Investigation of multi-criteria decision analysis approaches for agricultural decision-making in southern Ontario

by

Li Zhang

A thesis

presented to the University of Waterloo

in fulfillment of the

thesis requirement for the degree of

Master of Science

in

Geography

Waterloo, Ontario, Canada, 2016

Author's Declaration

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

I understand that my thesis may be made electronically available to the public.

Abstract

Land-use and land-cover change has significant impact on the Earth's ecosystems and global carbon cycle, which calls for well-planned land management strategies. This study presented a multi-criteria decision analysis (MCDA) for agricultural land-use allocation integrating environmental, social, and economic factors with human preferences. The agent-based modelling of agricultural land-use allocation shows that integrating a multi-objective decision analysis (MODA) of land amount allocation in land-use allocation will result in different land use allocation results from directly allocate land-use on fields. In addition to general land-use types of cropland, pasture, and woodland studied in MODA, a specific crop of corn was selected for site analysis with a multi-attribute suitability analysis based on soil, topography, and climate characteristics on potential sites and farmers' opinions about relative importance of these criteria. This study reveals that land management on land with heterogeneity is important and human preferences and decision-making strategies have significant impact on LUCC.

Acknowledgements

I would like to express my deepest appreciation to my supervisor Dr. Derek Robinson for his mentorship and patience through my Master’s study. He has been helping me so much with funding, learning, personal affairs, and all the other little things in my life. He has always been encouraging me no matter what. Thank you so much for everything!

I also want to thank all the colleagues in our Geospatial Innovation Lab for answering my questions, helping me academically and personally.

Lastly, I would like to thank my parents, my partner, and all my friends for supporting and encouraging me through my Master’s study.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Land-use and land-cover change (LUCC) involves a change in the use and management of land by humans and a corresponding change in terrestrial surface and subsurface (e.g., biota, soil, topography, surface and groundwater, and human structures characteristics) of the Earth (Lambin et al., 2000; Robinson et al., 2013). Most land-use activities necessary for human development involve the appropriation of natural resources and ecosystem services, which have negative impacts on the Earth's ecosystem both locally and globally (Vitousek, 1997; Foley et al., 2005). For example, due to the global increase in cropland and fertilizer use from 1960s to 1990s, environment damages were caused including water quality degradation, arable land loss, and soil erosion (Foley et al., 2005). According to an FAO study in 2004, land-use activities associated with agriculture and timber harvesting resulted in a net loss of about 7 to 11 million km^2 of forest over the previous 300 years. Consequently, approximately 40% of the global terrestrial surface is occupied by croplands and pastures (Foley et al., 2005). In addition to the impacts on the Earth's ecosystems, LUCC also has significant impacts on global carbon cycle. Agriculture, Forestry, and Other Land Use (AFOLU) sector accounted for about 25% of anthropogenic greenhouse gas (GHG) emissions. Agricultural practices contributed the most to the global anthropogenic non-CO_2 GHGs, the annual value of which accounted for about 10-12% of global anthropogenic emissions (Smith et al., 2014)

Given the impacts of LUCC on the Earth's ecosystem and global carbon cycle, there is an increasing demand for well-planned land management strategies, which require a trade-off among factors altering land management, for example, balancing economic development among multiple sectors, social benefits of different groups of people, and environment impacts on different regions (Beinat and Nijkamp, 1998). Multi-criteria decision analysis (MCDA) is a platform that can integrate multiple variables and importance of these variables into a decision process. It offers a structured framework to support decision-making problems through exploring objectives and concerns of multiple stakeholders. Its' capabilities of dealing with quantitative and qualitative data, multiple stakeholders' conflicts, and sensitivity and robustness of various choices make it a widely used application for decision analysis (Beinat and Nijkamp, 1998; Mendoza and Martins, 2006; Giove et al., 2009).

