness of fit (as assessed by the likelihood function) and discourages overfitting (increasing the number of parameters in the model). Use of the AIC index facilitated comparison between the overall model that results from a ‘global’ OLS linear regression model with those from the local GWR model. The AIC comparison revealed that an explicit spatial perspective significantly improved the model fit.

5.3. Geospatial Analysis

The main limitation of OLS and Stepwise "global" tests is that they do not consider the unique properties of space, having serious consequences concerning the statistical validity of results. In this context, a "global" spatial regression model refers to testing for spatial autocorrelation for the entire study area at once and deriving a single value for coefficients and adj-R^2. The underlying assumption of the OLS regression method is that the relationship under study is spatially constant (i.e., that estimated parameters remain constant over space). This assumption of homogeneous behavior of the estimated parameters across space has often been proven to be unrealistic. Essential special properties of geospatial data are spatial autocorrelation and spatial heterogeneity (non-stationarity). Modern methods of multivariate analysis on the other hand, draw attention to scale, redirecting the target of the analysis from the verification of spatial homogeneity to the observation of local spatial variation.

5.3.1. Global Moran's I: Spatial Autocorrelation Analysis

The Moran's *I* coefficient is the most commonly used coefficient in single variable autocorrelation analyses and is given as:

$$I = \left(\frac{n}{s}\right)\left[\frac{\sum_i \sum_j (y_i - \bar{y})(y_j - \bar{y})w_{ij}}{\sum_i (y_i - \bar{y})^2}\right]$$

(where n is the number of samples, y_i and y_j are the data values in quadrats i and j, $\bar{y}$ is the average of y and w_{ij} is an element of the spatial weights matrix W). Under the null hypothesis of no spatial autocorrelation (the spatial pattern is random), the Moran's *I* statistic has an expected value near zero for large *n*. *Global* Moran's *I* statistics test examines the overall presence of spatially auto-correlated residuals. The Moran's *I* statistics test determines whether there are some relationships between location and attribute values and examines the overall presence of spatially auto-correlated residuals. A significant positive statistic indicates that nearby locations of similar attribute values are more spatially clustered than randomly distributed. These clustering locations were of interest in the analysis of RQ4. In contrast, a significant negative statistic shows dissimilar values at nearby locations showing that similar values are spatially dispersed.

Moran's *I* global statistics were used to measure global spatial autocorrelation and answer the question: Is there a spatial pattern? Moran's *I* is not capable to explore distinctive local features as well as the non-stationarity of a spatial process. However, specific tests on the residuals are required (i.e., Moran's *I*) before any regression analysis results are interpreted to statistically demonstrate their spatial randomness. The objective was to identify whether spatial autocorrelation existed and what its strength was. If the relationships do not vary across space, the global model is an appropriate specification for the data. If relationships do vary across space, local models are required.

5.3.2. Local Indicators of Spatial Autocorrelation

Spatial patterns in the study area revealed spatially varying geographic processes over time (1978–1999) and facilitated testing of hypotheses about relations between pattern and diffusion process (Vidyattama, 2010). Influence on land use may be the result of diffusion of information across local community networks among farmers or be identified as clusters of farm households exhibiting high social capital. The Getis and Ord *G** Statistic or "Hotspot Analysis" provided a framework for identifying hot or cold spots among individual units. The local *G** statistic (Getis and Ord, 1992) was used to locate over-concentration of high clustering of high values (hot spots) or the clustering of low values (cold spots). In this study, the local G^* results specifically identified clusters or "hotspots" related to social capital (Anselin, 1995b). Further analysis and mapping using local G^* identified an increase in the number of hot spots or their areal size and a decrease in the number of cold spots or their areal size.

5.3.3. Geographic Weighted Regression (GWR) Analysis

GWR techniques use straightforward formulation and explicit treatment of spatial effects to generate local scale results. Although the GWR technique has been used to study limited dependent variables (e.g., crash counts (Hadayeghi et al., 2010b) and binary response (Páez, 2006), its application to parcel-level land use modeling is quite new. GWR has enjoyed broad application, in fields as diverse as ecology, wealth and epidemics. By contrast, GWR's application to land use change at the level of whole parcels and/or for discrete response in urban contexts remains very rare. Páez (2006) provided a binary-response application, using a binomial probit GWR to analyze development near transit lines.

Luo and Kanala (2008) extended GWR to multinomial cases. The former analyzed four types of conversion (from barren, crop/grassland, forest and water uses to urban land use) using a MNL (multinomial logit) GWR. Parcel-level MNL GWR models (Wang et al., 2011) were used to anticipate five categories of urban land use change while controlling for parcel geometry, slope, regional accessibility, local population density, and distance. In the context of land use attributes, Ghosh et al. (2008) analyzed impervious cover proportion via a continuous-response GWR framework. In their study of conversion of conventional farms to organic farms, Taus et al., (2012) identified where regional concentrations of certain factors were located. Limitations in design or lack of data, made it difficult in analysis of this type to effectively identify which factors contributed most to which types of change.

Research Question 4 (RQ4) required a different type of analysis. It was expected that land use change would be a function of non-economic variables in addition to economic factors, spatial scale (neighborhood vs. parcel) in the models and within study area locations. The OLS global model was calibrated with equally weighted data from across a study region and yielded global parameter estimates that did not analyze local heterogeneity. The spatial autocorrelations reduced the efficiency of the regression and made the OLS models unsuitable for identifying the relationships between independent variables and land use. Fortunately, GWR models improved the reliabilities of the relationships by reducing the spatial autocorrelations in residuals.

Using Geographically Weighted Regression (GWR), a local regression model, local spatial variations were explored across the entire data set. Model parameters, were used to expand standard regression for use with spatial data to answer the question: Where are there spatial patterns (on the map)? However, ArcGIS GWR does not have the strong diagnostics (i.e., coefficient p-values) that SPSS OLS does. Before moving to GWR to answer RQ4, a properly specified OLS model was necessary.

GWR-modeled spatial autocorrelation and spatial heterogeneity for subsets of the entire data set. Each subset was established around a regression point *i* with near data points exhibiting a higher influence than more distant data points. A crucial step in spatial modeling is the choice of an appropriate representation of space "weighting." GWR uses a *kernel* (also called a window or bandwidth) that moves over the study area and seeks to fit the best results for each subarea by minimizing the corrected (AIC_c) as described in Fotheringham et al., (2002). This provides the goodness-of-fit criterion and has the advantage of taking into account the fact that the degrees of freedom may vary among models centered on different observations.

The *bandwidth* is the radius or number of observations around a subject point and controls the distance decay in the weighting function. Observations are weighted in accordance with their proximity to focal point (*o*). The kernel size defined the rate at which the influence of the coefficients decreased as distance increased from point *o*. The setting of an appropriate bandwidth length of the weighting function is important in fitting estimations to each observation or location by applying the appropriate equation. For GWR kernel type parameters, common choices to specify local equation calibration, are based on a *fixed number* of closest neighbors to observations (adaptive) or on a *constant* bandwidth for all the observations (fixed). While the adaptive kernel can adjust bandwidths size larger in the locations where data are sparse and smaller where data are denser in order to maintain the number of neighbors, the fixed kernel may not have the same number of neighbors but maintains the same bandwidth length or distance from the observation at subject point (focal point (*o*). AIC_c and cross-validation (CV) were other optimization processes that were used to set bandwidth selections through software determined "optimal" distance. These different parameter choices were based on model fitting statistics (R2, AIC, and goodness of test fits) and were iteratively tested to identify the optimized fitting.

GWR model localized parameter estimates can be obtained for any location *i*. GWR facilitated exploration of the spatial structure of the model; that is, it measured the degree of spatial dependence present in the model and detected data clusters. This allowed for examination of continuous coefficient surfaces to observe spatial variability: how relationships being modeled changed across study area (Fotheringham et al., 1998). Maps generated based on the surfaces of parameter values also assisted in identifying non-stationarity or missing variables.

5.3.4. Mapping the Results of GWR

GWR used within (GIS) facilitated the production of a wide variety of maps using the generated results: dependent and independent variables, local R2, local coefficients (elasticities), t-values and standard residuals. Continuous surfaces of Local GWR results were mapped for each independent variable and GWR output (Local R2, t-value) providing an understanding of how the factors contribute to dependent variable outcomes. These combined generate a complete map of the spatial variation of the parameter estimates. GWR results, unlike OLS global model results, are mappable across the study area. Mennis (2006) observes that "a large number of potential parameter estimates can be produced; it is almost essential to map them in order to make some meaningful interpretation of results."

Mapping GWR results facilitates interpretation based on spatial context and known characteristics of the study area (Goodchild and Janelle, 2004). For each variable present two maps will be presented, one map showing the local parameter estimates for the variable and the other map showing the local R2 (t-values) for the same variable. Mapping local R2 values provides another means of observing where the model is predicting well or not so well. These were presented in tandem with parameter estimates; published GWR maps typically only show statistically significant results.

5.3.5. Comparison with OLS

After the OLS and GWR models were run, their regression results were compared to illustrate the differences in the relationship between the dependent variable and each independent variable explored by these two statistical methods. Afterward, the local regression results from GWR models, including parameter estimates, global R2, AIC_c, Moran's *I*, were further interpreted using spatial and statistical analyses to examine the spatial variations in the relationships between dependent and independent variables. It was expected that GWR would demonstrate improved explanatory power of the dependent variable.

Further, the farm-level non-economic, economic and environmental variables among the observations with different significance in the relationships were compared to analyze how the relationships vary spatially in response to the characteristics of this study area.

5.4. Data - Conceptual Model

This conceptual framework for the research was developed to support the empirical analyses of this paper**,** informing the selection of both farm observation units and variables. The conceptual framework explicitly identified relevant components of economic and social capital variables to aid in the conceptualization of land use choices and farm conversion.

This framework thus provided the rationale for choosing percent conversion of farm parcel (observation unit) as the dependent variable because it provided the means to more accurately represent the difficult to measure attributes of the landowner's inertia or attachment to the land as variables affecting the choice of land use.

There are some distinguishing aspects to this model. Each farmland observation is represented by the farm parcel, an aggregation of rural parcels based on ownership and configuration, which more accurately depicts the level of decision-making. Moreover, farm parcel conversion is represented as a partial process instead of complete change of land use for each unit.

As previously indicated, many land use studies consider land use change as a binary process ((Polimeni, 2005; Ready and Abdalla, 2005), the entire parcel is converted or remains in agriculture. In practice, many farmers choose to sell off small portions of their acreage (usually road frontage) that provide a high return for residential use while retaining high value agricultural land in the farmstead.

The basic model that has been utilized here represents a process of land use change which consists of a highly complex set of activities that generally take place over extended periods of time. This investigation will focus on agricultural-to-residential farmland conversion taking place in Eaton County, Michigan between 1978 and 1999. The first step in the modeling process is to estimate statistical models that explain land use change at the land parcel scale. The modeling process has determined what are the most important variables based on the theory of land use.

The primary expression of the general model is:

Land Use (Agricultural Use) = *f* (economic factors,

geographic factors, social capital factors).

Here the land use decision is a function of the interaction of economic variables related to consumer demand, and social capital variables associated with farmland attachment. The model's dependent variable is measured as a continuous and quantifiable value that describes specified agricultural land use (that is, land having potential of being farmed) as a percentage of total acreage within a farm parcel. A conceptual framework of land use change employed in this study is shown in Figure 5.1.

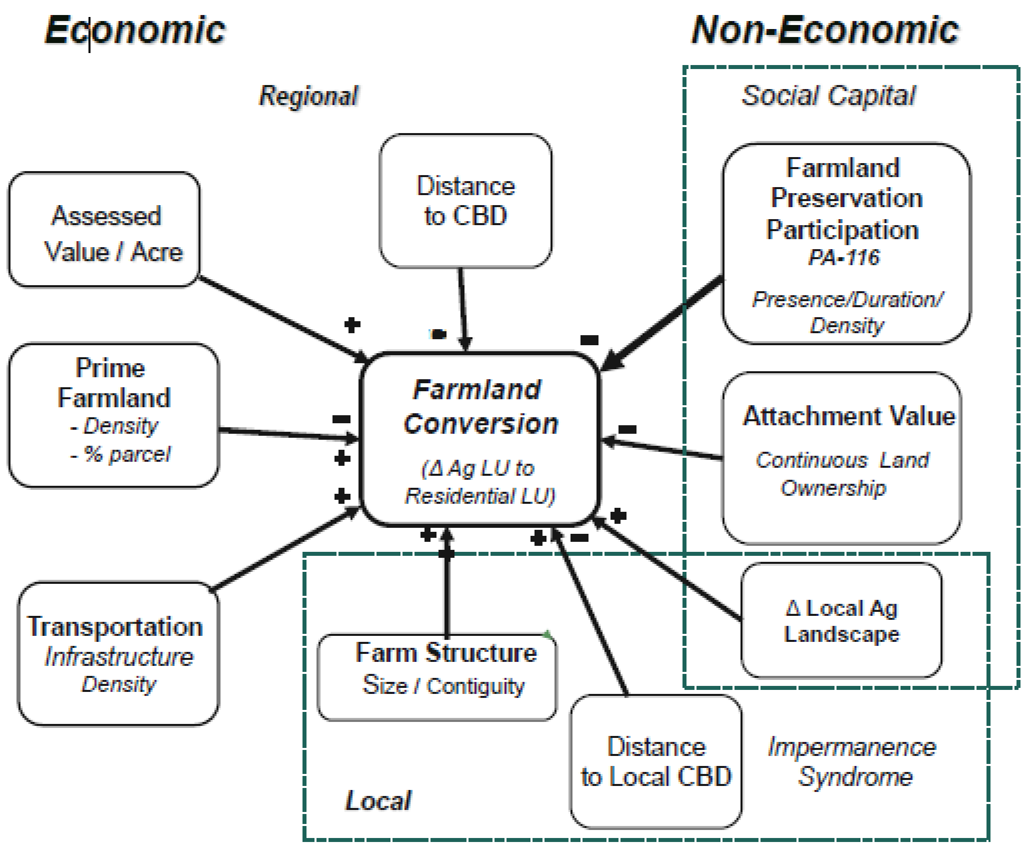


Figure 5.1 - Conceptual Framework: Land Use Change as a function of Economic and Social Capital variables.

5.4.1. Model Specification

Key interactions show the relative influence of economic and non-economic variables on agricultural-to-residential land use change. A "+" indicates that the variable positively influences farmland conversion; alternately, a "-" indicates that the variable's influence is negative. The model emphasizes the importance of scale (in terms of lot size or development density) while considering additional factors associated with distance effects. For instance, increased road densities and assessed property values associated with residential expansion are specified as economic variables expected to show positive correlation with farmland conversion. On the other hand, distance to CBD is expected to be negatively associated with farmland conversion (Alonso, 1964). Based on the literature, it is expected that some variables in this study would have aspects that have both a positive and negatively influence on land use change (i.e., prime farmland loss). The research should indicate which variable aspect will be stronger in this particular study area.

Empirical studies have shown that large parcels, with lower assembly costs, are more prone to conversion than are smaller parcels (Lynch and Lovell, 2003; Isgin et al., 2007). Farm size and proximity to an urban area can also effectively interrupt the spatial patterning of preservation programs (Roe et al., 2004) and active farms.

Variables that have a positive association with social capital are expected to act as deterrents to farmland conversion. These include *PA116* program participation (farm parcel and neighborhood scale) as well as attachment value variables associated with continuous ownership of local agricultural land. *"Impermanence Syndrome"* variables represent the condition where farmer expectation of maintaining a viable living in agriculture is o nthe decline (Berry, 1978). Variables that signal transition in land use such as neighborhood agricultural-to-residential landscape change are expected to diminish farmer attachment value, affecting land use change at farm parcel level.

5.4.2. Pilot Study

In the initial phase of this project, a pilot study was administered with results that informed the selection of both observation units and variables. Using a Michigan State University vetted survey instrument (Damon, 2001), an exploratory study was conducted to identify the potential impact that social capital (land attachment) had on farmland value. A formal questionnaire protocol was used in face-to-face interviews for 33 subjects (see Appendix

6.). The original intent of the survey was to measure and monetize attachment value based on farmer interaction with neighboring farmers, family and community organizations, and included the length of time that current farm owner held the property. The results which were not used directly in the study, but provided background information, were instrumental in identifying relationships between variables, and guided model selection. This survey also provided general information regarding farm operations in the study area. Ethical issues involving protection of confidentiality for each subject were maintained.

In an investigation of the factors influencing Attachment Value (AV), that is, the non-economic value that farmers place on their farmland, the highest land attachment values correlated with farmers having high social capital (including networked relations, length of ownership, etc.).

In this sample, most farmers were unwilling to sell their land, that is, they had a high "willingness to accept" (WTA) value. Individual farmers with the lowest WTA value were also least connected to his community and operated in isolation. In this descriptive survey (n = 33 survey observations), there was too much variability in the dependent variable (that is, infinite WTA or a never-sell condition). Additionally, the logistics in obtaining a meaningful sample indicated that there had to be a more empirical way of expressing attachment value (AV). Based on this survey study, the variable of interest and proxy for (AV became PA116). The data do not contain specific addresses or owner names due to confidentiality concerns.

5.4.3. Data Sources and Preparation

The data for this research were collected from a number of public agencies including Tri-County Regional Planning Commission, Michigan Department of Natural Resources (DNR), Michigan Department of Agriculture, and the City of Lansing IT/GIS Administration. A source map in ArcGIS shapefile format was also obtained from Eaton County (1999). The initial database contained more than 40,914 parcel records and covered the entire Eaton County area for a total of 361,901 acres. This digital basemap was then edited to conform to the original printed copy of the 1978 Eaton County plat map which included detailed parcel and ownership information for each of Eaton County's sixteen townships (Michigan DNR, 1978). The developed basemap contained the key observation units (farmland parcels) on which overlay analysis was conducted.

For this study, Land Use/Land Cover data refers to spatial data that is a result of classifying raw satellite imagery into "land use and land cover" (LULC) categories based on the return value of the satellite image. *MIRIS* Land Cover Maps were derived from a series of 1:24,000 (1"=2000') scale color-infrared and black-and-white aerial raster images. These raster data were then re-classed into categories of land use and vectorized into ArcGIS shapefile format. The resulting source land use classification maps (vector polygon layer) depicted some 52 categories of urban, agricultural, wooded, wetland, and other land cover types for the entire state of Michigan. This data format enabled overlay and other GIS analysis required for analysis. This map series was obtained from the Michigan DNR, Michigan Resource Inventory Program (MRIP).

Ortho-photo imagery (Tri-County RPC, 1987, 1991 and 1999) provided additional land cover identification was rectified at the 1:24,000 scale. Following standard air photo interpretation procedures, this remotely sensed data at this scale provided a level of visual detail that enabled distinguishing different farm units from each other and sub-parcel land use change. Specifically, the imagery was used to identify and correct for errors in MIRIS land use classification for 1978-99 and demarcate/adjust farm parcel boundaries. The purpose for collecting this data was to better reflect individual choice regarding farm conversion in the analysis. To limit the study to significant agricultural activity, a minimum size of five acres for agricultural land cover features was established. Agricultural parcels smaller than the five acre minimum and not associated with other farm parcels were not included in the study.

Table 5.1a - Independent Variables 1978-1991		Expected association with	Variable
Variable	Summary Explanation	AgLanduse change (Parcel)	Type
Agpct78	Original 1978 level of Ag - % of farm parcel	na	SC/EC
Agbdf7891	% Change of agricultural density - Neighborhood	+	SC/EC
AVacdf7891	% Change of Assessed Value - Farm Parcel	+	EC
AVbdf7891	% Change of Assessed Value - Neighborhood	+	EC
FmSz	Farm parcel size (1978 parcel-base)	-	EC
Locdstlog	Distance from local cbd - (nearest pop center) - ln10	-	D
LogCBD	Distance from Regional cbd - (Lansing, MI) - ln10	-	D
PAdf7891	% Change of PA116 enrolled - Farm Parcel	-	SC
PAbdf7891	% Change of PA116 density - Neighborhood	-	SC
PMdf7891	% Change of Prime farmland - Farm Parcel	-/+	EC
PMbdf7891	% Change of Prime farmland - Neighborhood	-/+	EC
Rdbd7891	Change of Road density - Neighborhood (5 mi buffer)	+	EC
Tow_7899	Ownership Index - majority owner/years	-	SC
	EC = Economic variable SC = Social Capital variable	D = Distance Variable	

5.1a: Variable Names - Anticipated Sign / Description / Type

Layers used as overlays for the base farm parcel map models ArcGIS shape format are as listed: Land Use, PA116, and Prime Farmland. These data were compiled and used as farm parcel map attributes in regression modeling and geospatial analysis (Wong, 2005).

The Prime Farmland layer (also in shapefile format) contained a single year (1999) spatial delineation of land designated as prime, optimal for crop production (USDA, 1993). Overall changes in land use from 1978-91 and 1992-99 were reflected in prime land base and used to develop prime land use reduction over during the same two periods.

The PA116 layer contained the spatial configuration of farmland enrolled in the Michigan Farmland Preservation Program (Public Act 116). The Michigan Department of Agriculture used digital resources to inventory the regular activity of transactions reflecting changes in farmland enrollment status. This spatial layer represented change at the individual decision-making scale often with sub-parcel adjustments in enrollment. This source data was based on a county-wide digital parcel (*.shp) map and supplemental program detail which depicted enrollment data for the PA116 program captured for each of the three sample years of the 1978-99 period. Additional sources obtained from the Tri-County RPC, and the Eaton County Assessor's Office included assessed value and ownership data at the farm parcel scale.

5.4.4. GIS: Farm Parcel Processing

ArcGIS was used to edit raw parcel data drawn from Eaton County resources, using a manual "merge", or aggregation of parcels to create the farm parcel base layer. Some of the variables developed were based on attributes that were contained in the farm parcel unit. Part of this study was interested in developing variables at the local scale to explore neighborhood effects on each observation unit. A spatial buffer of area was estimated surrounding each farm parcel centroid in order to derive attributes at neighborhood scale.