MCDA has been categorized in various ways. For example, Belton and Stewart (2002) divided MCDA into three categories of value measurement models, goal, aspiration or reference level models, and outranking models. Giove et al. (2009) provided four classification ways: multi-attribute decision analysis (MADA) versus multi-objective decision analysis (MODA), group decision maker versus individual decision maker, single step versus multiple steps, and under certainty versus under uncertainty. In this thesis, the commonly used classification of MADA and MODA was discussed with case studies (Figure 1-1). MADA defines a set of land-use decision alternatives and evaluates these alternatives to select the most suitable one or several based on multiple attributes (Phua and Minowa, 2005). The attributes are associated with scores representing their attractiveness to the decision. Multi-attribute value theory (MAVT)/multi-attribute utility theory (MAUT), outranking, and interactive methods are widely used in MADA.

In MAVT/MAUT, a value/utility function is constructed firstly for each criterion and normalized to a common numerical scale. Then the preference towards each criterion is determined based on stakeholders' willingness. Lastly, the value/utility for each criterion and its corresponding preference weight are aggregated to generate a final value for each decision alternative (Giove et al., 2009). Martin et al. (2000) adopted this method to analyze stakeholders' opinion on the development of leasable minerals on the San Juan National Forest in south-west Colorado. They interviewed three groups of stakeholders and asked them to value four attributes and six decision alternatives related to forest management. Using ordinal ranking and cardinal ranking method, the six decision alternatives were compared. This method is straightforward and decision alternatives can be quantified clearly with selected aggregation methods.

Outranking method uses pairwise comparison of each criterion for each decision alternative. It gives the explanation of which criterion is more preferred than the other, but does not provide information about cardinal measurement of preference relationships (Ananda and Herath, 2009). Kangas et al. (2000) applied outranking method in a study about landscape ecological forest planning analysis where they evaluated ten forest plan alternatives with five criteria. This method has some drawbacks that limit its application. For example, it is difficult to assign "the necessary parameters for understanding the meaning of the model as soon as the number of variables reaches real values" (Giove et al., 2009, p68).

Interactive method allows decision-makers to provide their opinions and make adjustments continuously during the decision-making process. Pykäläinen et al. (1999) applied an interactive decision analysis in the participatory strategic planning of natural resources management in Kainuu. In this study, four related parties were involved in this decision process about four forest strategies.

In contrast, A MODA approach is preferred when the land-use decision alternatives are not defined before a decision made. Instead, a set of objectives are defined and decision alternatives are generated that satisfy the objectives (Phua and Minowa, 2005). In this case, programming approaches are usually used to generate the best alternatives while respecting decision-makers' objectives and required constraints. Compromise Programming (CP) and Goal Programming (GP) are two approaches to solving MODA problems. CP method uses a distance measurement between an alternative and the ideal point to determine the best alternative. The shorter the distance is, the better the alternative is (Phua and Minowa, 2005). GP, adjusted from linear programming, constructs an objective function with deviational variables from goal constraints.

Then it solves the problem of minimizing the sum of weighted deviations from each goal while respecting all the other constraints (Ananda and Herath, 2009). Stewart et al. (2004) applied GP in a land use allocation problem in the Jisperveld region in the Netherlands, which has various constraints and conflicting objectives.

Although obvious differences exist between MODA and MADA, some of the aforementioned methods can be used cooperatively to make better decisions.