Table 5.1b - IndependentVariables 1992-1999		Expected association with	Variable
Variable	Summary Explanation	AgLanduse change (Parcel)	Type
Agpct78	Original 1978 level of Ag - % of farm parcel	na	SC/EC
Agbdf9299	Change of agricultural density - Neighborhood	+	SC/EC
AVacdf9299	% Change of Assessed Value - Farm Parcel	+	EC
AVbdf9299	% Change of Assessed Value - Neighborhood	+	EC
FmSz	Farm parcel size (1978 parcel-base)	-	EC
Locdstlog	Distance from Local cbd - (nearest pop center) - ln10	-	D
LogCBD	Distance from Regional cbd - (Lansing, MI) - ln10	-	D
PAdf9299	% Change of PA116 enrolled - Farm Parcel	-	SC
PAbdf9299	% Change of PA116 density - Neighborhood	-	SC
PMdf9299	% Change of Prime farmland - Farm Parcel	-/+	EC
PMbdf9299	% Change of Prime farmland - Neighborhood	-/+	EC
Rdbd9299	Change of Road density - Neighborhood (5 mi buffer)	+	EC
Tow_7899	Ownership Index - majority owner/years	-	SC
	EC = Economic variable SC = Social Capital variable	D = Distance Variable	

Table 5.1b: Variable Names - Anticipated Sign / Description / Type

Both an initial value model and a change model were employed for the study. For the initial value model, independent variables were specified to represent measures at the end of each of the three project years (1978, 1992, and 1999). By modeling the data in this manner, the influence of independent variables on the dependent variable at each discrete time point can be analyzed. The initial value model was designed to regress the values at a particular point in time, using three separate models for three individual years (1978, 1992, and 1999).

The initial formulation of the general model is:

$\textbf{Agricultural Land Use}_{(Ti)} = \beta_0 + \beta_1 Agpct78_{(T1)} + \beta_2 Agbdf7891_{(Ti)} + \beta_3 AVacdf7891_{(Ti)} + \beta_4 AVbdf7891_{(Ti)} + \beta_5 FmSz_{(T1)} + \beta_6 Locdstlog_{(T1)} + \beta_7 LogCBD_{(T1)} + B_8 PAdf7891_{(Ti)} + B_9 PAbdf7891_{(Ti)} + \beta_{10} PMdf7891_{(Ti)} + \beta_{11} PMbdf7891_{(Ti)} + \beta_{12} Rdbd7891_{(Ti)} + B_{13} Tow\_7899_{(T1)} + \varepsilon$

Where: $_{(T1)}$ = 1978 $_{(T2)}$ =1992 $_{(T3)}$ = 1999

However, the initial value model was limited in that it studies "momentary" effects but does not effectively model *change* over an extended period of time. Instead, land use change requires study of involved processes that may take decades to unfold. A change variable model was specified to capture the farmer decision as to whether or not an entire farm parcel or portion of a farm parcel was "converted" to non-agricultural use. Agricultural-to-residential conversion was modeled here as the percentage difference in agricultural acreage (original use) as compared to the use of a later period. From this model, the factors that influence land use conversion can be determined and the parameters of those conversion functions can be estimated. This change variable model is specified for two time periods (variable descriptions are listed in Table 5.1a and 5.1b). These estimated models take the form:

1978-1992 Δ **Agricultural Land Use** $_{(T1\text{-}T2)}$ = $\textbf{TT7891}_{\textbf{a}\ (T1\text{-}T2)}$

$\textbf{TT7891}_{\textbf{a}\ (T1\text{-}T2)} = \beta_0 + \beta_1 Agpct78_{(T1)} + \beta_2 Agbdf7891_{(T1\text{-}T2)} + \beta_3 AVacdf7891_{(T1\text{-}T2)} + \beta_4 AVbdf7891_{(T1\text{-}T2)} + \beta_5 FmSz_{(T1)} + \beta_6 Locdstlog_{(T1)} + \beta_7 LogCBD_{(T1)} + B_8 PAdf7891_{(T1\text{-}T2)} + B_9 PAbdf7891_{(T1\text{-}T2)} + \beta_{10} PMdf7891_{(T1\text{-}T2)} + \beta_{11} PMbdf7891_{(T1\text{-}T2)} + \beta_{12} Rdbd7891_{(T1\text{-}T2)} + B_{13} Tow\_7899_{(T1)} + \varepsilon$

Where: $_{(T1\text{-}T2)}$ = 1991-1978

1992-1999 Δ **Agricultural Land Use** $_{(T1\text{-}T2)}$ = $\textbf{TT9299}_{\textbf{a}}$

$\textbf{TT9299}_{\textbf{a}\ (T2\text{-}T3)} = \beta_0 + \beta_1 Agpct78_{(T1)} + \beta_2 Agbdf9299_{(T2\text{-}T3)} + \beta_3 AVacdf9299_{(T2\text{-}T3)}$

$+ \beta_4 AVbdf9299_{(T2\text{-}T3)} + \beta_5 FmSz_{(T1)} + \beta_6 Locdstlog_{(T1)} + \beta_7 LogCBD_{(T1)} +$

$B_8 PAdf9299_{(T2\text{-}T3)} + B_9 PAbdf9299_{(T2\text{-}T3)} + \beta_{10} PMdf9299_{(T2\text{-}T3)} +$

$\beta_{11} PMbdf9299_{(T2\text{-}T3)} + \beta_{12} Rdbd9299_{(T2\text{-}T3)} + B_{13} Tow\_7899_{(T1)} + \varepsilon$

Where: $_{(T2\text{-}T3)}$ = 1999-1992

5.5. Variables

5.5.1. Dependent Variables

Basically, land use conversion is defined as the change of farm parcel land use from active agriculture to a non-agricultural use. Once land is developed, the costs of reversing development are considered to be prohibitive, and therefore the development decision is viewed as irreversible (Irwin and Bockstael, 2004).

Agricultural Land Use change % – Farm parcel *(TT7891, TT9299)*$_a$

TT7891$_a$, *TT9299*$_a$ are defined as the percentage reduction of land in agricultural use within each farm parcel in the study area (agricultural acreage/parcel, standardized to % of parcel).

To account for land use change during the first time period (1978-91), agricultural acre value for parcels initial period T_1 (1978) are *subtracted from* parcel values in time periods T_2 (1991). To account for land use change during the second time period (1992-99) parcel values in time periods T_2 (1991) are *subtracted from* parcel values in time period T_3 (1999) in the land use analysis. The final variable used in the modelling is a log transformation (Lesaffre et al., 2007).

Change from agricultural to residential land use for designated rural parcels in the study area is expressed as acreage/parcel, standardized to percentage of a parcel. Land use percentage, the dependent variable, is expressed as a bounded continuous variable (0 to 1). These data were not expected to be normally distributed. To make the dependent variable more closely conform to the normality assumption required for multiple linear regression, a number of transformations (arcsine, log base 10, etc.) were tested.

The missing value dependent variable problem related to those farm parcels that had no change or entirely changed to non-agricultural uses. For the most part, this problem was resolved by aggregating individual parcels into farm parcels based on local ownership, proximity and farm configuration through interpretation of digital imagery the and use of GIS polygon layers. Using the ArcGIS editing tool, each parcel was matched to imagery and property line, combined, effectively enlarged the size of each observation (the farm parcel). With a larger farm parcel, the possibility of zero land use change for each observation was substantially reduced. This process also enabled a better spatial representation of the farm parcel or farmstead decision-making unit.

5.5.2. Observational Unit - Farm Parcel

The original 1978 plat map (Michigan DNR, 1978) included 40,914 Eaton county parcels covering a total area of 361,901 acres. Many of these parcels, covering an area of 55,839 acres, had already been urbanized prior to the first year of the study in 1978. Since the emphasis in this research is to explore decision-making on the part of agricultural households with respect to farmland conversion, these non-agricultural parcels were removed from the study. Once converted, these non-agricultural parcels do not revert back to agricultural use. Using a digital parcel map, the study area was reduced to 14,000 active agricultural parcels. However, this parcel map did not reflect decision-making units. The analyses required that observation units were appropriately scaled at farm parcel scale representing the individual landowner decision-making unit (Ansley, 2009). By aggregating these parcels to represent farm households, the number of observations was reduced further to a 3,056 farm parcel base map with 306,062 acres in active agriculture.

The U.S. Department of Agriculture (USDA) classifies real property which is used for commercial agriculture where 51% or more of the land area is devoted to an agricultural use as a "farm". This definition was used for the designation of whether a parcel was considered to be a part of a larger "farm parcel." However, the USDA farm definition is income-based with results reported at the county scale; this did not provide the detail required in this study.

Contiguous (or near-contiguous) parcels under single ownership generally indicate the presence of a farmstead, i.e., a complex of structures associated with a farming operation/workplace that includes residence, barns, other outbuildings and adjacent grounds suggestive of land under cultivation as one economic unit. Using remotely sensed data, multiple/contiguous parcels were treated as a single observation when observed farmstead configurations were apparent. The ArcGIS> Merge command was used to combine selected features of the parcel layer into one feature and modify the data set. To account for this new farm size, each observation took on the aggregate value of the attributes of the combined farm acres. The research data set contains only those parcels that had at least 5% percentage of agricultural land use in 1978**.** The data are available at the farmstead or neighborhood scale depending on the variable.

This framework provided the associated rationale for addressing the difficult to measure influences of a landowner's attachment to the land. Base map parcel specifications were fixed at the original study year 1978 in order to anticipate possible physical changes in parcel shapes (parcel merges, subdivision, and no-change conditions) over the 21-year study period. The resulting digital map (*1978 Parcel Boundary Base Map)* represented all ownership and lot dimension data and from the original 1978 plat map and enabled analysis in a GIS format. Additional source data at the farm parcel scale included assessed value, ownership, and PA116 program enrollment.

In this longitudinal dataset, each of three study years share the same base geometry (1978 parcel boundary) and are specified using the same set of independent variables. This enabled more direct comparison over time. A comparison of the USDA 1978 survey with respect to the 1978 farmstead database developed for this study indicated a significant difference in farm count. Again, USDA data, based on a different farm definition, emphasizes productivity surveys, and reports at the county scale, which are not intended to account for ownership. Designed for a different purpose, USDA was used in this study as a general reference source.

5.5.3. Independent Variables

Aside from the development of the initial period base parcel layer (1978), data preparation included production of multiple data sets of more recent thematic GIS data, all referencing the base map. Vector-based land use and prime farmland data overlays were directly input as overlays into the developed GIS (Tri County, 1999). Layers used as overlays for the base farm parcel map models in ArcGIS shape (*.shp) format are as included: Land Use, PA116, and Prime Farmland. These data were compiled and used as farm parcel map attributes in regression modeling and geospatial analysis.

Ortho-photo imagery (Tri County, 1987, 1991 and 1999) were used to classify land use within each parcel as either active agricultural (having potential of being farmed) or non-agricultural land use (mostly residential land use). The extent of alternate land uses (i.e., industrial or commercial) within the developed 1978 study area was negligible and was excluded from analysis. This imagery was also used to correct for errors in *MIRIS* land use classification for 1978 and adjust farm parcel boundaries.

By combining imagery interpretation and classified land use overlays, all original parcels that did not have any identifiable agricultural land use present within the digital farm parcel were removed from the analysis.

The Prime Farmland layer contained a single year (1999) shape file spatially delineating land classified as prime and optimal for crop production (USDA, 1993). Changes in land use over the 1978-91 and 1992-99 time periods were reflected in prime farmland base.

In the absence of comprehensive social capital data at the household level, participation in the PA116 program served as proxy for household farm attachment and community involvement. Many aspects of PA116 participation reflect high levels of attachment and social capital of the farmer. The PA116 layer contains the spatial configuration of farmland enrolled in Michigan farm preservation program Public Act 116. This source data was drawn from the Eaton County digital parcel data map with regular alterations to capture the change in program enrollment in the PA116 area (including sub-parcel level) during the three sample years.

5.5.3.1. Data Extraction – Neighborhood Scale: For this analysis, the “Neighborhood” is conceived as a zone of local influence (1 mile buffer or radius around a farm parcel centroid), setting a farm threshold of 1 mile. Specifically, the neighborhood is the area contained within the 1 mile radius around each farm parcel. This spatial buffer provides an accurate measure of agricultural land use change / density at this scale using a uniform geographic area to represent land owner response. Following York and Munroe (2013), the ranges of these buffers specified as one-mile Euclidean buffers also correspond to Michigan's legal definition of a farm operational area (Michigan DOA, 1978).

A *python* program was developed to extract data specific to each farm parcel from a large data set (see Appendix 7). The script generated a buffer about each farm parcel (centroid) and performed a GIS overlay analysis for variables of interest expected to influence land use change. Certain variables were expected to reduce land attachment, weaken local networks and signal a breakdown of social capital. Other variables are expected to represent factors that would constrict conversion in the rural-urban fringe (each buffered farm parcel area was excluded from its own buffer since a parcel cannot influence its own land use). Extracted variable values were measured as a percentage of each neighborhood at the three study data point years. The results of this operation were appended to each farm parcel record and used in the regression model and geospatial analysis (Appendix 8.).

Thirteen dependent variables were initially considered for each time period. Independent variables for each farm parcel are measured at farm parcel scale$_a$ or neighborhood scale$_b$. Anticipated direction of influence (sign) (-) or (+) for each independent variable with respect to the dependent variable is indicated below (and in tables 5.1a and 5.1b).

5.5.3.2. Social Capital Variables

<u>PA116 - Farm Parcel</u> (*PAdf7891* $_a$, *PAdf929* $_a$*)* (-)

Farmland preservation program *(PA116)* participation presence at farm parcel scale (acres/parcel) was calculated using a weighted average to reflect the length of contract term enrollment for agricultural land area protection.

In this case, property tax relief does not fully compensate the farmer for the loss of potential revenue from sale of land and reduced farm operational flexibility. Enrollment in program has indicated farmer attachment for specific land and, in general, for the agricultural way of life. Therefore, PA116 enrollment at the farm parcel or at the neighborhood scale can be used as a proxy for social capital in this study.

<u>PA116 - Neighborhood</u> ($PAdfb7891_b$, $PAdfb9299_b$) (-)

$PAdfb7891_b$, $PAdfb9299_b$ measure the density of *PA116* parcels in neighborhood.

PA116 density is measured as a percentage of agricultural land area within a one mile radius of a farm parcel that is enrolled in the farm preservation program (Roe et al., 2004).

Duration - Ownership of Land *(TOW_7899)* (-)

This variable accounts for time of ownership during study period and any change of the majority property holder. A continuous variable index was derived through hotspot analysis (Getis, 2003) from a source categorical variable (7, 14, 21). Newer owners are assumed to have no previous association with the land and therefore to have developed limited attachment value for the farm parcel.

<u>Agricultural neighborhood</u> ($Agbdf7891_b$, $Agbdf9299_b$) (+)

These variables signal a transition in land use. The influence of development within a neighborhood (conversion) typifies the “Impermanence Syndrome.” This local agricultural-to-residential landscape change is expected to diminish farmer attachment value, affecting land use change at parcel level. Spillover effects from neighboring land uses can create an interdependence among neighboring parcels. Landowner decisions regarding land use conversion (Irwin and Bockstael, 2002) are also likely to influence the value of a parcel in residential use (Geoghegan, Wainger, and Bockstael, 1997). Such interdependencies are likely to be temporally lagged, and therefore can be captured by measures of existing land uses within a parcel's neighborhood.

The influence of the neighboring land use variables is of interest, but the estimates must be interpreted with caution. As argued by Irwin and Bockstael (2002), land use externalities generated by land uses which are the result of past decisions by neighboring landowners are in some sense endogenous to the development process. In this case, while the effects are lagged over time and therefore not a simultaneously determined variable, the process by which neighbors were converted in the past is clearly very much related to the process that influences a parcel's conversion potential today.

Loss of agricultural land in neighborhood corresponds significantly to a loss of attachment value (landscape view) and the loss of local networks as well as an economic reduction of agricultural infrastructure. Local agricultural-to-residential landscape change is expected to diminish farmer attachment value, affecting land use change at parcel level.

5.5.3.3. Distance Variables

Regional CBD Distance $(LogCBD_a)$ (-)

$(LogCBD_a)$ is the transformation ($Base_{10}$) of the Euclidean distance (CBDist) from each parcel centroid to Lansing's central business district (CBD) in (miles). Levia (2000) found that distance to city center, nearby highways, and parcel size to be related to the probability of farmland conversion. The relationship between travel distance to the center of Lansing and conversion of use was uncertain. As noted in basic land rent theory, it suggests that residential use is a preferred use by individuals in proximity to the urban center, but other studies suggest living households in rural have a preference for separation from other settlement. Distance to the region's CBD is regularly used as a powerful covariate in models of land value and land use. In other studies, distance measures are often log transformed to normalize the data distribution (i.e., Zhou and Kockelman, 2009).

There were more commuters closer to Lansing, despite the presence of more appealing landscapes further from the city (U.S. Census, 2000). Preliminary results reveal that the influence of distance to large and small urban markets is significant, although not always in the expected direction. For those farm parcels located within approximately 14 miles of the outer boundary of the Lansing urbanized area, the probability of conversion decreases at a decreasing rate with distance from Lansing. However, for farm parcels located beyond this distance, the probability of conversion increases with distance from the urbanized boundary.

Local CBD Distance *(Locdstlog$_a$)* (+)

(Locdstlog$_a$) is the (Base$_{10}$) transformation of Euclidean travel distance from each farm parcel centroid to the closest local urban center. Small town locations of Charlotte, Eaton Rapids, Belleville, etc., are included to capture influence of local "urban" development on farm conversion. Locdist was transformed to Locdstlog (Log10) to normalize the data.

In 1992, during the middle part of the 1978-1999 study period, these small rural centers had populations ranging from 958-4,525 (U.S. Bureau of Statistics, 1990). McMillen (1989) found that distance to the nearest city of less than 10,000 was not statistically significant in differentiating between rural residential, agricultural and vacant land uses. However, Irwin et al. (2003) found that the logarithm of distance to the nearest small town was statistically significant and had a negative relationship to conversion to rural residential use.

Carrion-Flores and Irwin (2004) found that the log of distance to the nearest town had a statistically significant but positive relationship to conversion to residential use. This is consistent with the identified evidence that greater distance to small urban centers is sometimes viewed positively by “rural living” households (Nelson, 1993). In another “rural living” study, location within a small town sewer and water service area did not significantly affect the probability of very low-density residential development (Anstey, 2009). Due to the smaller size of these centers, a preference for proximity to their services may have overridden any desire of rural residential households for separation from any negative aspects of urban areas. However, this variety of results made it difficult to draw any conclusions about the influence of proximate small towns on rural residential development.

Overall, these results indicate that the spatial extent of the central city's pull on residential location is limited and that, all else being equal, new development is more likely to locate away from smaller urban places rather than adjacent to them. The lack or limited extent of the pull of a central city has been found in other studies as well (e.g., Waddell, Berry, and Hoch, 1993).

5.5.3.4. Economic Geographic Variables

Farm Size ($FmSz_a$) (+)

$FmSz_a$ measures the size of a farm parcel in Base Year (1978). As expected, larger farm sizes tend to decrease the likelihood of a merge event but increase subdivision tendencies. Farm parcel size may indicate a wealth effect; individuals with larger parcels may be more likely to depend on the land for income (from agriculture), affecting the observed configuration of land uses (Koontz, 2001). Empirical studies have shown that large parcels, with lower assembly costs, are more prone to conversion than are smaller parcels (Lynch and Lovell, 2003; Isgin et al., 2007). Farm size has been studied as a determinant of land use change farm size and proximity to an urban area can also alter the spatial patterning of preservation programs (Roe et al., 2004). Conversely, McMillen (1989) indicates that smaller parcels were more likely to be residential than agricultural. Other studies of conversion to rural residential use have included at least some parcels that were subdivided into smaller parcels, so their findings with respect to original parcel size are less relevant.

However, Hsu (1996) and Carrion-Flores and Irwin (2004), both of which studied subdivided and original parcels, also found that the probability of conversion to residential use decreased with increased parcel size. As one would expect, there was a strong correlation between *FmSz* and land use (see '*Data*'). Higher productive income is

Empirical studies have shown that large parcels, with lower assembly costs are more prone to conversion than are smaller parcels (Lynch and Lovell, 2003; Isgin et al., 2007). The combination of large farm size and proximity to an urban area can also effectively disrupt the spatial patterning of preservation programs (Roe et al., 2004) as well as existing active farms.

<u>Prime Farm</u> - Parcel *(PMdf7891, PMdf9299)*$_a$ (-)

PMdf7891, PMdf9299 measures the proportion of prime farmland present in a farm parcel (acreage/parcel). Prime farmland possesses a combination of physical characteristics considered optimal for crop production (USDA, 1993) and is regarded by farmers as a high-value asset, *least likely* to be converted to other uses (Brasier, 2005). However, prime farmland generally costs less to develop and is associated with higher assessed value. Therefore, prime farmland may also *positively* influence farmland conversion. A scatterplot analysis on this variable revealed a curvilinear pattern which required a square root function be applied to normalize the distribution.

<u>Prime Farm Neighborhood</u> *(PMbdf7891, PMbdf9299)*$_b$

(PMbdf7891, PMbdf9299)$_b$ measures the proportion of parcel land characterized as prime farmland by the Soil Conservation Service (*AGPRIME*) and is used as a measure of the value of land in agricultural use or agricultural profitability. Because this variable reflects the opportunity cost of converting from agricultural use to residential use, it is expected to have a negative influence on the hazard rate and reduce the probability of conversion, ceteris paribus. Prime Farmland possesses a combination of physical characteristics considered optimal for crop production (USDA, 1993) and is regarded by farmers as a high-value asset, least likely to be converted to other uses (Brasier, 2005). However, Prime Farmland generally costs less to develop and is associated with higher assessed value. Therefore, prime farmland may also positively influence farmland conversion.

Two studies even showed a positive relationship between conversion to rural living and soil quality, possibly due to reduced construction costs for new subdivisions and housing on good quality soils (Irwin et al., 2003; Carrion-Flores and Irwin, 2004). However, these studies were not focused on agricultural land use change, as such. Although weakly significant in the first model, when considered across all of the models, prime farmland was not a significant explanatory factor.

Road Density *(Rdbd7891, Rdbd9299)*$_b$ (+)

Rdbd7891, Rdbd9299 measure roadway lane miles within a buffer (lane miles /neighborhood) and indicates the density of major road infrastructure in neighborhood (5 mile radius). Use of this larger buffer was required to capture significant change.

Assessed Value *(AVacdf7891, AVacdf789)*$_a$ (-)

Assessed value per acre (price/acre/parcel) land valuation for individual farm parcel observation (+).

Assessed Value - Neighborhood *(AVbdf7891, AVbdf9299)$_b$*

Average land value in a neighborhood has typically been specified as dependent variable for many land use studies (Irwin and Bockstael, 2002; Irwin et al., 2003).

In general, variables that have a positive association with social capital are expected to act as deterrents to farmland conversion. *PA116* program participation (neighborhood) variables serve as a proxy variable for attachment value associated with continuous ownership of local agricultural land. By design, the *PA116* program encourages extended farmer land ownership.

Agricultural-to-residential conversion is modeled as the percentage difference in agricultural acreage (original use) compared to that of a later period. From this model, the factors that influence land use conversion can be determined and the parameters of those conversion functions can be estimated. This change variable model is specified for two time periods in the following table.

Finally, the distributions of the model's spatial fits (local R2 values) and the local b coefficients (and their significances) were mapped. These values were method to obtain continuous surfaces. This made it possible to analyze the local goodness-of-fit measure (R2) and perform a spatial analysis of the elasticity and significance of the independent variables

5.6. Summary

This chapter reviews the methodology that is used in this research to assess the relative importance and direction of association of certain variables in influencing agricultural land use change or farm conversion. The focus of the study is farmer land use choice and the influence of social capital variables on land use change. The beginning of this chapter discusses the extensions of the regression model in depth. This section provides a regression framework for analyzing the main research questions regarding social capital and land use change.

The first main research hypothesis was analyzed using OLS Regression; hypotheses two and three were tested using the "Regression/Linear" command (simple regression analysis) estimated in SPSS Version 18. Research Question 4 required a different sort of spatial analysis. The "Geographic Weighting Regression" module and other tools (ArcGIS version 10) were used to explore local spatial variations of the entire data set (see section 5.3.3 Geographic Weighted Regression) to answer Research Question 4.

Geographically Weighted Regression (GWR), a local regression model is used to explore local spatial variations of the parameters and estimate local standard errors, derive local t-statistics, calculate local goodness-of-fit measures, and calculate local leverage measures. The output from GWR was used to generate surfaces for each model parameter that can be mapped and measured. Each surface depicts the spatial variation of a relationship with the outcome variable. Implementation of GWR within GIS enabled the production of a number of maps using the generated results. OLS statistical models were performed using SPSS 18. All GWR analyses, GIS analyses and cartographic work were conducted using ArcGIS (ArcMap 10).

The Data section reviews how the model was specified and how data were acquired and developed for use in the model. Representing the influence of variables on agricultural land use change over two time periods required conversion of raw tabular and spatial data into continuous percentage change information. It was important to maintain that standard in order to accurately reflect farmer land use choice in detail, but it placed limitations on the types of analytical techniques employed.

Both general types of factors will be statistically modelled at the farm household decision-making and at neighborhood geographies in order to evaluate patterns over these different scales of analysis. The following chapter presents results for OLS stepwise regression, spatial analysis including “hotspot” analysis, and GWR models.

CHAPTER SIX
FINDINGS

6.1. Introduction

The overall research hypothesis is that farmland conversion is a result of many factors including non-economic social capital. Land value is based not only on economic factors but on a farmer owner's social capital which reflects a farmer's attachment to land as an expression of connection to family and community. This same emotional attachment can influence the decision of sale or retention of farmland (Robison et al., 2002). This research seeks to directly test the effects that participation in farmland preservation programs and other noneconomic factors may have in influencing conversion of agricultural land.

Previous research (Irwin and Bockstael, 2002; Capozza and Helsley, 1989) has indicated that land use change in the rural urban fringe can be strictly explained by economic and distance factors. These factors were statistically modelled over different scales of analysis. This chapter presents results for OLS stepwise regression and spatial analysis (maps) including "hotspot" analysis and GWR models. These models were used extensively to evaluate major hypotheses including a presentation of graphic evidence that non-economic factors do cluster, and further, demonstrate that non-economic factors do play a significant role in agricultural land use change. Key maps representing significant variables are presented here.

6.2. Statistical Results

In considering the appropriateness and scope of a study focused specifically on percentage conversion of farm parcels, it is noted that 7% of farms identified as agricultural land parcels in the first period (1978-91) lost over 50% of their land to development. Whereas in the second period (1992-99), 5% of farms identified as agricultural land parcels from which the observation units were drawn lost over 50% of their land to development. Another 5.2% farms retained their agricultural acres with virtually no land conversion over the entire study period (1978-1999). These results demonstrate (at least for this study area) that farm conversion is mainly a partial and incremental process.

6.2.1. Assessing the Hypotheses

The initial steps were taken to assess secondary research questions #2 and # 3 as the preparation for exploring neighborhood and distance effects were managed by use of simple one-step SPSS processing. The results were descriptive and not essential to model building. Research questions # 1 and #4 required a number of SPSS and GWR procedures before results could be viewed and analyzed.

6.2.1.1. Hypothesis #2: Neighborhood Effect: Following the concept of the impermanence syndrome, it was hypothesized in Chapter 3 that conversion of neighboring farmland to residential uses (*Agbdf7891*, *Agbdf929*), the independent variable, would diminish rural character and reduce farmer land attachment (*PAbdf7891*, *PAbdf9299*), the dependent variable. This hypothesis was tested using a simple linear regression.

The Adjusted R-square values for both models were 1978-91 (0.001) and 1992-99 (0.003) were low. However, the F-statistic and associated p-value for each of the models (5.019, 0.025) and (7.779, 0.005) respectively indicate that both models are statistically significant. For model 1978-91, Coefficient B *(Agbdf7891)* had a strength of -0.025 with a direction of sign that the variable was inversely related to the dependent variable; a greater change in the neighborhood was associated with less PA116 enrollment. For model 1992-99, Coefficient B *(Agbdf9299)* had a strength of 0.605 and is signed in a different direction than 1978-91. For this time period, greater change in the neighborhood is associated with increased PA116 enrollment. This result could be measuring a delayed response of greater resolve on the part of farmers to maintain agriculture in the neighborhood and would follow the impermanence syndrome literature.

6.2.1.2. Hypothesis #3: Distance Effect: It was hypothesized in Chapter 3 that distance from the CBD would influence neighborhood participation in the PA116 farmland preservation program. This hypothesis was also tested using a simple linear regression. The Adjusted R-square values for models 1978-91 and 1992-99 were 0.006, and 0.019 respectively with a statistical significance of 0.000 for both time periods. The F-statistic and associated p-value for each of the models (19.644, 0.000) and (49.449, 0.000) indicate that both models are statistically significant, however, the relationship is weak in both cases.

For model 1978-91, Coefficient B *(LogCbd)* has a strength of -.015. For model 1992-99, Coefficient B has a strength of -.117 and is signed in the same direction as 1978-91. The direction of sign indicates that the variable is inversely related to the dependent variable; greater distance from the CBD results in less PA116 enrollment.

This result may be counter to idea to what was expected. The rationale for farmer enrollment in PA116 enrollment was likely based on a more complex rationale than distance which emerged in GWR. For farmers close to urban encroachment the need to protect farmland may be more urgent than farmers in deep rural locations.

6.2.1.3. Hypothesis #4: Cluster Effect: It was also hypothesized in Chapter 3 that information exchange among farmers is generally a function of diffusion across local community networks (clusters of attachment value) which can exert spatial influence on farm parcel land use change. Geospatial analysis was applied to determine the existence of clustering of social networks, identify their locations in the study area, and determine if these clusters are random or the result of processes involving diffusion and social capital. Mapping specific to this effect will follow in section 6.3.2.

6.2.1.4. Assessing the Main Hypotheses #1: Multicollinearity tests are a crucial aspect throughout the study. Before specifying OLS models, it was important to identify highly correlated independent variables prior to the running the models as they may cause multicollinearity problems in both OLS and GWR models. In the initial phase of this study, Pearson correlation coefficients (bivariate correlations) among the candidate independent variables were calculated to test for multicollinearity (found in Appendix 1. and 2.). Identifying high multicollinearity values for a particular pair of independent variables may suggest that selection between independent variables with great care in order to eliminate redundancy. High coefficient values for specific independent/dependent variable pairings identified potential candidates for OLS modeling. This was useful if the measures were accurately taken and the logical direction of sign could better explain model relationships.

For the 1978-91 period, the highest correlation coefficients between independent variables was observed between the farm size and major road density variables (0.538**). During this period, new road construction was extended in areas where land was easily available. Correlation between the CBD Distance and neighborhood land assessment value (-0.387**) was correctly signed indicating higher assessed values are in areas closest to the CBD. Of the bivariate correlations between the independent and dependent variables prime farmland change - parcel and % farm conversion had the strongest correlation (.504). The sign direction (+) indicated that higher levels of farm conversion were linked to the increased level of prime farmland conversion.

For the 1992-99 period, high correlation coefficients were observed between independent variables *Agbdf9299* and *LogCBD* (-0.436**). This negative correlation can be interpreted as: an increased neighborhood loss of farmland is clearly associated with geographic proximity to the CBD. *LogCBD* and *AVbdf9299* (-0.382**) was also correctly signed indicating that higher assessed value would be located in areas closest to the CBD.

Overall, the number of 1992-99 correlated independent/dependent variable pairings that were statistically significant at the p= .000 level (**) of significance were much smaller than the pairings for the 1978-91 period. Of these pairings, the strongest correlation *was PMdf9299* (.236**) or prime farmland change variables at neighborhood scale with % farm conversion. Direction of signs for all variables was explainable. All correlations between independent variables for both time periods were well below the multicollinearity danger level of 0.7 (Clark and Hosking, 1986).

Using the data that was available and relevant for this study, models were constructed to represent the process of agricultural land use change at farm parcel scale over two discrete time periods. In a first iteration, both full regression models incorporated the available thirteen independent variables of which three (3) were related to the non-economic, (2) to distance, and (8) to the economic characteristics. Non-economic social capital variables that would include

PA116 program participation at local and neighborhood scale as well as other attachment value variables were expected to act as deterrents to farmland conversion.

6.2.1.5. Regression Analyses: OLS full Variable Models: Ordinary Least Squares were applied to sets of variables representing the two time periods. Multivariate analyses were useful in presenting the relative importance of the variables for the two models (see table 6.1.). The (1978-91) full variable OLS model (n= 3,056 observations) incorporated thirteen independent variables, with a global model fit of R^2_{adj} value of 0.445 accounting for less than 45% of the variability (% change in agricultural land use) for this time period. The overall F test indicated (F 8, 3055) = 189.456, p < .000. The (1978-91) model independent variables had two significant standardized regression weights related to prime farmland change (*prime farmland - parcel-square root),* Beta = .631, t = 44.212, p < .000; and (*prime farmland - neighborhood),* Beta = .041, t = 2.890, p < .004; and the social capital proxy *(PA116 change - parcel),* Beta = -.045, t = -3.264, p <.001). All three variables were significant contributors in predicting land use change and were signed as expected for the (1978-91) model. (For both time periods, a *square root transformation for the prime farmland parcel variable was used to improve model performance).*

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.669[a]	.447	.445	.93899141

a. Predictors: (Constant), Tow_7899, Agbdf7891, AVacdf7891, Rdbd7891, PAbdf7891, PAdf7891, PMbdf7891, Agpct78, LogCBD, PMdf7891sq, LocdstLog, AVbdf7891, FmSz

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2171.579	13	167.045	189.456	.000[a]
	Residual	2682.146	3042	.882		
	Total	4853.725	3055			

a. Predictors: (Constant), Tow_7899, Agbdf7891, AVacdf7891, Rdbd7891, PAbdf7891, PAdf7891, PMbdf7891, Agpct78, LogCBD, PMdf7891sq, LocdstLog, AVbdf7891, FmSz

b. Dependent Variable: TT7891a

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.886	.186		-4.771	.000
	FmSz	-8.018E-5	.000	-.007	-.411	.681
	Agpct78	.003	.001	.051	3.647	.000
	Agbdf7891	.078	.366	.003	.212	.832
	PAdf7891	-.228	.070	-.045	-3.264	.001
	PAbdf7891	-.026	.577	-.001	-.046	.964
	PMdf7891sq	4.921	.111	.631	44.212	.000
	PMbdf7891	3.198	1.107	.041	2.890	.004
	AVacdf7891	1.947E-5	.000	.047	3.033	.002
	AVbdf7891	2.239E-5	.000	.025	1.485	.138
	Rdbd7891	.003	.001	.060	3.572	.000
	LogCBD	-.207	.122	-.026	-1.693	.091
	LocdstLog	.018	.085	.003	.213	.832
	Tow_7899	-.133	.059	-.031	-2.234	.026

a. Dependent Variable: TT7891a

Table 6.1. OLS Full Model (1978-91)

For the *full* variable OLS model (1992-99) (n = 2,472 observations for the reduced set), the model (see table 6.2.) incorporated thirteen independent variables, with a global model fit of R^2_{adj} value of 0.159 or only 16% of the change in agricultural land use variability for this time period. A reduced set of observations was run to accommodate the GWR model (see 6.3.3.). In this continuous distribution (from 0 to 1 for dependent values) GWR does not perform well as response values approach 0 or 1, or similar to a binary response. The overall F test indicated (F 4, 2471) = 36.968, p < .000 for (1992-99) model. Two independent variables had significant standardized regression weights (*prime farmland - parcel-square),* Beta= .370, t = 19.521, p < .000; and *(Farm size),* Beta = -.094, t = -4.763, p <.000): each of the two is a significant contributor to predicting land use change.

As shown in the ANOVA sub-table, the overall F test indicates that the regression equation for both time periods are significant as independent variable models for explaining land use change. The variance inflation factor (VIF), measuring redundancy among all 13 independent variables in this OLS analysis did not exceed a conservative index of 2 (for 1978-91 the highest VIF is 1.346; for 1992-99, 1.013 is the highest VIF). These very low VIF indices suggest that there were no multicollinearity problems among the independent variables and it was appropriate to include all of the variables in the model.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.404[a]	.164	.159	.57175907

a. Predictors: (Constant), Rdbd9299, AVacdf9299, PAdf9299, PMdf9299sq, Tow_7899, PMbdf9299, Agpct78, Agbdf9299, PAbdf9299, FmSz, LocdstLog, AVbdf9299, LogCBD

b. Dependent Variable: TT9299a

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	157.105	13	12.085	36.968	.000[a]
	Residual	803.541	2458	.327		
	Total	960.646	2471			

a. Predictors: (Constant), Rdbd9299, AVacdf9299, PAdf9299, PMdf9299sq, Tow_7899, PMbdf9299, Agpct78, Agbdf9299, PAbdf9299, FmSz, LocdstLog, AVbdf9299, LogCBD

b. Dependent Variable: TT9299a

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.244	.141		1.730	.084
	FmSz	-.001	.000	-.094	-4.763	.000
	Agpct78	.003	.001	.094	4.874	.000
	LogCBD	.073	.095	.018	.766	.443
	LocdstLog	.084	.060	.029	1.403	.161
	Tow_7899	-.001	.040	-.001	-.037	.970
	Agbdf9299	1.977	1.129	.038	1.752	.080
	PAdf9299	-.041	.117	-.006	-.348	.728
	PAbdf9299	.151	.096	.031	1.575	.115
	PMdf9299sq	2.230	.114	.370	19.521	.000
	PMbdf9299	-.610	.185	-.066	-3.294	.001
	AVacdf9299	2.126E-6	.000	.019	.917	.359
	AVbdf9299	-2.767E-6	.000	-.012	-.535	.592
	Rdbd9299	.001	.003	.004	.180	.857

a. Dependent Variable: TT9299a

Table 6.2. OLS Full Model (1992-99)

6.2.1.6. Stepwise Regression: Variable Exclusion: For this research, the objective of variable reduction was to arrive at a parsimonious model that provides higher explanatory power with a lower number of variables to explain land use change. With model reduction, geospatial analysis was used to produce mapping analysis. In order to improve on the OLS full set variable results, an objective model selection provided variables that were based on several conventional SPSS statistical algorithm methods (Stepwise, Backward, Remove and Forward). After several trials, a stepwise regression model in SPSS (Method = Stepwise) provided the best overall results and was used in subsequent analysis.

The resulting model included only those independent variables for which the regression coefficients were statistically significant by minimizing the Akaike Information Criterion (AIC_c). In addition to the explanatory power of the model, the AIC_c also considers model complexity and resulted in a more parsimonious model.

The final stepwise multivariate regression model for 1978-91 period, including Beta coefficients, (regression weights) is as follows: SPSS output detail for stepwise modeling (1978-1991 period) is found in Appendix 3.a.

Dependent Variable: = TT7891 Δ Agricultural Land Use $_{(1992\text{-}1978)}$

TT7891 = β_0 + (.631) PMdf7891sq+ (.035) AVbdf7891 + (.060) Rdbd7891 +

(-.047) PAdf7891 + (.052) Agpct78 + (.042) PMbdf7891 + (.047) AVacdf7891 +

(-.032)Tow_7899+ ε

incorporated eight independent variables, (F 8, 3055) = 307.576, p < .000) including several with significant standardized regression weights *(prime farmland - parcel-square)*, Beta= -.631, t =

44.489, p < .000; *(PA116 change –parcel)*, Beta = -.047, t = -3.445, p <.001; and *(Road buffer change)*, Beta = .060, t = 4.371, p <.000): each of the three is a significant contributor to predicting land use change. The eight independent variables from the 1978-91 stepwise model explain slightly more of the variation in the dependent variable ($R^2_{adj} = 0.445$ for the stepwise versus $R^2_{adj} = 0.445$ for the full model), but also performed significantly better than the full model based on the AIC values (9245.3 for the stepwise versus 10090.4 for the full variable model).

The final stepwise multivariate regression model for 1992-99 period including Beta coefficients (regression weights) is as follows:

Dependent Variable: = TT9299 Δ Agricultural Land Use $_{(1999\text{-}1992)}$

TT9299 = β_0 + (.369) PMdf9299sq + (-.093) FmSz + (.092) Agpct78 + (-.061) PMbdf9299

(SPSS output detail for stepwise modeling (1992-1999) is found in Appendix 3.b).

Appendix 4.a. and 4b. incorporated four independent variables (F 4, 2471) = 105.070, p < .000) with significant standardized regression weights including (*Prime farmland - parcel-square)*, Beta= .369, t = 19.735, p < .000; and *(Farm size)*, Beta = -.093, t = -5.049, p <.000) ; and (*Ag% 1978 - parcel)*, Beta= .092, t = 4.911, p < .000; each of the three is a significant contributor to predicting land use change.

These four independent variables in the final stepwise model not only explain slightly more of the variation in the dependent variable ($R^2_{adj} = 0.160$ for the stepwise versus $R^2_{adj} = 0.145$ for the full model), but also perform significantly better than the full model based on the AIC values (7511.3 for the stepwise versus 7524.1 for the full model). However, there cannot be too much faith in the model as poor model performance R^2_{adj} = 0.160 is only explaining a limited amount of the variation. Interpretation of OLS model can be dangerous when explaining by increase in 1% for standardized beta coefficients.

As reported in the ANOVA table, the overall F test indicated that the regression equations are significant as independent variable models for explaining land use change. The resulting properly specified (Stepwise) OLS models provided the number of observations and variables and enabled spatial analysis and estimation of a GWR model in ArcGIS (v.10.0).

For both time periods (1978-91) and (1992-99), prime farmland farm at parcel and neighborhood scales emerged as a significant variables in the models. In comparison, some other studies have not shown such an important role for measures such as presence of prime farmland or average revenue per acre in explaining land use (Hsu, 1996; Kline and Alig, 1999).

Important proxy variables for non-economic factors influence on land use change emerged in the (1978-91) time period. These included PA116 program participation at farm parcel scale as well as the attachment value variable *TOW_7899* (time of ownership). The PA116 or like preservation variables were not found in the literature.

6.2.1.7. Discussion: The study found that *Agbdf7891* neighborhood agricultural land use change with respect to the dependent variable (land use change – parcel level) was not statistically significant. Instead, the finding that the Prime Farmland variable was strongest explanatory factor which had more weight than any other variable in explaining the farm conversion choice and was positive and highly statistically significant.

The decision to resort to spatial regression is warranted when it produced an improvement in the global fit and when it allowed the presence of spatial aggregations (clusters) in the distribution of residuals to be corrected.

6.3. Geospatial Analysis

6.3.1. Global Moran's I – Spatial Autocorrelation

A significant Moran's *I* statistic is a first clue that parameter estimates in an OLS regression maybe affected by spatial residual autocorrelation. Initially, their spatial distribution patterns were analyzed using the global Moran's *I* index (ArcGIS) to determine whether any autocorrelation was present (Fotheringham et al., 2000.) For this reason, the Moran's *I* statistic was calculated for both study periods for the two Stepwise models. For the 1978-1991 study period, all eight stepwise independent variables were included in the analysis. All of the variables gave estimated Moran's *I* values higher than the expected E(*I*) -0.0000327; thus, a positive spatial autocorrelation existed (Table 6.3.) with the greatest spatial dependency found for the following variables: *PMbdf7891* (0.746), *TOW_7891* (0.513), and *AVbdf7891* (0.356). Residual independence is also tested by the Moran's *I*. This test indicated significant spatial residual autocorrelation ($I = 0.179$; $p = 0.002$), violating the model's independence assumption.