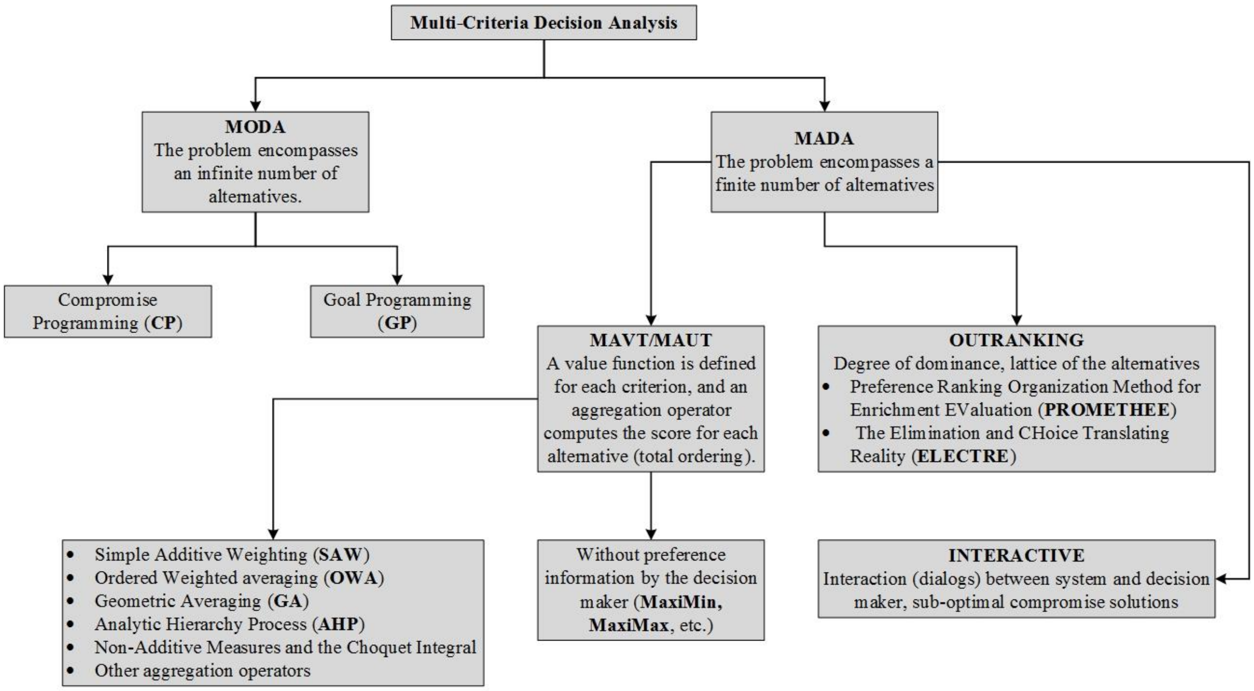


Figure 1-1 A classification of MCDA problems and methods. (Modified from Giove et al., 2009, p.60)

1.2 Objective and Sub-objectives

The overarching goal of the presented thesis is to gain insight into the application of MCDA for agricultural land-use decision-making. To fulfill this objective, this thesis presented two studies with emphasis on MODA and MADA, respectively. The research questions answered in the two studies are as follows:

1) how does the allocation of land-use on a farm differ when land suitability (environmental, social, and economic factors) and farmers' preferences towards these factors are applied at the farm versus the field level of spatial aggregation?
2) what is the spatial distribution and pattern of suitability scores of corn growth in Southern Ontario?

To answer the first research question, Chapter 2 presented:

- an algorithm to represent land suitability that integrates environmental, social, and economic factors;
- two agent-based models to simulate: land-use allocation originating at the farm level to individual fields on a farm (Farm-To-Field), and to directly allocate land uses to individual fields (Field);
- a quantitative comparison of the differences in land-use allocation when applied at the farm versus the field level.

To answer the second research question, Chapter 3 has the following objectives:

- to determine criteria and their corresponding weights for suitability score calculation;
- to perform a MADA to score and map suitability across Southern Ontario;
- to analyze the suitability scores to quantify the spatial distribution and patterns of suitable corn growing locations.

1.3 Thesis Structure

The next two chapters, Chapter 2 and Chapter 3, present two applications of MCDA for agricultural land-use decision-making with emphasis on MODA and MADA, respectively. Chapter 2 presents an agent-based modeling of decision making about land allocation for three general land-use types of cropland, pasture, and woodland in a subset of farms in the County of Middlesex. The decision-making process uses non-linear optimization to solve a multi-objective function integrating environmental, social, economic factors, and farmers' preferences toward these factors. Beyond decision making about general types of agricultural land uses in Chapter 2, Chapter 3 focuses on one specific crop (corn) site analysis. It applied a multi-attribute suitability analysis for corn growth in Southern Ontario based on soil, topography, and climate characteristics on potential sites and farmers' opinions about relative importance of these criteria. The final Chapter 4 provides recommendations, suggestions, and conclusions for this study.