Moran's I calculations

7891	def threshold		Moran's I	ExpIndex	Variance	Z-score	p value
TT7891a			0.106701	-0.000327	0.000035	18.210746	0.000000
AVbdf7891	7971.5240		0.356153	-0.000327	0.000034	61.499188	0.000000
PMdf7891sq	7971.5240		0.636521	-0.000327	0.000034	105.674680	0.000000
PAdbf7891	7971.5240		0.448970	-0.000327	0.000034	7.704214	0.000000
Rdbd9299	7971.5240		0.192901	-0.000327	0.000034	103.660580	0.000000
Agpct78	7971.5240		0.153922	-0.000327	0.000034	26.251302	0.000000
AVacdf7891	7971.5240		0.043287	-0.000327	0.000034	8.234905	0.000000
PMbdf7891	7971.5240		0.746132	-0.000327	0.000034	127.060522	0.000000
TOW_7899	7971.5240		0.512942	-0.000327	0.000034	87.335011	0.000000
9299							
TT9299a	7971.5240		0.088007	-0.000405	0.000054	11.976248	0.000000
PMdf9299sq	7971.5240		0.105312	-0.000405	0.000054	14.339906	0.000000
FmSz	7971.5240		0.044847	-0.000405	0.000054	6.145580	0.000000
PAdbf9299	7971.5240		0.679719	-0.000405	0.000054	92.153984	0.000000
PMbdf9299	7971.5240		0.65003	-0.000405	0.000054	88.104105	0.000000

Table 6.3. Moran's *I* calculations

For the 1992-1999 period, results indicated that all of the four stepwise independent variables also exhibited significant global positive spatial autocorrelation. All tested variables also gave estimated Moran's *I* values higher than the expected E(*I*) -0.000405; thus, a positive spatial autocorrelation existed (Table 6.3). The greatest spatial dependency was found for the *PAdbf9299* (PA116) variable at (0.679) and the *PMbdf9299* prime parcel variable (0.650). Residual independence was tested by the Moran's *I*. This test shows significant spatial residual autocorrelation ($I = 0.179$; $p = 0.002$), also violating the model's independence assumption.

Table 6.3. indicates the spatial patterns of the independent variables included in the final model. Positive Moran's *I* index for all the variables indicated a tendency towards clustering. The z-scores and p-values allowed rejection of the H_o, and that features were randomly distributed across the study area. After an examination of the regression residuals for spatial correlation, the Moran's *I* statistic of 0.746 strongly suggested that the standard OLS regression

estimates could not be trusted. Moran's *I* provided global information but did not provide differentiation across the study area. Hotspot analysis and GWR were then used when there is spatial autocorrelation in the residuals from the aspatial regression. Sufficient evidence, therefore, existed for resorting to the use of GWR.

6.3.2. Getis and Ord G* Statistic - Hotspot Analysis

Prior to GWR analysis, the Getis-Ord G* statistic (i.e., Hotspot analysis) was used to determine the areas of significant autocorrelation and reveal the spatial distribution of a single variable having significant positive spatial autocorrelation. Statistically significant clusters of high (i.e., hot spots) and low values (i.e., cold spots) were mapped. Positive spatial autocorrelation (red shaded area) meant that similar values tended to occur in adjacent areas, whereas negative autocorrelation implied nearby locations tended to have dissimilar values.

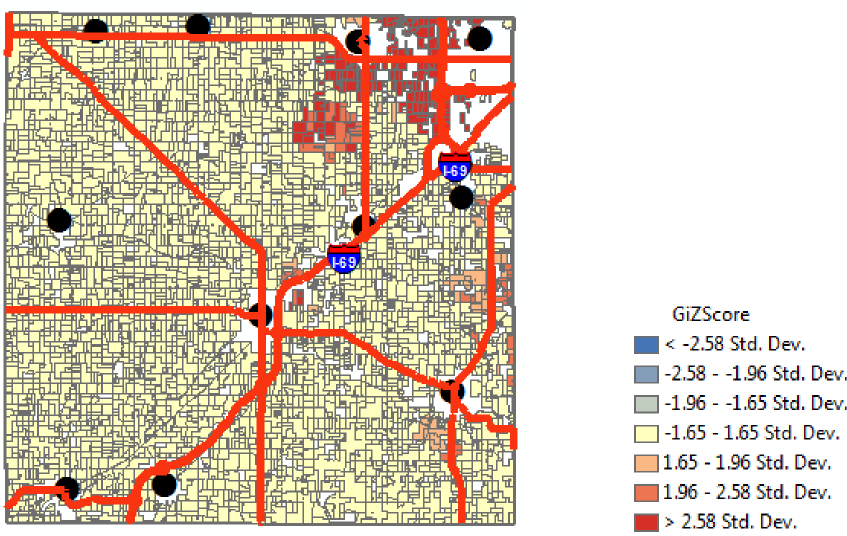


Fig 6.1 Hotspot *Avacdf7891* (1978-91)

For this study, the mapping of this statistic indicated clustering of high values of the assessed value variable (land price), important in the first period from 1978-91. During this period, this cluster is located in the northeast corner of the study area nearest to Lansing CBD. The value increase shown reflects change of land price immediately before the changeover from agricultural to residential use.

In Eaton County, the mapping of this statistic indicated clustering of high values of the PA116 variable in 1978-91. West of Charlotte, there is a large cluster indicating strong networking for PA116. For the 1992-99 map, there is a distinct shift of correlated areas. However, hotspot analysis is limited as it only represents one variable not associated with the rest of the modelled variables.

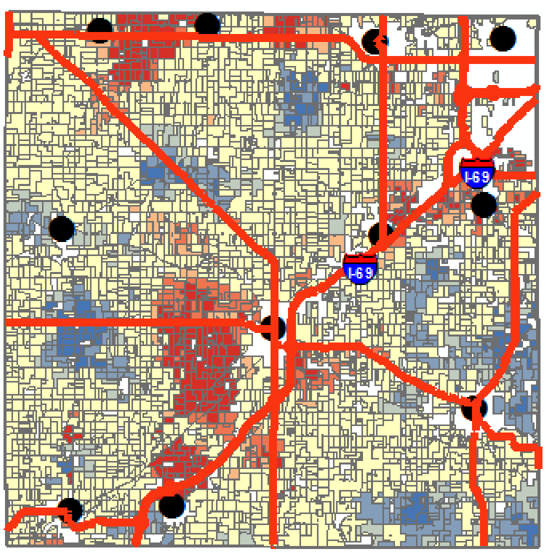


Fig 6.2 Hotspot *PA116* (1978-91)

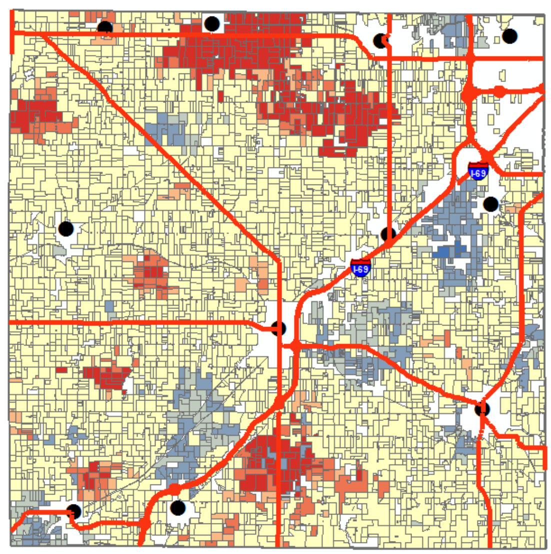
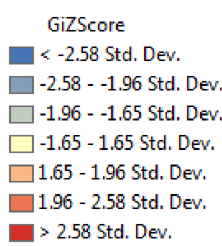


Fig 6.3 Hotspot *PA116* (1992-99)



The 1978-91 distribution clearly indicates a large significant high variance cluster of PA116 in the southwest (red districts) and a large significant cluster of low (variance) in the eastern portion (blue districts) of the study area. Sections in beige shading exhibited an insignificant spatial distribution of spatial autocorrelation for PA116. In these areas, a large part of the mapping, the spatial arrangement would be completely random from one farm parcel to another.

6.3.3. Geographic Weighted Regression

Additionally, in regression analysis, the actual concern is not the spatial autocorrelation in the dependent and independent variables, but in that of model residuals (English et al., 2003). Using the aspatial OLS model, the relationships between land use change and the independent variables remain stationary (i.e., constant) across the entire study area of Eaton County. However, multiple studies have indicated that such relationships between land use and independent variables are in fact non-stationary and vary across the study area. Local spatial regression models take such “non-stationarity” into account. With the GWR method, it was possible to analyze the spatial variability of the local coefficients of dependent variables (i.e. elasticities) and analyze how these relationships vary over space. These maps also suggest that further investigations of local estimate spatial patterns would help to establish an understanding of possible causes.

For GWR modeling, multicollinearity is of great concern and will disrupt estimates of both the betas and the standard errors. The Condition Number is a diagnostic used in GWR to evaluate local collinearity. In the presence of strong local collinearity, results become unstable. Results associated with condition numbers larger than 30, may be unreliable. In this study area during the (1978-91) period, the condition number that evaluated local collinearity had a minimum of 10.39 and maximum of 21.23 and with a mean condition number of 13.548. For the (1992-99) time period, the condition number had a minimum of 5.591 a maximum of 11.516 with a mean condition number of 8.246. For both periods, the highest condition values were observed in the northwest corner of the county. Overall, multicollinearity does not have a strong influence on the models. For this model, the number of observations was reduced to enable the GWR regression software provide results. Observations with dependent variables approaching 0 (no land use change), or approaching 1 (complete land use conversion) were removed from the data set.

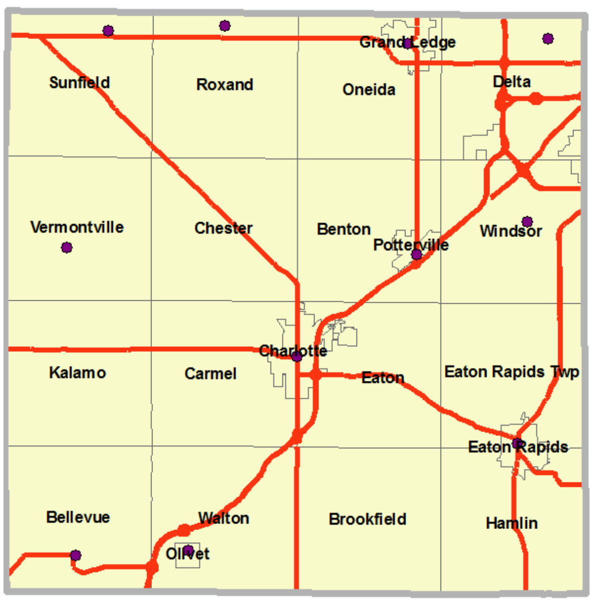
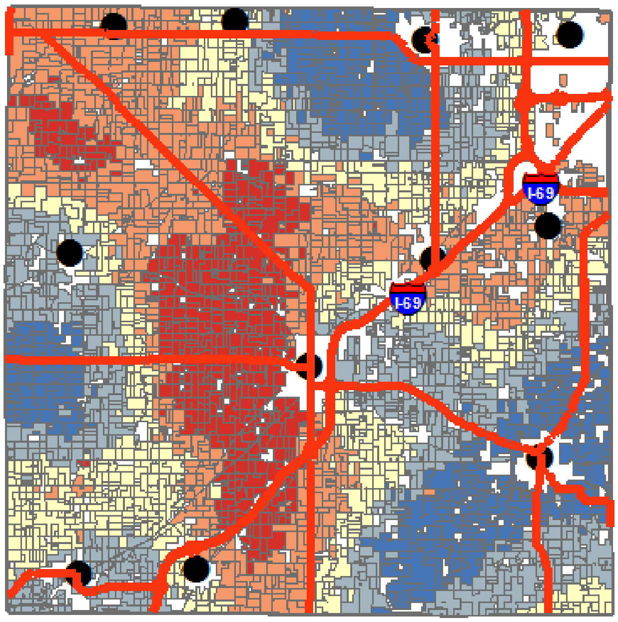


Fig. 6.4. Eaton County Township map

6.3.3.1. Local R2 Mapping: A GWR local model was applied to analyze how independent variable relationships changed from one farm parcel to another. A localized multivariate regression was also allowed the parameters of a regression estimation to change locally and map distribution of R2 values. From this “confidence map” it was obvious that the value of R2 was not homogeneously distributed in all regions. For 1978-91 (Fig 6.5.), the overall GWR regressions were fitted best in a north-south region including Carmel, Chester, and Sunfield Townships (refer to Fig. 6.4.). This model did not fit well in small noncontiguous areas, and this could imply that additional covariates were needed to explain the farm conversion in those areas. For the 1992-99 period (Fig 6.6.), the overall pattern of GWR regressions were fitted best in similarly located but smaller- sized, and more scattered areas.



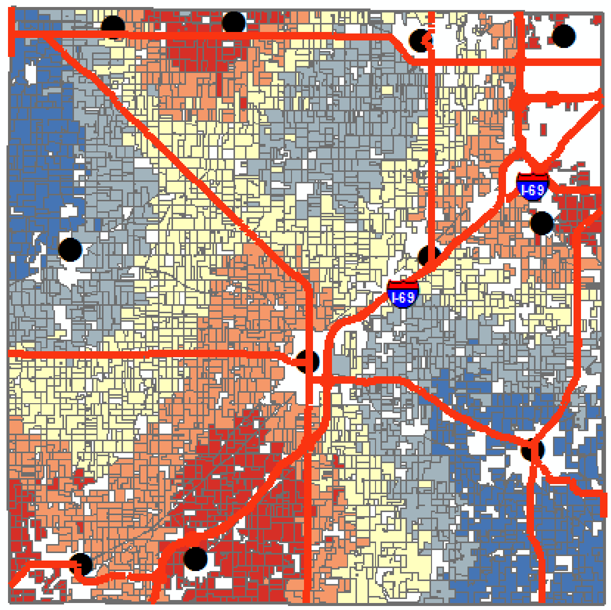


Fig 6.5. R2 value 1978-91

Fig 6.6. R2 value 1992-99

Local R2
0.279039 - 0.395779
0.395780 - 0.447838
0.447839 - 0.494914
0.494915 - 0.545229
0.545230 - 0.626943

Local R2
0.060344 - 0.116003
0.116004 - 0.142133
0.142134 - 0.165386
0.165387 - 0.193075
0.193076 - 0.295558

Therefore, it was possible to identify where the GWR model has a better fit (R2), how relations between the variables vary across space (estimated coefficients) and with what statistical significance. Thus, spatial instability observed in relationships could be explained by the fact that some relationships were intrinsically different across space.

6.3.1.2. Coefficient Maps: However, the spatial variation of the coefficients had to be interpreted carefully. These coefficient values were used to obtain continuous surfaces. This made it possible to analyze the local goodness-of-fit measure (R2) and perform a spatial analysis of the elasticity and significance of the independent variables.

Individual independent variables were also interpreted; each independent variable was mapped to represent the fitting level for each specific variable under GWR (Figures 6.7. - 6.10.). The significant *elasticities,* that is, values that express the marginal effects on a common scale, (i.e., they are the percentage change in dependent variable relative to the percentage change in the independent variable) are shown as, blue and red sections, indicated that the parameter estimations in these areas were reliable.

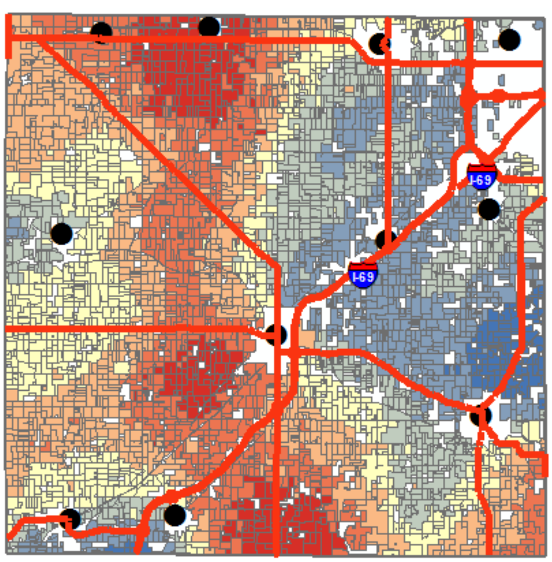


Fig. 6.7.   PA116 Coefficient 1978-91

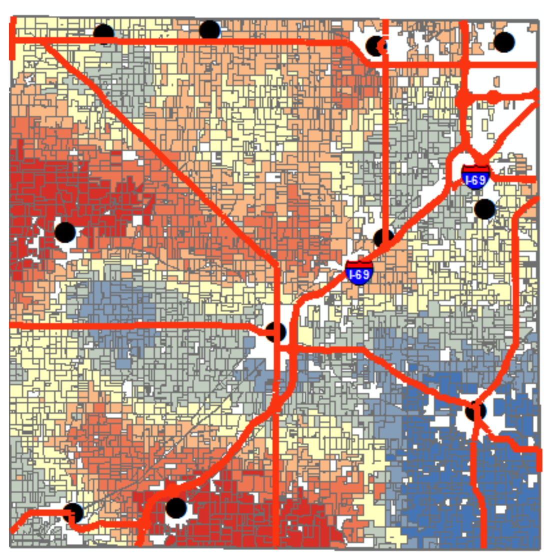


Fig. 6.8. Prime Farmland Coefficient 1978-91

Coefficient #5 PAdf7891
-1.031326 - -0.651630
-0.651629 - -0.472421
-0.472420 - -0.348965
-0.348964 - -0.204440
-0.204439 - -0.057886
-0.057885 - 0.124867
0.124868 - 0.510339

Coefficient #1 PMdf7891sq
3.318501 - 3.947310
3.947311 - 4.454421
4.454422 - 4.823964
4.823965 - 5.149160
5.149161 - 5.508873
5.508874 - 6.050071
6.050072 - 7.866620

PA116 elasticities (Fig 6.7.) corresponded well with the Local R2 mapping (i.e. high confidence in coefficient results) and indicated a high level of elasticity in a large region in the west section of the county. Mapped prime farmland change (Fig. 6.8.), corresponds to large scale residential development and changes in the Interstate I-69 corridor. In both cases, the coefficient signs match the theoretical direction.

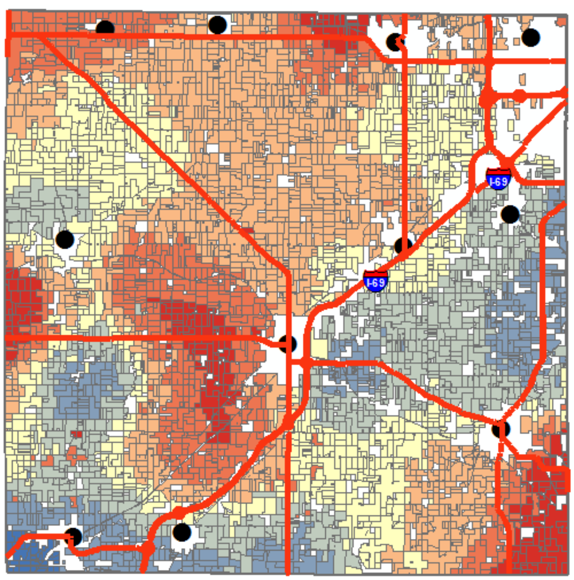


Fig. 6.9. Road Density Coefficient 1978-91

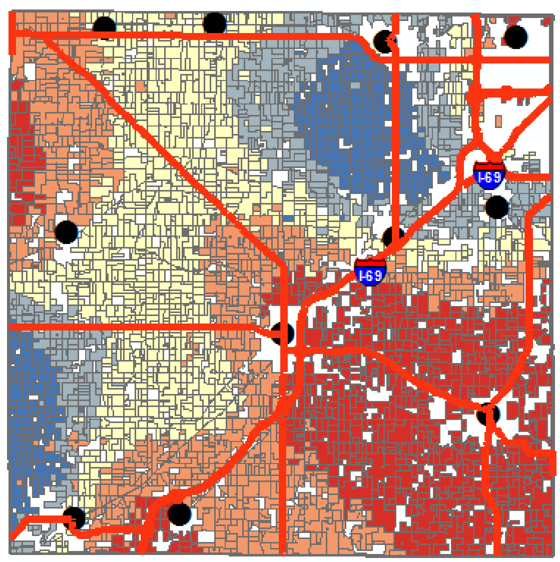


Fig 6.10. Farm Size Coefficient 1978-99

Coefficient #3 Rdbd7891
-0.007238 - 0.000648
0.000649 - 0.002416
0.002417 - 0.003878
0.003879 - 0.005587
0.005588 - 0.009935

Coefficient #1 FmSz
-0.001265 - -0.000974
-0.000973 - -0.000798
-0.000797 - -0.000637
-0.000636 - -0.000469
-0.000468 - -0.000194

For road density (Fig. 6.9.), the mapping suggests back-filling of the road network to anticipate completion of I-69 during the 1978-91 time period. These results correspond well with Local R2 mapping and improve confidence in the elasticities represented.

Smaller farms in this study area are more likely converted. As mapped (Fig 6.10.), areas with large farms are more resistant to development. The results from GWR analyses, suggested that the relationships actually varied over space. By comparing the varying relationships across different regions of the study area, this research was able to capture the inconsistency in the associations between the dependent variable and non-economic and economic factors.

In order to avoid compensating effects from other independent variables, this research has applied both OLS and GWR analysis on the dependent variable. Single parameter mapping for each independent variable represented the fitting level for each specific variable under GWR. Disaggregation of the global coefficient of determination (R2) into local coefficients and analysis of their geographical distribution made it possible to recognize where the independent variables have greater or lesser explanatory power (Fotheringham et al., 2002; Lloyd, 2010). Again, positive spatial autocorrelation (red sections) meant similar values tended to occur in adjacent areas, while negative autocorrelation (blue sections) implied nearby locations tended to have dissimilar values. If no spatial autocorrelation was found, then the spatial arrangement would be completely random from one parcel to another.

6.4. Summary: Interpretation of Findings

What did the Data Analysis reveal?

RQ1: In 1978, 32 % of study area land use was considered prime farmland. Over the time frame of this study that percentage remained at a close 34% of study area (changes in prime/study area composition remained the same) indicating that there was a strong relationship between dependent variable and the strongest independent variable.

There was considerable difference between the variables that explained 1978-91 and 1992-99 models. Models variables saw a shift from social capital/economic in 1978-92 to in economic variables during 1992-1999. The PA116 variables did not explain land use change in the second period.

As a result of public policy change, a statewide property tax reduction in the early 1990s led to a disincentive for farmers to enroll in the program. New PA116 contracts were limited as the program came close to termination. (Following a change in property tax assessment in 1999, the PA116 program increased the number of new contracts to tenfold that of the 1992 annual rate). The implication is that for further study, the PA116 will again be a relevant factor in land use change.

Other changes can be explained, in part, by several major developments in Eaton County. After completion of Interstate I-69 in 1992 Eaton County was no longer an isolated rural area. Instead, major industrial development and a steady increase of residents into the county (as indicated by the number of housing permits) changed the character of Eaton County from a farming region to more of a bedroom community for Lansing, MI.

RQ2: For the model 1978-91, *(Agbdf7891)* had a weak relationship with PA116 enrollment and inverse relationship PA116 enrollment; a greater change in the neighborhood associated with less PA116 enrollment was expected. Instead, for the model 1992-99, *(Agbdf9299)* had a weak relationship and was signed in a different direction than in the 1978-91 period.

RQ3: For the model 1978-91, *(LogCbd)* had a weak relationship with PA116 enrollment. Model 1992-99 also had a weak relationship and is signed in the same direction as 1978-91. The direction of sign indicates that the variable is inversely related to the dependent variable; that is, greater distance from the CBD results in less PA116 enrollment. In other words, in certain areas close to the CBD, one may find strong areas of PA116 enrollment.

RQ4: For the model 1978-91, using hotspot analysis, PA116 enrollment pattern was clustered indicating that networking among farm decision-makers may have been a significant factor in the land use change.

6.4.1. Model Improvement - Comparison GWR with OLS

The residuals from the GWR model were smaller than those from the OLS model. Likewise, analysis of the residuals showed better results for both GWR models for the (1978-91) and (1992-99) models than in the OLS model.

Respectively, OLS models as compared to the GWR models explained only about 45 % of the variance in the land use change. As expected, GWR model outperform the corresponding global OLS (Full) model ($F = 2.363$; $p < 0.001$), it also now explains between close to 50% of the variance in R. In addition, based on the AIC criteria and Pearson's correlation coefficient, it can be deduced that GWR and give us better predictions than the non-spatial OLS estimator. The spatial stationary F statistic test and Akaike's Information Criteria (AIC_c) values, reported at the bottom of Table 6.4, indicate that GWR model performed better than OLS (for interpretation, a decrease in the AIC_c value indicates better model performance.

Once the two OLS models were obtained, they were compared for their global fit and for the distributions of their residuals. The summary results of fitting these models using GWR are listed in Table 6.4. Some improvement in model performance in modeling land use was evident for GWR over OLS from both the values of AIC_c and adjusted *R*2 for the (1978-91) models. Virtually little improvement was shown in the (1992-99) models.

Model Comparison 1978 -91 / 1992-99				
Model	AIC	AdjR2	n	#Variables
1978-91 (Full)	10090.38	0.445	3056	13
1978-91(Step)	9245.63	0.445	3056	8
1978-91 (GWR)	8143.37	0.491	3056	8
1992-99 (Full)	4682.76	0.148	2472	13
1992-99 (Step)	4682.72	0.149	2472	4
1992-99 (GWR)	4276.71	0.168	2472	4

Table 6.4. Model Comparison 1978-91 / 1992-99

6.4.2. Implications of Study

These models were used to predict the log of agricultural land use change per farm household. It was concluded that some spatial autocorrelation and spatial heterogeneity of the different variables of our models are present. Then, as shown here, the strongest factors may vary from region to region. Such results may be used to inform policy makers and preservation initiatives, which may then be tailored to the local needs in addition to global spatial independent variables. Specific results provided for each location can be used as evidence to support local policies and decision-making; which is why these spatial techniques are frequently referred to as *"place-based"* (de Smith, Goodchild, & Longley, 2009). This conclusion might have policy implications for choosing urbanization pattern for regional planning, subdivision policy as well as informing Department of Agriculture (DOA) policy regarding the optimal size and location of preserved farmland.

Mapping and spatial analyses of land use are crucial steps for identification and analysis of farm conversion; land use can be highly heterogeneous phenomena among various areas (i.e. in the RUF). Spatial heterogeneity may be related to initial endowments (education, access to basic infrastructure, market access facilities). Also, whatever range of economic conditions, type of agriculture and land suitability/productivity are considered, regional industry viability would also be a precondition.

PA116 has been identified as a significant social capital variable that has had an important influence on agricultural land use change by encouraging farm retention and reducing the rate of farm loss to other types of uses. Policy, in accordance with a standard economic scarcity argument, preservation of land in neighborhoods with little remaining farmland appears to be of greater value at the margin than preservation in neighborhoods with much remaining farmland. This implies that in locations where it may be cheapest to implement farmland preservation, that is, where agricultural land remains plentiful (and less expensive), may provide the smallest marginal values.

A better understanding of the spatial relationship between social capital and land use in rural areas will enable policymakers to develop more effective tools to preserve farmland. Current Department of Agriculture programs allocate funding for farm preservation. Eligibility for participation in preservation programs is determined based on criteria that include sustainability, environmental, and economic factors, as well as by cluster size of participating farms. An expansion of criteria for participation would include unconventional non-economic variables as revealed in this research through the use of spatial analysis of spatial autocorrelation in further investigation. Farmland preservation should be focused on strategies to avoid unplanned rural living, rather than determine what is required for a viable farm.

In this study, the 1992-1999 period was one of relatively high commodity prices with a resulting increase in land value (potentially changing the rate of conversion). In general, other external economic conditions may alter land values for agriculture and land values for rural resident living.

It is also important to note that the scope of this research has been limited to a definition of farm conversion impact to direct loss of agricultural land from production. The significance of other impacts such as land use and land management conflicts was not evaluated in this study. Further research would be necessary to consider the significance of those other impacts in shaping land use and subdivision policy.

The following chapter provides a brief summary of this research and concludes with plans for future research on rural / urban fringe land use.

CHAPTER SEVEN
CONCLUSION

7.1. Summary

This research attempted to better identify important factors that lead to land use change (conversion) in the rural-urban fringe. The main research questions that guided this dissertation were:

1. The primary objective for this study was to test the hypothesis whether changes in measures of social capital are associated with a meaningful change in land-use in the rural-urban fringe. Using PA116 participation as a proxy for social capital or attachment value, research questions 2 and 3 were:
2. Does neighborhood land use change influence attachment value?
3. Does distance from the CBD influence neighborhood participation in the PA116 farmland preservation program?
4. Do clusters of attachment value exert spatial influence on farm parcel land use change?

The assumption of overall research hypothesis is that farmland conversion is a result of many factors including non-economic social capital. Previous studies have focused on the economic criteria of land value and location as drivers of land use change (Alonso, 1964; Tsoodle et al., 2006; Carrion-Flores et al., (2004.) have shown that land use change in the rural urban fringe can be strictly explained by economic and distance factors. Land value can be based on social capital which also reflects a farmer's attachment to land as an expression of connection to family and community. This same emotional attachment can influence the sale or retention of agricultural land (Flora, 1998; Robison et al., 2002). In effect, high levels of social capital can impede farm conversion rate. This research sought to directly test the roles that participation in farmland preservation programs and other noneconomic factors have in reducing urban sprawl by assessing their impact on land conversion in comparison to other factors at the farm household decision-making scale. Initial field research indicated that there was an important association of strong, local, attachment value and the well-studied elements of land value and land use. This finding justified the selection and specification of variables for the two models.

The main findings of this research were that: 1) prime farmland change is an important factor to consider in understanding land use change; 2) non-economic factors do cluster and explain local resistance to land conversion; 3) this clustering effect suggests that "place" or local scale is important to understanding the larger processes of land use change in region; and 4) spatial expression in local areas is related to local network diffusion of ideas (specifically participation in farm preservation programs) (Hägerstrand, 1967). The geographical models indicated that there may be significant spatial clusters of *PA116* in farm households during study period 1978-91.

Chapter 6 presented and discussed findings for the regression and GWR models, extensively evaluated the main hypothesis, and presented graphic evidence that further demonstrate that non-economic factors do play a significant role in agricultural land use change. The testing of the first question used statistical modelling and a geographical approach to determine whether the nature of farmland transactions, specifically farm conversion, may or may not be strictly a function of economic profitability, but may also be subject to "intangible assets." This study developed a model to investigate the economic and non-economic aspects and spatial patterns of rural land use change. The objective has been to provide insight into non-economic influences on unanticipated patterns of agricultural and residential development which a strictly economic model fails to adequately explain.

The geographic contribution of this dissertation provided a basis for reasonable analysis by developing and pairing variable and confidence mapping. Resulting variable mapping were explainable based on local knowledge. The GWR spatial techniques used were sensitive to local variance and approached decision-maker scale to describe spatial arrangement of the variables within the model and capture sub-farm parcel changes. Using a strictly statistical approach to the analysis would have limited results to non-mappable study area scale.

The second question was intended to demonstrate the “impermanence syndrome” (Berry, 1978) in which farm conversion was a function of change in the neighborhood surrounding the farm. A simple linear regression did not capture this relationship. It is very possible that better specification of neighborhood change needs to be explored.

As tested, the third question, a simple linear regression did not reflect the complexity of the PA116/distance relationship. Instead, a GWR analysis of indicted that PA116 location was subject to distance. Location of high PA116 value fell into a contiguous, specific range in the study area located between the CBD and deep rural areas (see figure 6.7.).

The fourth question regarding clustering and its impacts on land use change were demonstrated in hotspot and GWR analyses. By identifying spatial clusters it was determined that these clusters were not random but the result of processes involving diffusion and social networks.

The results were expected to demonstrate that retention of farmland (low rate of conversion) is correlated with non-economic variables. So the results from the four hypotheses’ tests show support for three of the research questions: non-economic variables are significant in land use change, clustering of values (evidence of rural networks) is present in the study area, and that CBD/rural distance affects level of attachment value/social capital for the 1978-91 model.

The model for study period 1992-99 was not effective in modeling land use change despite using dependent variables similar to 1978-91. The two models did not provide similar results given the vast changes in infrastructure, residential patterns, and policy – (specifically those affecting PA116-social capital variable) during 1992-99 period.

With available data, social capital was measured using a change in in acreage and time of ownership, producing a relatively crude specification of a complex variable. There is a need to explore if there are additional data elements to compliment PA116 and if there are other improvements that can be made in representing social capital /noneconomic variables. Since 2001, policy change regarding social capital (PA116) has made the program more robust and more representative of typical enrollment patterns than the anomalous 1992-99 period.

Expanding this type of quantitative study would be ideal for capturing social capital variables, but time resource constraints in conducting a large scale survey were prohibitive. Additionally, even after this effort, there were no other comparable data sets found that could be used to validate or reject such a study.

Due to limitations of methods to collect social capital variables, PA116 data was the best available source comprising a complete data set at parcel/sub-parcel scale for the entire study area. There are limitations on the use of PA116 data namely that it was originally collected in a manner that was not intended for this study. However, the PA116 variable was statistically significant for all models in the study.

7.2. Future Research

Improving understanding of the relationship between social capital and land use in rural areas will enable policymakers to develop more effective tools to preserve farmland. Current Michigan Department of Agriculture programs allocate funding for farm preservation. Eligibility for participation in preservation programs is determined based on criteria that include sustainability, environmental, and economic factors, as well as by cluster size of participating farms. An expansion of criteria to include unconventional non-economic variables as revealed in this research suggested that application of spatial analysis to farm parcel data can be used in regional analysis. Some aspects of farm choice can be revealed without the use of qualitative survey

Methods incorporating social capital variables such as those used in this research could be applied in future land change analyses, providing a means to analyze spatial patterns at particular locations that could trigger change in agricultural land use. It is anticipated that measurable changes in the local agricultural landscape may also contribute to an understanding of the farmer's decision process for participation in farm preservation programs and the even more basic choice to remain in agriculture.

Consistent with Drozd and Johnson's (2004) concept of a 'unique crossover point' for decisions to subdivide for "rural living" or continue farming, circumstances are too variable to propose a universal solution. Given the findings of this research, any such further research would need to consider the following:

(a) A range of potential future economic conditions, in terms of both the agricultural and residential demand for rural parcels. From an agricultural perspective, the range of historical conditions may provide the best guidance in this regard. However, in a growing urban region, demand for rural living and values are likely to increase compared to the historical circumstances:

(b) Whether another existing urbanizing region can provide guidance as to future conversion. Historical conditions in the region do not cover the expected range of future economic conditions. Measuring what has happened in terms of land use change in an area would be useful, but would not provide a complete basis for policy making.

The outcomes found here still need replication based on other counties parcel level data examined model of land use change is an example for further interesting research questions. Current literature has not been found that identified the determinants of agricultural decisions within a parcel. Given the increasing availability of land use mapping resources, digital data, and geospatial techniques, there will be added opportunities to conduct detailed analysis.

GWR model's spatial distribution and elasticities provided complementary and highly relevant information. These results demonstrate some of the advantages of the proposed model and argue in favor of its use in rural planning. However, GWR is still considered an exploratory method; therefore, all of the inferences and statements derived from analysis should be interpreted carefully.

This knowledge can be of great assistance to political decision-makers and the planners because it puts more realistic forecasts at their disposal. These models are useful not only for determining the effects of land use policies on dependent variables

A key part of future analysis is going to have to control for neighborhood effects. A farmer's neighbors are going to impact the individual farming decisions. If farm preservation acres have an impact above and beyond normal neighborhood effects, then it is going to be important to properly specify those spatial effects. Neighboring farmer neighbors share a number of characteristics, such as soil type, slope, agricultural prices, input prices, and access to roads, etc., that all influence their farming decisions. When neighbors change their behaviors, they will influence local land market prices; this too, will influence individual farmer decisions.

For future study, it would be prudent to explore how an important variable such education quality impacts residential development (related to land use issues). At this point in time, there was a lack of consistent available resources for use this study. Better quality data would reveal the effect of school district level attributes on land use change (much of the attributes would be associated with funding policy).

There is no planned validation testing for the Eaton County study. However, the validity of this model's conclusions would help establish independence outside of coincidence.

In addition to adding education attributes to the study, better specified non-economic variables would improve further study. Associating change of social capital with changing acres under PA116 contract was successful for this study, but in a limited way. However, there may be better approaches to accomplish this. With the PA116 fully active and making progress again, it might be useful to better research the DOA data set. Better specification for the "time of ownership" variables would also provide better results.

SELECTED REFERENCES

1992 Census of Agriculture: *Geographic area series.* Michigan, Volume 1, Part 2

1997 Census of Agriculture: *Geographic area series*. Michigan, Volume 1, Part 2

Abdullah, Saiful Arif, Adnan A. Hezri, 2008. "From forest landscape to agricultural landscape in the developing tropical country of Malaysia: pattern, process, and their significance on policy." *Environmental Management* 42 (5): 907-917.

Abelairas-Etxebarria, Patricia and Inma Astorkiza, 2012. "Farmland prices and land-use changes in periurban protected natural areas." *Land Use Policy* 29: 674- 683.

Alonso, W., 1964. *Location and land use: toward a general theory of land rent.* Cambridge, MA: Harvard University Press.

Amara, Mohamed, and Mohamed Ayadi, 2013. "The local geographies of welfare in Tunisia: does neighborhood matter? " *International Journal of Social Welfare* 22:90-103.

American Farmland Trust, 1997. *Saving American Farmland: What Works.*

American Farmland Trust, 2002. *Farming on the edge.* http://www.farmland.org/farmingontheedge/.

Anderson, John E., 1993. Use-Value Property Tax Assessment: Effects on Land Development *Land Economics* 69 (3): 263-269.

Anselin, Luc, 1995b. "Local indicators of spatial association – LISA." *Geographical Analysis,* 27(2): 93-115.

Anstey, Geoff, 2009. "Unplanned rural living and its policy implications: some findings from Bundaberg, Australia." *Land Use Policy* 26: 401-413.

Arnold, Chester L. Jr., C. James Gibbons, 1996. "Impervious surface coverage: The emergence of a key environmental indicator." *Journal of the American Planning Association* 62 (2): 243.

Audirac, I., 1999. "Unsettled views about the fringe: rural-urban or urban-rural frontiers?" In: Owen J. Furuseth and Mark B. Lapping (eds.) *Contested countryside: the rural urban fringe in North America.* Brookfield, VT: Ashgate.

Barbieri, Carla, and Edward Mahoney, 2009. "Why is diversification an attractive farm adjustment strategy? Insights from Texas farmers and ranchers." *Journal of Rural Studies* 25: 58-66.

Barlowe, Raleigh, 1986. *Land Resource Economics: The Economics of Real Estate*, 4th edition. Englewood Cliffs, N.J.: Prentice Hall.

Bell, Kathleen P. and Elena G. Irwin, 2002. "Spatially explicit micro-level modelling of land use change at the rural-urban interface." *Agricultural Economics* 27: 217-232.

Berry, Brian J. L., 1980. "Urbanization and counter-urbanization in the United States." *Annals of the American Academy of Political and Social Science*, 451: 13-20, Changing Cities: A Challenge to Planning.

Berry, D., 1978. "Effects of urbanization on agricultural activities." *Growth and Change* 9(3): 2-8.

Berry, D., and T. Plaut, 1978. "Retaining agricultural activities under urban pressures - a review of land-use conflicts and policies." *Policy Sciences* 9(2): 153-178.

Bierlaire, M., 1997**. "**Discrete choice models.", In: M. Labbé, G. Laporte, K. Tanczos and Ph. Toint (eds.), *Operations Research and Decision Aid Methodologies in Traffic and Transportation Management, NATO ASI Series, Series F: Computer and Systems Sciences*, 166 203-227.

Blewett, R. A., and J. I. Lane, 1988. "Development rights and the differential assessment of agricultural land: fractional valuation is ineffective for preserving open space and subsidizes speculation." *American Journal of Economics and Sociology* 47(2): 195-205.

Bocci, Chiara, Alessandra Petrucci, and Emilia Rocco, 2005. "An application of geographically weighted regression to agricultural data for small area estimates." In: Atti del convegno *"Metodi d'Indagine e di Analisi per le Politiche Agricole"*, Universit`a di Pisa.

Bockstael, N.E., 1996. "Modelling economics and ecology: the importance of a spatial perspective." *American Journal of Agricultural Economics* 785: 1168-1180.

Bockstael, N.E. and K. Bell, 1998. "Land use patterns and water quality: the effect of differential land management controls." In: R Just, S. Netanyahu, (eds.), *Conflict and Cooperation on Trans-Boundary Water Resources.* Norwell, MA: Kluwer Academic Publishers pp. 169-191.

Brasier K.J., 2005. "Spatial analysis of changes in the number of farms during the farm crisis." *Rural Sociology* 70(4): 540-560.

Brown, Gregory, and Christopher Raymond, 2007. "The relationship between place attachment and landscape values: Toward mapping place attachment." *Applied Geography* 27: 89-111.

Brueckner, Jan K, 1990. "Growth controls and land values in an open city." *Land Economics* 66(3): 237-248.

Brueckner, J., 2000. “Urban sprawl: diagnosis and remedies.” *International Regional Science Review* 23: 160-179.

Brueckner, Jan K., and David A. Fansler, 1983. “The Economics of Urban Sprawl: Theory and Evidence on the Spatial Sizes of Cities.” *The Review of Economics and Statistics* 65(3):479-482.

Brueckner, Jan K., and Ann G. Largey, 2006. “Social interaction and urban sprawl.” *University CESifo Issue 1843 of Working Paper Series.*

Brunsdon, Chris A., Stewart Fotheringham, and Martin E. Charlton, 1996. “Geographically weighted regression: a method for exploring spatial nonstationarity.” *Geographical Analysis* 28(4): 281-298.

Bukenya, James O., Ericka Branch, and Constance Wilson, 2005. “Examining relationship between sprawl and neighborhood social conflicts: preliminary results” - *Selected Paper to be presented at the American Agricultural Economics Annual Meeting. July 24-27, 2005 Providence, Rhode Island.*

Burchell, Robert W., George Lowenstein, William R. Dolphin, and Catherine Galley, 2002. *TCRP RT 74-Costs of Sprawl*—2000 Center for Urban Policy Research Rutgers, The State University of New Jersey New Brunswick, NJ.

Burchfield, M., H.G. Overman, D. Puga, M.A.Turner, 2006. “Sprawl: a portrait from space.” *Quarterly Journal of Economics* 121 (2): 587-633.

Butler, R.W., 1980. The concept of a tourist area cycle of evolution: implications for the management of resources.” *The Canadian Geographer / Le Géographe canadien* 24(1): 5-12.

Capozza, D.R., and R.W. Helsley, 1989. “The fundamentals of land prices and urban growth.” *Journal of Urban Economics* 26: 295- 306.

Carrion-Flores, Carmen and Elena G. Irwin, 2004. “Determinants of residential land use at the rural-urban fringe *American Journal of Agricultural Economics* 86(4):889-904.

Carver, A.D., and J.E. Yahner, 2004. “Defining prime agricultural land and methods of protection.” *Agronomy Guide* 69: 149-151. https://www.extension.purdue.edu/extmedia/AY/AY-283.html.

Castle, Emery N., 2001. "Wanted: a rural public policy." *Choices* 16 (1): 26-30.

Chicoine, David L., 1981. "Farmland values at the urban fringe: an analysis of sale prices." *Land Economics* 57(3): 353-362.

Cho, S., D.M. Lambert, S.G. Kim, and S. Jung, 2009. "Extreme coefficients in geographically weighted regression and their effects on mapping." *GIScience and Remote Sensing* 46(3): 273-288.

Cleveland, William S. and Susan J. Devlin, 1988. "Locally weighted regression analysis by local fitting," *Journal of the American Statistical Association*, 83: 596-610.

Clark, W.A.V., and P.L. Hosking, 1986. "*Statistical Methods for Geographers."* 528 pgs. Hoboken: Wiley & Sons.

Cliff, A., and J. Ord. 1981. *Spatial Processes: Models and Applications.* London: Pion.

Clonts, H.A., Jr., 1970. "Influence of urbanization on land values at the urban periphery." *Land Economics* 46: 489-97.

Clouser, Rodney L., 2005. *Issues at the rural-urban fringe: methods to sustain agricultural land - use value assessment.* Department of Food and Resource Economics, Florida Cooperative Extension Service, Gainesville, FL: Institute of Food and Agricultural Services.