Chapter 2

Comparison of farm- and field-level decision-making strategies on agricultural land-use allocation and farm utility

2.1 Introduction

It has been conceptualized that the allocation of land by humans for different activities (i.e., land-use) consists of three processes: a land suitability assessment, land demand estimation, and land location allocation (Karimi et al., 2012). First, land needs to be evaluated to determine if it is suitable for a specific land-use type, which is typically a composite index of the environmental, social, and economic conditions at a location. Second, the quantity of area required or demanded for each land-use type is determined by a governing body (e.g., as in China), a planning authority (e.g., as in Canada), or the market. Third, based on the assessment result of land suitability and demand, a land-use type is allocated for each land unit (Karimi et al., 2012; Pilehforooshha et al. 2014). Many land-use models are constructed to represent one or more of these processes of land allocation and apply them at regional or larger spatial extents (e.g. Verburg et al., 1999; Carsjens and Van Der Knaap, 2002; Sante-Riveira et al, 2008; Nguyen et al., 2015). However, how heterogeneous land-uses can be allocated at a small spatial extent (e.g. an individual farm) with similar characteristics has rarely been studied.

Existing models simulating on-farm land-use allocation (e.g. LUDAS, Le, 2005; Aporia, Murray-Rust et al., 2014), usually include only two of the three aforementioned land-use allocation processes: land suitability assessment and land location allocation. In these types of models, a decision-making agent evaluates the suitability of each field on a farm for a variety of land uses and then allocates land uses to fields based on those that maximize the agent's objectives, which is usually represented as a fitness or utility score. As a consequence, land-use allocation is optimized at the field level and ignores the overarching structural entity of the farm. Similarly, in most existing models, the demand driving the allocation of different land-uses has no relationship to overarching governance structures and is often ignored or is a function of the farmer's response to global crop prices and on-farm constraints (e.g., knowledge and biophysical conditions; Verburg et al., 1999; Wang et al., 2004).

Land-use and land-cover change (LUCC) is a process that involves interactions among actors and between actors and the natural system (Rindfuss et al., 2004; Robinson et al., 2013). Due to heterogeneity among actors, it is essential to improve our understanding about the drivers that affect the variation in land-use decisions under similar biophysical site conditions (Kelley and Evans, 2011). Drivers of variation in land-use decisions include land suitability (Wang et al., 2004), decision makers' preferences (Wu et al., 2004; Le, 2005), and spatial externalities (Marshall, 2004). Under the same biophysical conditions, land suitability can vary based on social and economic factors, but variation in all three factors is typically cited (e.g., FAO, 1976).

Decision maker's preference describes the degree of his/her concerns or happiness about a possible action or factor. Spatial externalities typically includes neighbourhood or adjacency effects on decision making, for example, adjacent land-use types tend to impact farmers' decisions (Kelly and Evans, 2011).

Various models have been developed to model LUCC. Parker et al. (2003) discussed the pros and cons of seven types of models: equation-based, system dynamics, statistical, expert, evolutionary, cellular, and hybrid models. These models overlap each other to some extent. They either have high dependence on mathematics and statistics (e.g. equation-based, system dynamics, statistical), or focus on landscape and transitions (e.g. cellular). Therefore, these models have limited ability to represent complex land management processes. Agent-based models (ABMs), which focus on human actions, have the ability "*to represent real-world actors and their interactions amongst each other and with their environment*" (Rounsevell et al., 2012, p.260) locally using virtual agents. An agent can be a person, an organization, an animal, or any entity that is programmed with a goal and methods to achieve that goal. (Railsback and Grimm, 2012).The agents are autonomous and can behave rationally to achieve their objectives. They can also communicate and interact with each other to share environment and "make decisions that tie behavior to the environment" (Parker et al., 2003)

As LUCC is a dynamic spatial process that usually involves individual human decisions and interactions, ABM is widely used to model LUCC. A typical LUCC ABM consists two key components, a landscape on which agents make decisions and decision-making strategies for agents within the system. Through the interaction among agents and between agents and the landscape, the two components are integrated to represent a coupled human-natural system (Parker et al., 2001).