Coleman, J. S., 1988. "Social capital in the creation of human-capital." *American Journal of Sociology* 94: S95-S120.

Conklin, W.G. and W.G. Lesker, 1977. "Farm-value assessment as a means for reducing premature and excessive agriculture disinvestment in the urban fringe." *American Journal of Agricultural Economics* 59: 755-759.

Cordes, Sam, John Allen, Richard C. Bishop, Gary D. Lynne, Lyndon J. Robison, Vernon Ryan, and Ron Shafer, 2003. "Framework and application of contingent valuation." *American Journal of Agricultural Economics* 85: 1201-1207.

Cramb, R.A., 2006. "The role of social capital in the promotion of conservation farming: the case of 'Landcare' in the southern Philippines." *Land Degradation & Development* 17: 23-30.

Cropper, Maureen L., and Wallace E. Oates, 1992. "Environmental economics: a survey." *Journal of Economic Literature* 30(2): 675-740.

Damon, Amy L., 2001. "Attachment value and farmland prices: an empirical investigation." East Lansing: *Michigan State University, Department of Agricultural Economics.*

Daniels, T., 1999. *When city and country collide*. Washington, DC: Island Press.

Daniels, Tom, 2000. "Integrated working landscape protection: the case of Lancaster County, Pennsylvania." *Society and Natural Resources* 13: 261-271.

Danner, J. C. 1997. "TDRs - great idea but questionable value." *The Appraisal Journal* 65(2): 133-142.

Davis, Judy S., Arthur C. Nelson, and Kenneth Dueker, 1994. “The new burbs - the exurbs and their implications for planning policy.” *Journal of the American Planning Association* 60(1):45-59.

de Smith, Michael, Michael Goodchild, and Paul A. Longley, 2009. *Geospatial Analysis – a comprehensive guide to Principles, Techniques and Software Tools - Third Edition.*

DiBari, J., 2007. “Evaluation of five landscape-level metrics for measuring the effects of urbanization on landscape structure: the case of Tucson, Arizona, USA.” *Landscape and Urban Planning* 79: 308-313.

Dillman, D. A., 1978. *Mail and telephone surveys: the total design method.* New York: Wiley Publishers.

Donnelly, Shanon, and Tom P. Evans, 2008. “Characterizing spatial patterns of land ownership at the parcel level in south-central Indiana, 1928-1997.” Landscape and Urban Planning 84, (3-4): 230-240.

Drozd, D., and B. Johnson, 2004. “Dynamics of a rural land market experiencing farmland conversion to acreages: The case of Saunders County, Nebraska.” *Land Economics* 80(2): 294-311.

Drummond, M.A., and R. Auch, 2012. “Land cover change in the United States Great Plains.” Washington, DC. *USGS Land Cover Trends Project* pp.1-18.

Duke, J. M., and L. Lynch, 2006. “Four classes of farmland retention techniques: comparative evaluation and property rights implications.” *Land Economics* 82(2): 189-213.

Eaton Zone Ordinance Article (7.3) *Act 282 of the Public Acts of 1945*, as amended Public Act 110 of 2006.

Erickson, Daniel L., Sarah Taylor Lovell, and V. Ernesto Méndez, 2011. “Landowner willingness to embed production agriculture and other land use options in residential areas of Chittenden County, VT.” *Landscape and Urban Planning* 103:174-184.

Evans, T. P., G. Green, and L. Carlson, 2001a. “Multi scale analysis of landcover composition and landscape management of public and private lands in Indiana.” In A. C. Millington, and S. J. Walsh (eds.), *GIS and remote sensing applications in biogeography and ecology* (pp. 271-287). Boston, MA: Kluwer Academic Publications.

Farber, Steven, and Antonio Pa´ez, 2007. A systematic investigation of cross-validation in GWR model estimation: empirical analysis and Monte Carlo simulations.” *Journal of Geographic Systems* 9:371-396.

Fey, Susan, Corry Bregendahl, and Cornelia Flora, 2006. "The measurement of community capitals through research." *Online Journal of Rural Research & Policy*: 1: 1.

Fischel, William A., 1982. “The urbanization of agricultural land: a review of the National Agricultural Lands Study.” *Land Economics* 58(2): 236-259.

Flora, J.L., 1998. “Social capital and communities of place.” *Rural Sociology* 63(4): 481-506.

Flora, J.L., J. Sharp, B.L. Newton, and C.B. Flora, 1997. “Entrepreneurial social infrastructure and locally initiated economic development in non-metropolitan United States.” *The Sociological Quarterly* 38(4):623-645.

Fotheringham, A.S., C. Brunsdon, and M.E. Charlton, 2002. “Sense of the patterns they display.” *Demographic Research,* Volume 26:7. Article 6.

Fotheringham, A.S., M.E.,Charlton, and C. Brunsdon, , 1998. “Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis.” *Environment and Planning A* 30(11): 1905-1927.

Fotheringham, A. S., Martin E. Charlton, and C. Brunsdon, 2000. *Quantitative geography: perspectives on spatial data analysis*. London: SAGE Publications Ltd.

Fotheringham, A. S., Martin E. Charlton, and C. Brunsdon, 2002. Geographically weighted regression: The analysis of spatially varying relationships. London: Wiley.

Franczyk, Jon, and Heejun Chang, 2009. “The effects of climate change and urbanization on the runoff of the Rock Creek basin in the Portland metropolitan area, Oregon.” *USA Hydrological Processes* 23(6) 805-815.

Freshwater, David, 2009. “Farmland conversion: the spatial dimension of agricultural and land-use policies.” *OECD Policy Forum of the Committee for Agriculture.*

Fuguitt, G.V. and D.L. Brown, 1990. “Residential preference and population redistribution 1972-1988.” *Demography* 27 (4): 589-600.

Fujita, M., 1982. “Spatial patterns of residential development.” J*ournal of Urban Economics* 12(1): 22-52.

Galbraith, John Kenneth, 1952. *American capitalism, the concept of countervailing power.* Boston, MA: Houghton Mifflin.

Galster G., R. Hanson, M.R. Ratcliffe, H. Wolman, S. Coleman, and J. Freihage, 2001. “Wrestling sprawl to the ground: defining and measuring an elusive concept.” *Housing Policy Debate* 12: 681-717.

Gardner, Bruce L., 2002. “American agriculture in the 20th century: how it flourished and what it cost.” Cambridge: Harvard University Press.

Geoghegan, J., and N.E. Bockstael, 2000. "Smart growth and the supply of sprawl." *Paper presented at the Association of Environmental and Resource Economists Workshop, La Jolla, CA.*

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: 251-264.

Getis, A., and J. K. Ord, 1992. "The analysis of spatial association by use of distance statistics." *Geographical Analysis* 24: 189-206.

Ghosh, Debarchana, and Steven M. Manson, 2008. "Robust principal component analysis and geographically weighted regression: Urbanization in the Twin Cities Metropolitan Area of Minnesota." *Journal of Urban Regional Information Systems Association* 20(1):15-25.

Glaeser, Edward and Ludwig Glaeser, 2008. *Cities, Agglomeration, and Spatial Equilibrium-Lindahl lectures.* Oxford: Oxford University Press.

Glaeser, Edward L. and Matthew E. Kahn, 2003. "Sprawl and urban growth." *Issue 9733 of Working paper series (National Bureau of Economic Research).*

Global Land Project: Science Plan and Implementation Strategy, 2005. IGBP Secretariat.

Gobster, Paul H., and J. Rickenbach, 2004. "Introduction" / *Landscape and Urban Planning* 69: 149-151.

Goodchild and Janelle, (eds.), 2004. *Spatially Integrated Social Science.* Oxford: Oxford University Press.

Goovaerts, Pierre and Geoffrey M. Jacquez, 2005. "Detection of temporal changes in the spatial distribution of cancer rates using local Moran's I and geostatistically simulated spatial neutral models." *Journal of Geographical Systems* 7.

Gordon, P. and H.W. Richardson, 1997. "Are compact cities a desirable planning goal?" *Journal of the American Planning Association* 63(1): 95-106.

Gourieroux, C., J. P. Laurent, and O. Scaillet, 2000. "Sensitivity analysis of values at risk." *Journal of Empirical Finance* 7(3-4): 225-245.

Granovetter, M., 1985. "Economic action, social structure, and embeddedness." *American Journal of Sociology* 91: 481-510.

Griffith, Daniel A., 2001. *White Paper - Spatial Autocorrelation.* Department of Geography, Syracuse University.

Grimm, Nancy B., Stanley H. Faeth, Nancy E. Golubiewski, Charles L. Redman, Jianguo Wu, Xuemei Bai, John M. Briggs, 2008. "Global change and the ecology of cities." *Science* 319(5864) 756-760.

Hadayeghi, A., A. Shalaby, and B. Persaud, 2010b. "Development of planning level transportation safety tools using geographically weighted poisson regression." *Accident: Analysis and Prevention*, 42 (2): 678-688.

Hägerstrand, T., 1967. *Innovation Diffusion as a Spatial Process.* The University of Chicago Press, Chicago.

Harris, C.D., and E.L. Ullman, 1945. "The nature of cities." *Annals of the American Political and Social Science* 7-17.

Harris, C.D., J.A. Bissonette, and J.L. David, 1998. "The behavior of landscape metrics commonly used in the study of habitat fragmentation." *Landscape Ecology* 13 167-186.

Hart, John Fraser, 2003. *The changing scale of American agriculture.* University of Virginia Press.

He, C., A. Wei, P. Shi, Q. Zhang, and Y. Zhao, 2011. "Detecting land-use/land cover change in rural-urban fringe areas using extended change-vector analysis. *International Journal of Applied Earth Observation and Geoinformation* 13(4):572-585.

Heimlich, R.E., and W.D. Anderson, 2001. "Development at the urban fringe and beyond." *Agricultural Economic Report Number 803.*

Heimlich, R.E., and D. H. Brooks, 1989. "Metropolitan growth and agriculture: farming in the city's shadow." *AER-619.* Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Hellerstein, D., C. Nickerson, J. Cooper, P. Feather, D. Gadsby, D. Mullarkey, A. Tegene, and C. Barnard, 2002. "Farmland protection: the role of public preference for rural amenities."*AER-815*, Washington, DC : U.S. Department of Agriculture, Economic Research Service.

Henning, Steven A., Lonnie R. Vandeveer, Huizhen Niu, and Gary A. Kennedy, 2000. "Spatial economic analysis of a rural land market." *Southwestern Economic Review*, series 2000.

Hirschl, T.A., and C.R. Long, 1993. "Dairy farm survival in a metropolitan area: Dutchess County, New York, 1984-1990." *Rural Sociology* 58:(3): 461-474.

Ilbery, B.W., 1985. *Agricultural geography: a social and economic analysis.* New York: Oxford University Press.

Inwood, Shoshanah M., and Jeff S. Sharp, 2012. "Farm persistence and adaptation at the rural-urban interface: Succession and farm adjustment." *Journal of Rural Studies* 28: 107-117.

Irwin, Elena G., Kathleen P. Bell, and Jacqueline Geoghegan, 2003. “Modeling and managing urban growth at the rural-urban fringe: A parcel-level model of residential land use change.” *Agricultural and Resource Economics Review* 32(1) 83-102.

Irwin, Elena G., and Nancy Bockstael, 2002. “Interacting agents, spatial externalities and the endogenous evolution of land use patterns.” *Journal of Economic Geography* 2: 31-54.

Irwin, Elena G., and Nancy E. Bockstael, 2004. “Land use externalities, open space preservation, and urban sprawl.” *Regional Science and Urban Economics* 34: 705-725.

Irwin, Elena G., and Nancy E. Bockstael, 2007. “The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation.” B. L. Turner II (ed.) *Proceedings of the National Academy of Sciences* 104(52): 20672-20677.

Isgin, Tamer, Abdulbaki, Bilgic, D. Lynn Forster, and Marvin T. Batte, 2007. “Using count data models to determine the factors affecting farmers, quantity decisions of precision farming adoption.” *Computers and Electronics in Agriculture* 62(2): 231-242.

Jeanty, P.W., M. Partridge and E. Irwin, 2010. “Estimation of spatial simultaneous equation model of population migration and housing price dynamics.” *Regional Science and Urban Economics* 40(5): 343-52.

Johnson, K., A. Nucci, L. Long, 2005. ”Population trends and nonmetropolitan America: Selective deconcentration and the rural rebound.” *Population Research and Policy Review* 24: 527-542.

Kline, J.D., and R.J. Alig, 1999. “Does land use planning slow the conversion of forest and farm land?” *Growth and Change* 30(1):3-22.

Kline, J.D., A. Moses, and R.J. Alig, 2001. “Integrating urbanization into landscape-level ecological assessments.” *Ecosystems* 4(1):3-18.

Koontz, T. M., 2001. “Money talks—But to whom? financial versus nonmonetary motivations in land use decisions.” *Society and Natural Resources*, 14:51–65.

Lesaffre, Emmanuel, Dimitris Rizopoulos, and Roula Tsonaka, 2007. “The logistic-transform for bounded outcome scores.” *Biostatistics*, 8(1): 72-85.

Levak, A.E., 1956. “Michigan Centennial farms and farmers.” *The Quarterly Bulletin*, 38 (3): 338-344.

Levia, Jr., Delphis F., and Daniel R. Page, 2000. “The use of cluster analysis in distinguishing farmland prone to residential development: a case study of Sterling, Massachusetts.” *Environmental Management* 25(5): 541-548.

Lockeretz, W., 1989. “Secondary effects on Midwestern agriculture of metropolitan development and decreases in farmland.” *Land Economics* 65(3): 205-216.

Lockeretz, W., J. Freedgood, and K. Coon, 1987. “Farmers views of the prospects for agriculture in a metropolitan-area.” *Agricultural Systems* 23(1): 43-61.

Lopez, Rigoberto A., Farhed A. Shah, Marilyn A. Altobello, 1994. “Amenity benefits and the optimal allocation of land.” *Land Economics* 70(1): 53.

Lubowski, R.N., M. Vesterby, S. Bucholtz, A. Baez, and M. J. Roberts, 2008. “Major uses of land in the United States, 2002.” *Economic Information Bulletin No. (EIB–14).*

Luo, J., and N.K. Kanala, 2008. “Modeling urban growth with geographically weighted multinomial logistic regression.” *Geoinformatics and Joint Conference on GIS and Built Environment: The Built Environment and Its Dynamics, SPIE.*

Luo, Jun, and Y.H. Dennis Wei, 2009. “Modeling spatial variations of urban growth patterns in Chinese cities: The case of Nanjing.” *Landscape and Urban Planning* 91:51-64.

Lynch, L., and J. Carpenter, 2003. “Is there evidence of a critical mass in the mid-Atlantic agricultural sector between 1949 and 1997?” *Agricultural and Resource Economics Review* 32: 116-128.

Lynch, Lori and Sabrina J. Lovell, 2003. “Combining spatial and survey data to explain participation in agricultural land preservation programs.” *Land Economics* 79(2): 259-276.

Lyson, Thomas A., 2004. “Civic Agriculture: Reconnecting farm, food, and community.” Medord, MA: Tufts University Press Series: *Civil Society: Historical and Contemporary Perspectives.*

Lyson, Thomas A., and Gilbert W. Gillespie Jr., 1995. “Producing more milk on fewer farms: Neoclassical and neostructural explanations for changes in the dairy industry.” *Rural Sociology* 60: 493-504.

Massey, D., 1990. “Social structure, household strategies, and the cumulative causation of migration.” *Population Index* 56(1): 3-26.

McMillen, D.P., 1989. “An empirical model of urban fringe land use.” *Land Economics* 652: 138-145.

McMillen, Daniel P., 1996. “One hundred fifty years of land values in Chicago: a nonparametric approach.” *Journal of Urban Economics* 40: 100-124.

Mennis, Jeremy, 2006. “Mapping the results of geographically weighted regression”. *The Cartographic Journal* 43(2): 171-179.

Michigan Department of Agriculture, 2011.

Michigan DNR, 1978. *MI Geographic Data Library MIRRIS*.

Mieszkowski, Peter, and Edwin S. Mills, 1993. "The causes of metropolitan suburbanization." *The Journal of Economic Perspective* 7(3): 135-147.

Mills, E.S., 1969. "The value of urban land." In H. Perloff, (ed.) *The quality of the urban environment.* Baltimore: Johns Hopkins University.

Mills, Edwin S. 1999. "The brawl over so-called sprawl." *Illinois Real Estate Letter,* 1-7.

Mills, Edwin S. and Bruce Hamilton, 1989. *Urban Economics.* Glenview: Scott, Foresman and Company.

Munroe, Darla K., Cynthia Croissant, and Abigail M. York, 2005. "Land use policy and landscape fragmentation in an urbanizing region: assessing the impact of zoning." *Applied Geography* 25(2):121-141.

Muth, R.F., 1969. *Cities and Housing*. Chicago: University of Chicago Press.

National Agricultural Statistics Service - Revised FY 2000 and FY 2001 Annual Performance Plans: National Resources Conservation Service Survey, 1993. *Soil Survey Manual (USDA Handbook 18).*

Naveh, Zeev, and Arthur S. Lieberman, 1994. *Landscape ecology: theory and application Springer series on environmental management* . University of Michigan: Springer-Verlag.

Nelson, A., 1992. "Characterizing exurbia." *Journal of Planning Literature* 6(4): 350-368.

Nelson, A. C., 1993. "Disamenity influences of edge cities on exurban land values - a theory with empirical-evidence and policy implications." *Urban Studies* 30(10): 1683-1690-276.

Nelson, Arthur C., and Thomas W. Sanchez, 1997. "Exurban and suburban residents: a departure from traditional location theory," *Journal of Housing Research* 8(2): 249 Nelson, Arthur C., 1990. "Economic critique of U.S. prime farmland preservation policies: Towards state policies that influence productive, consumptive, and speculative value components of the farmland market to prevent urban sprawl and foster agricultural production in the United States." *Journal of Rural Studies* 6(2):119-142.

Newburn, D.A. and P. Berck. 2006. "Modeling suburban and rural residential development beyond the urban fringe." *Land Economics* 82(4): 481-499.

Nielsen-Pincus, M., C.S. Goldberg, A. Pocewicz, *et al.,* 2010. "Predicted impacts of residential development on a northern Idaho landscape under alternative growth management and land protection policies." *Landscape and & Urban Planning* 94: 255-263.

Nieminen, T., T. Martelin, S. Koskinen, J. Simpura, E. Alanen, and T. Härkänen, 2008. "Measurement and socio-demographic variation of social capital in a large population-based survey." *Social Indicators Research* 85(3): 405-423.

Onyx, J., and P. Bullen, 2000. "Measuring social capital in five communities." *Journal of Applied Behavioral Science*, 36: 23-42.

Páez, Antonio, 2009. "Spatial analysis of economic systems and land use change." *Papers in Regional Science* 88(2): 251-258.

Parton, W.J., M.P. Gutman, and D. Ojima, 2007. "Long-term trends in population, farm income, and crop production in the Great Plains." *BioScience* 57(9): 737-747.

Paterson, Robert W., and Kevin J. Boyle, 2002. "Out of sight, out of mind? Using GIS to incorporate visibility in hedonic property value models." *Land Economics* 78(3): 417-425.

Plantinga, A. J., J. Maudlin, and D. J. Miller, 1999. "An econometric analysis of the cost of sequestering carbon in forests." *American Journal of Agricultural Economics* 814: 812-824.

Polimeni, John M, 2005. "Simulating agricultural conversion to residential use in the Hudson River Valley: scenario analyses and case studies." *Agriculture and Human Values* 22: 377-393.

Polsky, C., and W.E. Easterling III, 2001. "Adaptation to climate variability and change in the US Great Plains: A multi-scale analysis of Ricardian climate sensitivities." *Agriculture, Ecosystems & Environment* 85(1-3):133-144.

Pope, C.A. 1987. "More than economics influences allocation of rangeland resources." *Choices.* Fourth Quarter 24-25.

Pryor, R., 1968. "Defining the rural-urban fringe." *Social Forces* 47: 202-13.

Putnam, R., 1993. "Bowling alone: America's declining social capital." *Journal of Democracy* 6(1): 65-87.

Putnam, Robert D., 2000. *Bowling alone: the collapse and revival of American community*. New York: Simon & Schuster.

Ready, Richard C., and Charles 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.

Ricardo, David, 1817. *On principles of political economy and taxation.* London: John Murray.

Robison, Lindon J., A. Allan Schmid, and Marcelo E. Siles, 2002. “Is social capital really capital?” *Review of social economy*, 1-21.

Robison, L.J., Robert J. Myers, and Marcelo E. Siles, 2002. “Social capital, the terms of trade for farmland.” *Review of Agricultural Economics* 24 (1): 44-58.

Robison, L. J., and M. E. Siles, 2000. “Social capital: sympathy, socio-economic goods, and institutions.” *Michigan State University, Department of Agricultural Economics–Staff Paper Series. 2000-45.*

Roe, Brian, Elena G. Irwin, and Hazel 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, Sherwin, 1974. “Hedonic prices and implicit markets: product differentiation in pure competition.” *The Journal of Political Economy* 82(1): 34-55.

Salamon, Sonya, 1985. “Ethnic Communities and the Structure of Agriculture.” *Rural Sociology* 50 (3): 323.

Sancar, Cenap, Sanem Özen Turan, and Ali Lhsan Kadioğullari, 2009. “Land use-cover change processes in urban fringe areas: Trabzon case study, Turkey.” *Scientific Research and Essay* 4 (12): 1454-1462.

Scalenghe, Riccardo, and Franco Ajmone Marsan, 2009. “The anthropogenic sealing of soils in urban areas.” *Landscape and Urban Planning* 90(1-2), 15:1-10.

Schmid C., and M.D.A. Rounsevelle, 2006. “Are agricultural land use patterns influenced by farmer imitation?” *Agricultural Ecosystems and Environment* 115: 113-127.

Searchinger, Timothy, Ralph Heimlich, R. A. Houghton, Fengxia Dong, Amani Elobeid, Jacinto Fabiosa, Simla Tokgoz, Dermot Hayes, Tun-Hsiang Yu, 2008. “Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change.” Science 319(5867) 1238-1240.

Sharp, Jeff S., and Jill K. Clark, 2008. “Between the country and the concrete: rediscovering the rural-urban fringe.” *City & Community* 7:1.

Shariff, N.M., S. Gairola, A. Talib, 2010. “Modelling urban land use change using geographically weighted regression and the implications for sustainable environmental planning” In: Swayne, D.A. et al., (eds.), *“Modelling for environment’s sake: Proceedings of the Fifth Biennial Conference of the International Environmental Modelling and Software Society, Ottawa, Canada.*

Sharp, J.S., and M.B. Smith, 2004. “Farm operator adjustments and neighboring at the rural-urban interface.” *Journal of Sustainable Agriculture* 23 (4): 111-131.

Sharp, J.S., and M.B. Smith, 2002. "Social capital and farming at the rural-urban interface: the importance of nonfarmer and farmer relations." *Agricultural Systems* 76: 913-927.

Siegel, Jay, 1975. "Intrametropolitan migration: A simultaneous model of employment and residential location of white and black households." *Journal of Urban Economics* 2 (1): 29-47.

Siles, M. E., L. J. Robison, B. Johnson, G. Lynne, and D. Baveridge, 2000. "Farmland exchanges, selection of trading partners, terms of trade, and social capital." *Journal of the American Society of Farm Managers and Rural Appraisers* 61(1): 127-140.

Soil Conservation Service (AGPRIME).

State of Michigan, 1994. MCL 36101- Section 324.36101 - *Natural Resources and Environmental Protection Act – Act 451 of 1994.*

Stobbe, Tracy E., Alison J. Eagle, Geerte Cotteleer, and G. Cornelis van Kooten, 2011. "Farmland preservation verdicts—rezoning agricultural land in British Columbia." *Canadian Journal of Agricultural Economics* 59: 555-572.

Sullivan III, W.C., 1994. "Perceptions of the rural-urban fringe: citizen preferences for natural and developed settings." *Landscape and Urban Planning* 29: 85-10.

Syphard, Alexandra D., Keith C. Clarke, and Janet Franklin, 2005. "Using a cellular automaton model to forecast the effects of urban growth on habitat pattern in Southern California." *Ecological Complexity* 2: 185-203.

Taus, Alina, Yelena Ogneva-Himmelberger, and John Rogan, 2012. "Conversion to organic farming in the Continental United States: A Geographically Weighted Regression analysis." *The Professional Geographer* 65(1): 87-102.

Tobler, W., 1979. "Smooth pyncophylactic interpolation for geographical regions (with discussion)." *Journal of the American Statistical Association* 74:519-536.

Tri-County Regional Planning Commission (TCRPC), 1999, 2001. *Regional growth plan.* Lansing, Michigan.

Tsoodle, Leah J., Bill B. Golden, and Allen M. Featherstone, 2006. "Factors influencing Kansas agricultural farm land values." *Land Economics* 82 (1): 124-39.

Turner, B. L., II, Eric F. Lambin, and Anette Reenberg, 2007. "The emergence of land change science for global environmental change and sustainability" *Proceeding of the National Academy of Sciences of the United States of America* 104 (52).

Turner, B. L., II, David Skole, Steven Sanderson, Günther Fischer, Louise Fresco, and Rik Leemans, 1995. *Land-Use and Land-Cover Change: Science/Research Plan*. *IGBP Report 35.* Stockholm: Royal Swedish Academy of Sciences.

Turner, M.G. 1989. Landscape ecology: the effect of pattern on process. *Annual Review of Ecologic Systems* 20:171-197.

Turner, M.G., and RH. Gardner. 1991. *Quantitative Methods in Landscape Ecology. Ecological Studies 82,* New York, NY: Springer-Verlag.

U.S. Department of Agriculture, 1999. *Census of Agriculture, 1997.* Washington, DC: U.S. Department of Agriculture, National Agricultural Statistics Service

U.S. Department of Housing and Urban Development, 2000. *The state of the cities 2000*. Washington, D.C.: U.S. Department of Housing and Urban Development.

U.S. Environmental Protection Agency, 2007. "Smart growth and open space conservation."

United States Census Bureau, 2000. *Population profile of the United States.* Washington, DC United States Census Bureau, 2000, American Community Survey Five-year estimates. Special Tabulation: Census Transportation Planning – Journey-to-Work.

USDA, National Agricultural Statistics Service - *Census of Agriculture, 1997*. County Level Data: Eaton County, Michigan.

United Nations, 1996. "Urbanizing world: global report on human settlements." *United Nations Center for Human Settlement (HABITAT).* Oxford University Press.

van Oort, Guy, 1999. "Rural-urban fringes: another approach." In *New perspectives in Urban Geography*. S.B. Singh (ed.) New Delhi: M.D. Publications.

Vesterby, Marlow and Ralph E. Heimlich, 1991. "Land use and demographic change: results from fast-growth counties." *Land Economics*. 67(3): 279-291.

Vidyattama, Yogi, Rebecca Cassells, Jonathan Corcoran, 2010. "Trapped in jobless household areas: the spatio-temporal dynamics of children in jobless households - metropolitan Australia." *Australian Geographer,* 41(3):367-389.

von Thünen, Johann Heinrich, 1966 [1826]. "Isolated state." *Der isolierte staat in beziehung auf landwirtschaft und nationalokönomie,* translated by Carla M. Wartenberg; Peter Hall ed. NY: Pergamon Press.

Waddell, P., B. Berry, and I. Hoch, 1993. "Residential property-values in a multinodal urban area-New evidence on the implicit price of location." *Journal of Real Estate Finance and Economics* 2:117-41.

Wagner, Matthew, Ronald Kaiser, Urs Kreuter, and Neal Wilkins, 2007. “Managing the commons Texas style: wildlife management and ground-water associations on private lands.” *Journal of the American Water Resources Association (JAWRA)* 43(3):698-711.

Wang, Yiyi, Kara M.Kockelman, and Xiaokun (Cara)Wang, , 2011. “Anticipating land use change using geographically weighted regression models for discrete response.” *Transportation Research Record No. 2245:111-123, Presented at the 90th Annual Meeting of the Transportation Research Board, January 2011.*

Wong, David S. and Jay Lee, 2005. *Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS.* Hoboken, NJ: John Wiley & Sons.

Wu, J. and R. Hobbs, 2002. Key issues and research priorities in landscape ecology: An idiosyncratic synthesis. *Landscape Ecology* 17:355-365.

Wilson, Geoff, 2009. “Multifunctional ‘quality’ and rural community resilience.” *Transactions of the Institute of British Geographers* pp. 364-381.

Wooldridge, M., 1999. “Intelligent agents. In: Weiss, G. (ed.), *Multiagent systems: a modern approach to distributed artificial intelligence*.” MIT Press: Cambridge, MA, pp. 22-27.

Workman, S.W., and S.C. Allen, 2003. “The practice and the potential of agroforestry in Southeastern United States.” Center for Subtropical Agroforestry, School of Forest Resources and Conservation, University of Florida. *http://cstaf.ifas.ufl.edu/whitepaper.htm*

Wyckoff, Mark, 1987. *Planning and zoning for farmland protection: A community based approach: American Farmland Trust.*

York, Abigail M., Richard Feiock, and Annette Steinacker, 2013. “Explaining city economic development and growth management policy choices.” *State and Local Government Review* 45(2): 86-97.

York, Abigail M., and Darla K. Munroe, 2010. “Urban encroachment, forest regrowth and land-use institutions: Does zoning matter?” *Land Use Policy.* 27(2): 471–479.

Zhou, Bin, and Kara M. Kockelman, 2007. “Neighborhood impacts on land use change: a multinomial logit model of spatial relationships.” *Annals of Regional Science*, 42(2):321-340.

Zhou, Bin, and Kara M. Kockelman, 2009. “Transportation and land use policy analysis using integrated transport and gravity-based land use models.” *Transportation Research Record* 2133: 123-132. *Presented at the 88th Annual Meeting of the Transportation Research Board.*

APPENDICES

Appendix 1. - Bivariate Correlation: 1978-91 Full Model

Correlations 1978-91

Response Variable		FmSz	Agpct78	Agbdf7891	PAdf7891	PAbdf7891	PMdf7891	PMbdf7891	AVacdf7891	AVbdf7891	Rdbd7891	LogCBD	LocdstLog	Tow_7899
TT7891a	Pearson Correlation	-.078**	-.055**	-.016	-.117**	.018	0.504**	.214**	.140**	.103**	.046*	-.61**	.003	-.069**
	Sig. (2-tailed)	.000	.002	.386	.000	.327	.000	.000	.000	.000	.010	.001	.877	.000
Explanatory Variables														
Agpct78	Pearson Correlation	.084**												
	Sig. (2-tailed)	.000												
TT7891a	Pearson Correlation	-.078**	.055**											
	Sig. (2-tailed)	.000	.002											
Agbdf7891	Pearson Correlation	-.046*	.052**											
	Sig. (2-tailed)	.012	.004											
PAdf7891	Pearson Correlation	.174**	.139**	-.053**										
	Sig. (2-tailed)	.000	.000	.004										
PAbdf7891	Pearson Correlation	-.038*	.008	-.041*	-.012									
	Sig. (2-tailed)	.035	.647	.025	.511									
PMdf7891	Pearson Correlation	-.163**	0.047**	-.036	-.094	.002								
	Sig. (2-tailed)	.000	.009	.048	.000	.920								
PMbdf7891	Pearson Correlation	-.119**	-.124**	-.116**	-.083**	.031	.223							
	Sig. (2-tailed)	.000	.000	.000	.000	.088	.000							
AVacdf7891	Pearson Correlation	-.063**	-.037*	.023	-.056**	.019	.084**	.036*						
	Sig. (2-tailed)	.001	.042	.203	.002	.301	.000	.046						
AVbdf7891	Pearson Correlation	-.075**	-.028	.061**	-.065**	.043*	.046*	.076**	.498**					
	Sig. (2-tailed)	.000	.124	.001	.000	.017	.011	.000	.000					
Rdbd7891	Pearson Correlation	.538**	.104**	.006	.066**	.004	-.057**	-.020	.002	.045*				
	Sig. (2-tailed)	.000	.000	.745	.000	.838	.002	.267	.912	.013				
LogCBD	Pearson Correlation	.093**	-.056**	-.092**	.044*	-.080**	.010	-.037*	-.184**	-.387**	-.149**			
	Sig. (2-tailed)	.000	.002	.000	.015	.000	.595	.040	.000	.000	.000			
LocdstLog	Pearson Correlation	.078**	.057**	-.140**	.034	.088**	.002	-.040*	-.069**	-.141**	.099**	.198**		
	Sig. (2-tailed)	.000	.002	.000	.061	.000	.924	.028	.000	.000	.000	.000		
Tow_7899	Pearson Correlation	-.012	-.030	.000	-0.08	-.069**	-.043*	-.033	-.021	-.047**	-.061**	.008	-.247**	
	Sig. (2-tailed)	.513	.100	.999	.672	.000	.018	.070	.242	.009	.001	.648	.000	

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Appendix 2. - Bivariate Correlation: 1992-99 Full Model

Correlations 1992-1999

Response Variable		EmSz	Agpct78	LogCBD	LocdstLog	Tow_7899	Agbdf9299	PAdf9299	PAbdf9299	PMdf9299	PMbdf9299	AVacdf9299	AVbdf9299	Rdbd9299
TT9299a	Pearson Correlation	.059**	.093**	-.061**	-.037*	.003	.052**	-.026	.004	.286**	.016	.031	.032	.055**
	Sig. (2-tailed)	.001	.000	.001	.039	.847	.004	.148	.837	.000	.363	.087	.081	.002
Explanatory Variables														
Agpct78	Pearson Correlation	.084**												
	Sig. (2-tailed)	.000												
LogCBD	Pearson Correlation	.094**	-.056**											
	Sig. (2-tailed)	.000	.002											
LocdstLog	Pearson Correlation	.078**	.057**	.198**										
	Sig. (2-tailed)	.000	.002	.000										
Tow_7899	Pearson Correlation	-.012	-.030	.008	-.247**									
	Sig. (2-tailed)	.513	.100	.648	.000									
Agbdf9299	Pearson Correlation	-.040*	.095**	-.436**	-.173**	.010								
	Sig. (2-tailed)	.028	.000	.000	.000	.588								
PAdf9299	Pearson Correlation	-.034	-.027	.016	-.026	.021	-.010							
	Sig. (2-tailed)	.057	.135	.390	.157	.235	.570							
PAbdf9299	Pearson Correlation	-.095**	-.167**	-.168**	-.254**	.084**	.052**	.033						
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.004	.068						
PMdf9299	Pearson Correlation	-.082**	.091**	-.025	-.086**	.013	.019	-.012	.027					
	Sig. (2-tailed)	.000	.000	.167	.000	.468	.290	.496	.135					
PMbdf9299	Pearson Correlation	.026	.160	.242	.233	-.004	-.057	-.028	-.173	.078				
	Sig. (2-tailed)	.156	.000	.000	.000	.817	.002	.121	.000	.000				
AVacdf9299	Pearson Correlation	-.020	.017	-.181**	-0.090**	-.030	.025	.009	.116**	.030	-.081**			
	Sig. (2-tailed)	.281	.361	.000	.000	.094	.159	.635	.000	.096	.000			
AVbdf9299	Pearson Correlation	-.085**	-.010	-.382**	-.176**	-.020	.053**	.012	.230**	.050**	-.158**	.458**		
	Sig. (2-tailed)	.000	.596	.000	.000	.271	.003	.499	.000	.005	.000	.000		
Rdbd9299	Pearson Correlation	.314**	.129**	-.178**	.068**	-.063**	.255**	-.020	-.114**	.009	.101**	.002	.004	
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.280	.000	.638	.000	.899	.837	

Appendix 3.a. - OLS/Stepwise: Model Summary 1978-91

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PMdf7891sq	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	AVbdf7891	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Rdbd7891	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	PAdf7891	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
5	Agpct78	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
6	PMbdf7891	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
7	AVacdf7891	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
8	Tow_7899	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: TT7891a

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.656[a]	.430	.430	.95146365
2	.659[b]	.435	.434	.94794702
3	.662[c]	.439	.438	.94484439
4	.664[d]	.440	.440	.94350591
5	.665[e]	.443	.442	.94185317
6	.666[f]	.444	.443	.94069777
7	.668[g]	.446	.445	.93945062
8	.668[h]	.447	.445	.93876326

Appendix 3.b. - OLS/Stepwise Regression 1978-91

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.803	.020		-40.714	.000
	PMdf7891sq	5.112	.106	.656	48.037	.000
2	(Constant)	-.852	.022		-38.579	.000
	PMdf7891sq	5.083	.106	.652	47.864	.000
	AVbdf7891	5.997E-5	.000	.066	4.868	.000
3	(Constant)	-.978	.035		-27.824	.000
	PMdf7891sq	5.099	.106	.654	48.142	.000
	AVbdf7891	5.733E-5	.000	.063	4.665	.000
	Rdbd7891	.003	.001	.062	4.592	.000
4	(Constant)	-.959	.036		-26.915	.000
	PMdf7891sq	5.062	.106	.650	47.571	.000
	AVbdf7891	5.496E-5	.000	.061	4.469	.000
	Rdbd7891	.003	.001	.065	4.795	.000
	PAdf7891	-.214	.069	-.043	-3.109	.002
5	(Constant)	-1.138	.063		-18.012	.000
	PMdf7891sq	5.049	.106	.648	47.501	.000
	AVbdf7891	5.604E-5	.000	.062	4.564	.000
	Rdbd7891	.003	.001	.061	4.445	.000
	PAdf7891	-.246	.069	-.049	-3.546	.000
	Agpct78	.003	.001	.047	3.423	.001
6	(Constant)	-1.215	.068		-17.755	.000
	PMdf7891sq	4.963	.110	.637	45.067	.000
	AVbdf7891	5.397E-5	.000	.060	4.393	.000
	Rdbd7891	.003	.001	.061	4.451	.000
	PAdf7891	-.239	.069	-.048	-3.454	.001
	Agpct78	.003	.001	.052	3.765	.000
	PMbdf7891	3.193	1.095	.041	2.915	.004
7	(Constant)	-1.220	.068		-17.845	.000
	PMdf7891sq	4.929	.111	.633	44.574	.000
	AVbdf7891	3.288E-5	.000	.036	2.329	.020
	Rdbd7891	.003	.001	.061	4.508	.000
	PAdf7891	-.237	.069	-.047	-3.421	.001
	Agpct78	.003	.001	.053	3.855	.000
	PMbdf7891	3.306	1.094	.043	3.021	.003
	AVacdf7891	1.937E-5	.000	.047	3.017	.003
8	(Constant)	-1.163	.072		-16.063	.000
	PMdf7891sq	4.919	.111	.631	44.489	.000
	AVbdf7891	3.162E-5	.000	.035	2.239	.025
	Rdbd7891	.003	.001	.060	4.371	.000
	PAdf7891	-.238	.069	-.047	-3.445	.001
	Agpct78	.003	.001	.052	3.797	.000
	PMbdf7891	3.247	1.094	.042	2.968	.003
	AVacdf7891	1.943E-5	.000	.047	3.028	.002
	Tow_7899	-.134	.057	-.032	-2.338	.019

a. Dependent Variable: TT7891a

Appendix 3.c. - OLS/Stepwise Summary 1978-91

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.668[a]	.447	.445	.93876326

a. Predictors: (Constant), Tow_7899, PAdf7891, AVacdf7891, Rdbd7891, PMbdf7891, Agpct78, PMdf7891sq, AVbdf7891

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2168.476	8	271.060	307.576	.000[a]
	Residual	2685.249	3047	.881		
	Total	4853.725	3055			

a. Predictors: (Constant), Tow_7899, PAdf7891, AVacdf7891, Rdbd7891, PMbdf7891, Agpct78, PMdf7891sq, AVbdf7891

b. Dependent Variable: TT7891a

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-1.163	.072		-16.063	.000
	Agpct78	.003	.001	.052	3.797	.000
	PAdf7891	-.238	.069	-.047	-3.445	.001
	PMdf7891sq	4.919	.111	.631	44.489	.000
	PMbdf7891	3.247	1.094	.042	2.968	.003
	AVacdf7891	1.943E-5	.000	.047	3.028	.002
	AVbdf7891	3.162E-5	.000	.035	2.239	.025
	Rdbd7891	.003	.001	.060	4.371	.000
	Tow_7899	-.134	.057	-.032	-2.338	.019

a. Dependent Variable: TT7891a

Appendix 4.a. - Stepwise Summary 1992-99

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PMdf9299sq	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	FmSz	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Agpct78	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	PMbdf9299	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: TT9299a

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.377[a]	.142	.142	.57770619
2	.387[b]	.150	.149	.57503239
3	.397[c]	.157	.156	.57273720
4	.401[d]	.161	.160	.57162661

a. Predictors: (Constant), PMdf9299sq

b. Predictors: (Constant), PMdf9299sq, FmSz

c. Predictors: (Constant), PMdf9299sq, FmSz, Agpct78

Appendix 4.b. - OLS/Stepwise 1992-99

ANOVA[e]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	136.297	1	136.297	408.389	.000[a]
	Residual	824.349	2470	.334		
	Total	960.646	2471			
2	Regression	144.241	2	72.121	218.109	.000[b]
	Residual	816.405	2469	.331		
	Total	960.646	2471			
3	Regression	151.073	3	50.358	153.517	.000[c]
	Residual	809.573	2468	.328		
	Total	960.646	2471			
4	Regression	154.537	4	38.634	118.235	.000[d]
	Residual	806.109	2467	.327		
	Total	960.646	2471			

a. Predictors: (Constant), PMdf9299sq

b. Predictors: (Constant), PMdf9299sq, FmSz

c. Predictors: (Constant), PMdf9299sq, FmSz, Agpct78

d. Predictors: (Constant), PMdf9299sq, FmSz, Agpct78, PMbdf9299

e. Dependent Variable: TT9299a

Appendix 6. Pilot Study: Farming Alone Field Survey Instrument

Farming Alone – A Geography of Social Capital in the Rural-Urban Fringe

A Survey for Michigan Farmers

SURVEY INSTRUCTIONS

Good Morning\Good Afternoon

You are invited to participate in a study about farmers in the Lansing, Michigan metropolitan area using a social capital approach. I am a student at Michigan State University. We are interested in learning about your perspectives on farming, your relationships within the community, and aspects of your farming history. The survey will be directed during interview. You will be asked a few background questions regarding aspects of the operation of your farm in your local area, how you manage your time, and your experience with interactions with other farmers. We will also ask you some questions regarding your interaction with local agricultural infrastructure.

If you complete this survey, as we hope you will, you will also be asked about the relative importance of economic characteristics and non-economic factors that determine the minimum sell prices of Michigan farmland. We identify the minimum sell price at which you would sell farmland under several hypothetical situations. You are asked to assume that you own the 10-acre tract of farmland described in the survey. Then you are asked to record the minimum sell prices you would accept in exchange for the farmland under the conditions described in the survey. The minimum sell price you are asked to report is the price at which you would be indifferent to selling or not selling the farmland described in the survey. *PLEASE THINK CAREFULLY ABOUT EACH HYPOTHETICAL FARMLAND SALE AND ANSWER AS THOUGH YOU WERE ACTUALLY GOING TO EXPERIENCE THE CONSEQUENCES OF THIS FARMLAND SALE.*

***Thank you** for participating in this survey.*

Section I. Your Farmland

Ql. Are you currently involved in producing agricultural products on you farmland? (Please check the correct answer.)

Yes [ ] No [ ]

Q1A. How many acres do you currently operate?

_____ acres

Q2. What is the longest time you or your direct ancestors have **continuously owned** farmland of 10 acres or more? (Please indicate the number of years you or your direct ancestors have continuously owned 10 acres or more of farmland.)

_____ years

Q3. Considering the farmland that you or your direct ancestors have continuously owned for the length of time reported in the previous question, what is its **primary use**? *(Please indicate the primary use of the farmland described in Q2 by checking one of the blanks below.)*

A. growing crops [ ]

B. growing fruits [ ]

C. used for pasture [ ]

D. other (Please indicate in the space provided.)

[ ]

Q3A. What are the other current uses of the farmland ? ____________________________

____

____

Q3B. What was the **primary use** of the farmland ago?

10 years ago? **20** years

A. [ ] growing crops [ ]

B. [ ] growing fruits [ ]

C. [ ] d for pasture [ ]

D. [ ] other *(Please indicate in the space provided.)*

Q4. *Are you a* ***Centennial Farmer****?* A Centennial Farmer owns at least 10 acres of farmland that have been in the family for 100 years or more. (Please check the correct answer.) *Yes [ ] No[ ]*

Q5. Have you ever **sold farmland in the past**? *(Please check the correct answer.)*

Yes [ ] No[ ]

Section II. Farmland Characteristics

Assume you own a 10 acre tract of farmland with the characteristics described below.

a. You have owned the farmland for the number of years you reported in Q2.

b. The farmland is average quality and used for the purpose you described in

c. There are no buildings or other improvements on the farmland.

d. The farmland is located near where you live. It is also located near serviceable roads and located
within 5 miles of a town of nearly 5,000 persons.

e. The farmland has development potential.

f. There are no mineral rights associated with the farmland.

Assume you are considering the sale of the 10 acre tract of farmland with the characteristics described above. The characteristics of the sale, if it oc **nancing (no seller financing is required.**

b. The seller (you) will pay 5 % of the farmland sale price for commissions and other legal fees associated with the sale.

c. Payment for the sale will be provided to you in the form of a cashier's check at the time of sale closing,

d. Your financial condition does not require you to sell the farmland.

Section III. Minimum Sell Prices

Q6. What price per acre would you expect *a professional appraiser* to value the farmland described above at the end of the year 2003? *(Please fill in the blank below.)*

_____/acre

Q7. What price per acre would you expect a *tax assessor* employed by the local government to value the farmland described above before any sale occurred at the end of the year 2003? *(Please fill in the blank below.)*

_____/acre

Section IV. Economic and Non-Economic Properties / Minimum Sell Prices for Farmland

Farmland may be valued for both its economic and non-economic properties. Some farmland characteristics that may influence its economic value include its productivity, its **development potential**, its **location**, and its **recreational potential**. Some of farmland's non-economic value may be **associated with the expectations of others** that you will continue to own the farmland, **your commitment** to keep the farmland in agricultural use, and the farmland's association with others and events that are important to you.

Considering both the economic and non-economic properties of the farmland and the conditions under which the farmland would be sold that were described in Section II, we would like to know the following. What is your minimum sell price you would accept for the farmland and that part of the minimum sell price would be compensation for the farmland's economic characteristics and what part of the minimum sell price is compensation for the farmland's non-economic characteristics?

Q8. If you owned the farmland described in section II, what is the *lowest* price per acre you would accept for your farmland from *a complete stranger who intends to farm the land* and whose agent will arrange for and guarantee that the terms of the sale will be fulfilled? *(Please fill in the blank below.)*

$_______/acre

Q9. Consider the minimum sell price reported in Q8. Now divide that price between compensation for the land's economic value and its non-economic value. *(Please fill the blanks below.)*

Q9a. **$______/ acre** equals that portion of the minimum sell price reported in Q8 that compensates for the farmland's economic properties.

Q9b. **$______/ acre** equals that portion of the minimum sell price reported in Q8 that compensates for the farmland's non-economic properties.

Please note that the sum of the dollar amounts listed in Q8a and Q8b must equal the minimum sell price reported in question Q8. If the answer to part Q8b is zero, please skip to question Q10. If the answer to part Q8b was not zero, please continue.

Q9c. Regarding the non-economic portion of the minimum sell price (Q9b), what reasons can you give for the difference from minimum sell price? Could you allocate100 points to following reasons?

Farming as a way of life **______%** Care for family **______%**

Care for neighbors **______%** Value for community **______%**

Future Value of the land **______%** Other **______%**

Q10. **Please divide the non-economic value of the farmland you reported in Q9b among those non-economic properties that contributed to its value.** *(Please read carefully the description of the non-economic properties below and write your answers in percentages in the blanks below.)*

Q10a. **______%** equals that portion of the *non-economic value* reported in Q9b that compensates for disappointing others, including family members, neighbors, and friends, who expected that the land would remain in the family.

Q10b. **______%** equals that portion of the ***non-economic value*** reported in part Q9b that compensates for no longer owning or having access to a place associated with others and events that are important to you.

Q10c. **______% equals that portion of the *non-economic value*** reported in part Q9b that compensates for other factors ***(Please describe the* non-economic values below).**

Please note that the sum of the percentages on lines Q10a, Q10b, and Q10c must equal **100 percent.**

***(Please describe the* non-economic values below).**

____

____

____

Q11. If you owned the farmland in Section II, what is the *lowest* price per acre you would accept for your farmland from a complete stranger *who intends to use the land for non agricultural purposes such as development* and whose agent will arrange for and guarantee that the terms of the sale will be fulfilled? *(Please fill in the blank below.)*

$_______/ acre

Q12. Please divide the minimum sell price reported in Q11 between compensation for the land's economic value and its non-economic value. *(Please fill the blanks below.)*

Ql2a. **$______/ acre** equals that portion of the minimum sell price reported in Q10 that compensates for the farmland's economic properties.

Ql2b. **$_______/ acre** equals that portion of the minimum sell price reported in Q10 that compensates for the farmland's non-economic properties.

*Please note that the sum of the dollar amounts listed in Ql2a and Ql2b must equal the minimum sell price reported in question Q11. If the answer to part Ql2b is **zero**, please skip to question Ql4. If the answer to part Ql2b was **not** zero, please continue.*

Q13. Please divide the non-economic value of the farmland you reported in Q12b among those non-economic properties that contributed to its value. *(Please read carefully the description of the non-economic properties below and write your answers in percentages the blanks below.)*

Ql3a. ______% equals that portion of the value reported in Ql2b that compensates for *disappointing others, including family members, neighbors, and friends, who expected that the land would remain in the family*.

Ql3b. ______% equals that portion of the value reported in part Ql2b that compensates for *no longer owning or having access to a place associated with others and events that are important.*

Ql3c. ______% equals that portion of the value reported in part Ql2b that compensates for *selling your farmland to a buyer who intends to use it for non-agricultural purposes*.

Ql3d. ______% equals that portion of the value reported in part Ql2b that compensates for *other factors (Please describe the non-economic factors below).*

(Please note that the sum of the percentages on lines Ql3a, Ql3b, Ql3c and Ql3d must equal 100 percent).

Section V. Relationships and Minimum Sell Prices

If you owned the farmland described in Section II, what is the minimum sell price per acre you would sell your farmland to **each** of the following people? Please consider each buyer listed below in Q14 through Q17 **individually** as if they were the only ones who approached you with an offer to buy your land. Then, indicate the lowest price you would accept from each buyer.

Q14. *A. friendly neighbor* whom you have known for more than 10 years and whose income and wealth are equal to your own. When you have had an emergency in the past, such as a machinery failure during a critical time, this neighbor has always been willing to help. This person will keep the land in farming. (Please fill the blank below).

$________ / acre

Q15. A *neighbor* whom you have known for more than 10 years and whose income and wealth are equal to your own. In the past, you and this neighbor have rarely ever spoken since you disagree on nearly every important topic including politics, religion, and how to raise children and crops. If this neighbor sees you shopping or other places, he/she will avoid speaking to you. This person will keep the land in farming. *(Please fill the blank below).*

$________ / acre

Q16. An *influential person* in your community who holds an important elected office and sits on the board of the financial institution where you have borrowed money in the past. This person's income and wealth are equal to your own. Although you do not know this person very well and have never had to ask for special favors in the past, having this person as a friend in the future might be helpful. This person will keep the land in farming. (*Please fill the blank below).*

$________ / acre

Q17. The *township/community* which you live in intends to develop the land for recreational purposes. The land will be used for youth sporting events and other community activities. *(Please fill the blank below).*

$________ / acre

Section VI. Allocation of Free Time

We would like to ask you to think about how you would allocate your free time under several hypothetical situations.

Ql8. Assume you live in a farming community and **have 40 hours of free time** to allocate during one month in the off-season.. **(***Please indicate below how you would use your free hours among a variety of hypothetical alternatives).*

Q18a. In your community, there are off-farm employment opportunities. How many of your 40 hours would you spend relaxing or working at home? *(Please fill the blank below).*

________ hours

Q18b. Your elderly friends need help with repairs around their home. Your friends are away for several days and if you perform the repairs during your 40 hours of free time, no one is likely to know of your efforts. How many of your 40 hours would you spend making repairs for your elderly friends? *(Please fill the blank below).*

________ hours

Q18c. A farmer in your community requested your help in learning how to use an innovative **computer program** that you installed on your farm several months ago. You promised to provide the needed help. In the past, you **have had little interaction with this farmer, but you did promise to help**. How many of your 40 hours would you spend helping train this fanner? *(Please fill the blank below).*

________ **hours**

Q18d. There is a farmer in your community whose spouse works at the bank where you obtain your loans. This farmer requested your help in learning how to use an innovative computer program that you installed on your farm several months ago. In the past, you have **had little interaction with this farmer.** You know that in the future, you **will need a loan from the bank where this farmer's spouse works.** How many of your 40 hours would you spend helping train this farmer? *(Please fill the blank below).*

________ **hours**

Q18e. There is an opportunity to assist local schools to develop a program that educates students about Michigan's agriculture. This activity will undoubtedly lead to improved contacts with students and faculty at the school. As a result of this activity, you can expect to have a greater interest in the community and its schools. How many of your 40 hours would you give to this project? *(Please fill the blank below).*

________ **hours**

Please note that the sum of hours listed in Q18a through Q18e must equal 40.

Section VII. Some questions about you.

Q19. What is your age? *(Please fill the blank below).*

_______ **years**

Q20. Please check the highest level of formal education you have completed.

A. Grade school	[ ]
B. High school	[ ]
C. Community college or trade school	[ ]
D. College	[ ]

E. Graduate school [ ]

Q21. Last year, my after-tax household income, including off-farm income, was equal to *(Please check the correct amount):*

A. Less than $20,000 [ ]

B. From $20,000 to $40,000 [ ]

C. From $40,000 to $60,000 [ ]

D. From $60,000 to $80,000 [ ]

E. More than $80,000 [ ]

Q22. In general, the following description best describes the relationship between you and your <u>immediate</u> family members. ***Immediate family*** *refers to one's closest relatives, usually parents, children, and siblings.* ***(Please check what you feel is the more appropriate description below):***

A. Extremely close [ ]

B. Close [ ]

C. Somewhat close [ ]

D. Neutral [ ]

E. Not close [ ]

Q23. In general, the following description best describes the relationship between you and your <u>extended</u> family members. *Extended family refers to an entire family including several generations who may live in other households. (Please check what you feel is the more appropriate description below):*

A. Extremely close [ ]

B. Close [ ]

C. Somewhat close [ ]

D. Neutral [ ]

E. Not close [ ]

Q24. How many of your family members, including children and adults, live within 20 miles of your primary residence? *(Please fill the blank below).*

________ number of immediate family members

________ number of extended family members

Q25. The **sense of tradition** in farming varies from farm to farm. How important would you say the tradition of farming is to you and your family? *(Please check the correct answer).*

A. Very important [ ]

B. Somewhat important [ ]

C. Not very important [ ]

D. Don't know [ ]

Q26. Do you expect that the next generation of your family will take over your farmland? *(Please **check the correct answer.)***

Yes [ ] No[ ]

Q27. Do you belong to any community organizations or groups? *(Please **check the correct answer.)***

Yes [ ] No[ ]

Q28. *If Yes* to question Q29, **which ones? *(Please check all answers that apply.)***

A. PTA or school board [ ]

B. Church organization [ ]

C. Service club [ ]

D. Local government organizations [ ]

E. Environmental organizations [ ]

F. Other (please describe below) [ ]

Q29. How do you perceive support by your community of your farm? *(Please check the correct answer.)*

A. Very supportive [ ]

B. Supportive [ ]

C. Somewhat supportive [ ]

D. Neutral [ ]

E. Not supportive [ ]

Q30. Have you ever been adversely affected by the actions of a non-farming neighbor?

Yes [ ] No [ ] NA [ ]

Section VIII. Transactions with Neighbors / Local Agricultural Infrastructure

For these questions please ***state a location*** *(township or city). A map will available for reference.*

Q31. Can you indicate where in the Tri-County area (Clinton, Eaton & Ingham) you buy your goods from other farmers?

Q31a. Can you indicate where in Michigan buy your goods from other farmers?

Q32. What percentage of income derives from interactions with other farmers in the Tri-County area?

0-10% [ ] 11-20% [ ] 21-30% [ ] 31-50% [ ]51-75% [ ]76-100% [ ]

Q33. At what distance (locations) are the farmers with which you have the most interactions? Please indicate the distance (locations) of the **five** farmers that that you have the most frequent contact.

Distance (Location)	Frequency
1.	
2.	
3.	
4.	
5.	

Q34. What types activities are you engaged with this group of farmers?

Q35. Can you indicate where in your local area that you joint harvest with other operators?

How often is this done? Sometimes [ ] Usually [ ]

Q36. Can you indicate where in your local area that you share equipment with other operators?

How often is this done? Sometimes [ ] Usually [ ]

Q37. Can you indicate where in your local area that you perform/receive custom work with other operators

How often is this done? Sometimes [ ] Usually [ ]

Q38. Can you indicate where in the Tri-County area (Clinton, Eaton & Ingham) you sell your goods to other farmers?

Q38a. Can you indicate where in Michigan you sell your goods to other farmers?

Q39. Can you indicate the locations in the Tri-County area (Clinton, Eaton & Ingham) of the agricultural supply dealers that you frequent?

Q39a. Can you indicate the locations in Michigan of the agricultural supply dealers that you frequent?

Q40. Do you **haul your goods** to a processor?

Yes [ ] No [ ] NA [ ]

Q40a. *If yes:* Can you indicate the base locations of **agricultural processors** that you employ in the Tri-County area (Clinton, Eaton & Ingham)?

Q40b. Can you indicate the base locations of **agricultural processors** that you employ in Michigan?

Q41. Do you **store your crops** at other farmers' facilities?

Yes [ ]   No [ ]   NA [ ]

Q41a. *If yes*, Can you indicate the locations where you **store crops** on other than your own farm in the Tri-County area

(Clinton, Eaton & Ingham)?

Q41b. Can you indicate the base locations where you **store crops** on other than your own farm in Michigan?

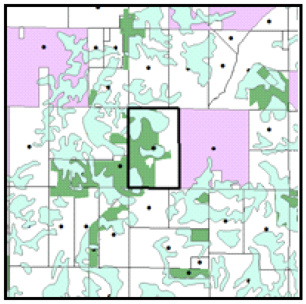
***Thank you** for your help and cooperation. Your opinion on each question counts a great deal. If you would like to share any additional comments, please write them on this page:*

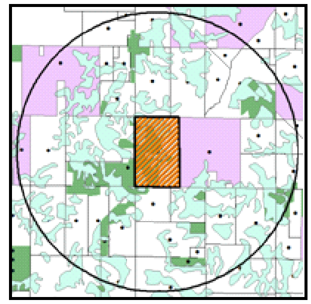
Appendix 7. Data Extraction: (Script example)

```
import arcgisscripting, sys
gp = arcgisscripting.create()

# Each of the input feature classes has an STFID, which is the
# combination of the Tract ID and Block ID for each block.  We
# want to separate these values out from this field into two new
# fields, TRACTID and BLOCKID.

gp.workspace = r"C:\Data\CityBlocks.mdb"
outfc = r"C:\Data\CityBlocks.mdb\AllBlocks"

# Create a fieldmappings and two new fieldmaps
fieldmappings = gp.createobject("FieldMappings")
fldmap_TRACTID = gp.createobject("FieldMap")
fldmap_BLOCKID = gp.createobject("FieldMap")

# List all the feature classes in the workspace that have the word
# block in their name and are of polygon feature type.
fcs = gp.listfeatureclasses("blocks*", "Polygon")
fc = fcs.next()

# Create a value table that will hold the input fc to Merge.
vt = gp.createobject("ValueTable")

while fc:
    # Adding a table is the fast way to load all the fields from the
    # input into fieldmaps held by the fieldmappings object.
    fieldmappings.AddTable(fc)

    # In this example we will also create two fieldmaps by 'chopping
up'
    # an input field. We need to feed the field we are chopping up into
    # the new fieldmaps.
    fldmap_TRACTID.AddInputField(fc, "STFID")
    fldmap_BLOCKID.AddInputField(fc, "STFID")

    # Populate the input value table with feature classes.
    vt.AddRow(fc)

    fc = fcs.next()

# Set the starting and ending position of the fields going into the
# TractID fieldmap this is the location in the STFID field where the
# TractID falls.
for x in range(0, fldmap_TRACTID.InputFieldCount):
    fldmap_TRACTID.SetStartTextPosition(x, 5)
    fldmap_TRACTID.SetEndTextPosition(x, 10)

# Set the Name of the Field output from this field map.
fld_TRACTID = fldmap_TRACTID.OutputField
fld_TRACTID.Name = "TRACTID"
fldmap_TRACTID.OutputField = fld_TRACTID
```

```
      # Set the starting and ending position of the fields going into the
      # BlockID fieldmap, this is the location in the STFID field where the
      # blockID falls.
      for x in range(0, fldmap_BLOCKID.InputFieldCount):
          fldmap_BLOCKID.SetStartTextPosition(x, 11)
          fldmap_BLOCKID.SetEndTextPosition(x, 16)

      # Set the Name of the Field output from this field map.
      fld_BLOCKID = fldmap_BLOCKID.OutputField
      fld_BLOCKID.Name = "BLOCKID"
      fldmap_BLOCKID.OutputField = fld_BLOCKID

      # Add our custom fieldmaps into the fieldmappings object
      fieldmappings.AddFieldMap(fldmap_TRACTID)
      fieldmappings.AddFieldMap(fldmap_BLOCKID)

      # Run the merge tool
      gp.Merge(vt, outfc, fieldmappings)

      Intersect
      # Purpose: Determine the type of vegetation within 100 meters of all
stream crossings

      # Create the Geoprocessor object
      import arcgisscripting
      gp = arcgisscripting.create()

      try:
          # Set the workspace (to avoid having to type in the full path to
the data every time)
          gp.Workspace = "c:/projects/RedRiverBasin/data.mdb"

          # Process: Find all stream crossings (points)
          gp.Intersect_analysis("roads ; streams ", "stream_crossings", "#",
1.5, "point")

          # Process: Buffer all stream crossings by 100 meters
          gp.Buffer("stream_crossings","stream_crossings_100m", "100 meters")

          # Process: Clip the vegetation feature class to
stream_crossing_100m
          gp.Clip("vegetation", "stream_crossings_100m",
"veg_within_100m_of_crossings")

          # Process: Summarize how much (area) of each type of vegetation is
found within 100 meter of the stream crossings
          gp.Statistics("veg_within_100m_of_crossings",
"veg_within_100m_of_crossings_stats","shape_area sum","veg_type")

      except:
          # If an error occurred while running a tool print the messages
          print gp.GetMessages()
```

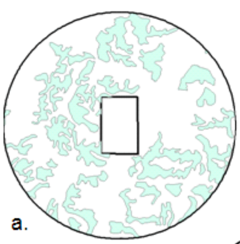
Appendix 8. Data Extraction: Parcel level (Cartographic Visualization) - identify spatial characteristics that potentially influence land use change within locale surrounding a parcel.

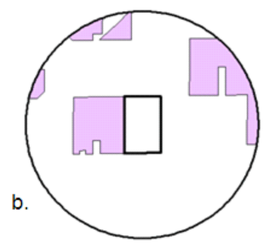


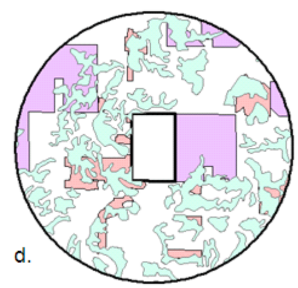


1. Initial undifferentiated data

2. Python Program delineates **1 mile radius** about parcel centroid /removes parcel area from local measurements.







Parcel #	Parcel Ac	Prime Ac	PA116 Ac	Urban Ac
060-022-300-050-00	100.28	567.664	344.483	204.14

3. Data extraction (year 1999) a. **Prime** farmland b. **PA 116** parcels

c. **Urban** land use

d. Compilation of extracted data - 3 iterations) and sample change to a single parcel record.

Appendix 8 (cont.). Data Extraction: Parcel level

4. The extraction process continues to iteratively process spatial information within each locale until parcel records are exhausted (optimal processing size = Township: 400-600 records).

Parcel #	Parcel Ac	Prime Ac	PA116 Ac	Urban Ac
060-021-200-005-00	167.53	379.152	231.345	193.63
060-021-200-025-00	15.16	439.135	478.290	182.88
060-021-200-028-00	18.05	453.563	488.498	197.09
060-021-200-080-00	40.02	470.033	430.846	219.79
060-021-400-010-00	102.16	461.413	352.886	213.46
060-021-400-053-00	42.49	525.493	315.099	228.82
060-021-400-090-00	2.94	568.069	328.569	230.78
060-022-100-025-00	77.02	488.116	514.922	215.91
060-022-100-035-00	79.88	582.609	528.339	196.01
060-022-200-010-00	34.53	633.010	557.358	178.57
060-022-200-020-00	10.25	641.732	592.878	122.31
060-022-200-070-00	98.61	578.111	567.466	146.59
060-022-300-050-00	100.28	567.664	344.483	204.14
060-022-400-016-00	138.90	546.248	220.309	268.16
060-027-100-010-00	39.94	611.097	185.433	250.81
060-027-100-031-00	40.41	563.400	195.582	268.68
060-027-100-051-00	68.65	593.184	140.211	264.81
060-027-200-010-00	55.21	464.087	292.197	256.11
060-027-200-080-00	86.05	362.372	403.718	176.24
060-028-200-012-00	50.87	582.926	147.576	296.50
060-028-200-020-00	38.59	585.559	194.414	289.89
060-028-200-031-00	12.01	574.001	275.016	256.46
060-028-200-057-00	2.44	604.301	110.344	302.46
060-028-200-072-00	48.44	597.402	175.046	284.22

In this case, Parcel records are populated with the three different layers.