Agent-based Models have been widely used in land use management with emphasis on various aspects. Robinson et al. (2013) used an ABM entitled Aporia to simulate on-farm decision making and to explore the impact of different socio-economic scenarios on ecosystem services in rural landscapes. The Aporia model included farm agents, farming regimes for farm agents to evaluate and select, and land cover and management practices associated with the farming regimes. Farm agents needed to evaluate available farming regimes based on total expected utilities they would obtain from each regime considering economic, environmental, and social factors. An ecosystem process model (LPJ-GUESS) was also integrated in this study to represent the ecosystem. Kelley and Evans (2011) presented an ABM to explore how "landowners' land-use decisions are influenced by heterogeneous land-use preferences, spatial externalities, and unique suitability features" (Kelley and Evans, 2011, p1). In this model, landowner agents needed to obtain a portfolio of labor and land allocation for farm, tree, esthetics, and off farm activities on cell and parcel level with the objectives of maximizing total utility. Unlike Aporia model, this model calculated total expected utility based on economic returns only from the four activities taking risk aversion into account.

Based on Aporia model and Kelly and Evan's work, the presented research uses an agent-based modelling approach to represent on-farm land-use allocation. The overarching question this chapter seeks to answer is how does the allocation of land-use on a farm differ when land suitability (environmental, social, and economic factors) and farmers' preferences towards these factors are applied at the farm (land amount allocation for each land use activities) versus the field level (land location allocation for each land use activities) of spatial aggregation? To answer this question this chapter presents an algorithm to represent land suitability that integrates environmental, social, and economic factors; two agent-based models to simulate: land-use allocation originating at the farm level to individual fields on a farm (Farm-To-Field), and to directly allocate land uses to individual fields (Field); and lastly a quantitative comparison of the differences in land-use allocation when applied at the farm versus the field level.

A variety of different platforms can be used to build agent-based models. The five most widely used platforms are NetLogo, Repast, Objective-C version of Swarm, Java Swarm, and MASON. Among the five platforms, NeloLogo is the most widely used due to its flexibility and modeling power. Repast, Swarm, and MASON provide a framework for model design that requires higher level of programming skills. MASON is the least mature while has the fastest running time among the five platforms (Railsback & Jackson, 2006). Each of the platforms has its own advantages and disadvantages in different aspects. It is the researchers' justification of which one to use with the consideration of model objectives and requirements. The model in this study is designed using the platform of NetLogo. It is an open source platform with simple dialect program language. It allows users to design agent-based models for natural and social phenomena. It makes it possible for researcher to investigate individual agent behaviors, as well as the interaction amongst them, which can ultimately emerge temporal or spatial patterns (NetLogo, 2013).

The remainder of this chapter first presents the study area used to situate the model experiments. Then a detailed explanation of the designed model is provided, which describes the landscape, agents, and land-use allocation strategies. Following the model description, experiments of the two land-use allocation strategies are discussed and results are presented. Lastly, issues associated with the model design, broader implications of the presented research, and potential directions for future research are discussed.

2.2 Study Area

The presented research is situated in the Census Subdivision (CSD) of North Middlesex, in the County of Middlesex, Ontario, Canada (Figure 2-1). North Middlesex, with a total area of approximately 603 km^2 and a total population of 6658 (Statistics Canada, 2012), is located in the center of Southern Ontario between Lake Huron and Lake Erie. The climate in this region produces adequate heat and precipitation for agriculture (Hannam et al., 2015) such that more than 60% of the total land area in Middlesex has been classified with an agricultural suitability that has no significant or moderate limitations for the growth of agricultural crops (Hagerty and Kingston, 1992). Land in crops, pasture, and woodland accounted for 78%, 3.4%, and 7.8% of the total area in North Middlesex, respectively. Among the farms, wheat, corn, and soybeans are the dominate crops cultivated.

The Agri-food industry affiliated with agricultural production in Middlesex generated an economic impact of 1.2 billion Canadian dollars and accounted for about 15.2% of employment in the County, making it the largest employer in 2015 (Hannam et al., 2015). Total farm capital in the County was substantially higher, yielding approximately 5.05 billion Canadian dollars, which account for about 16% of the farm capital in Southern Ontario (Statistics Canada, 2011.). These statistics demonstrate that agriculture plays a substantial role in the livelihoods of individuals and the economy in the County of Middlesex.

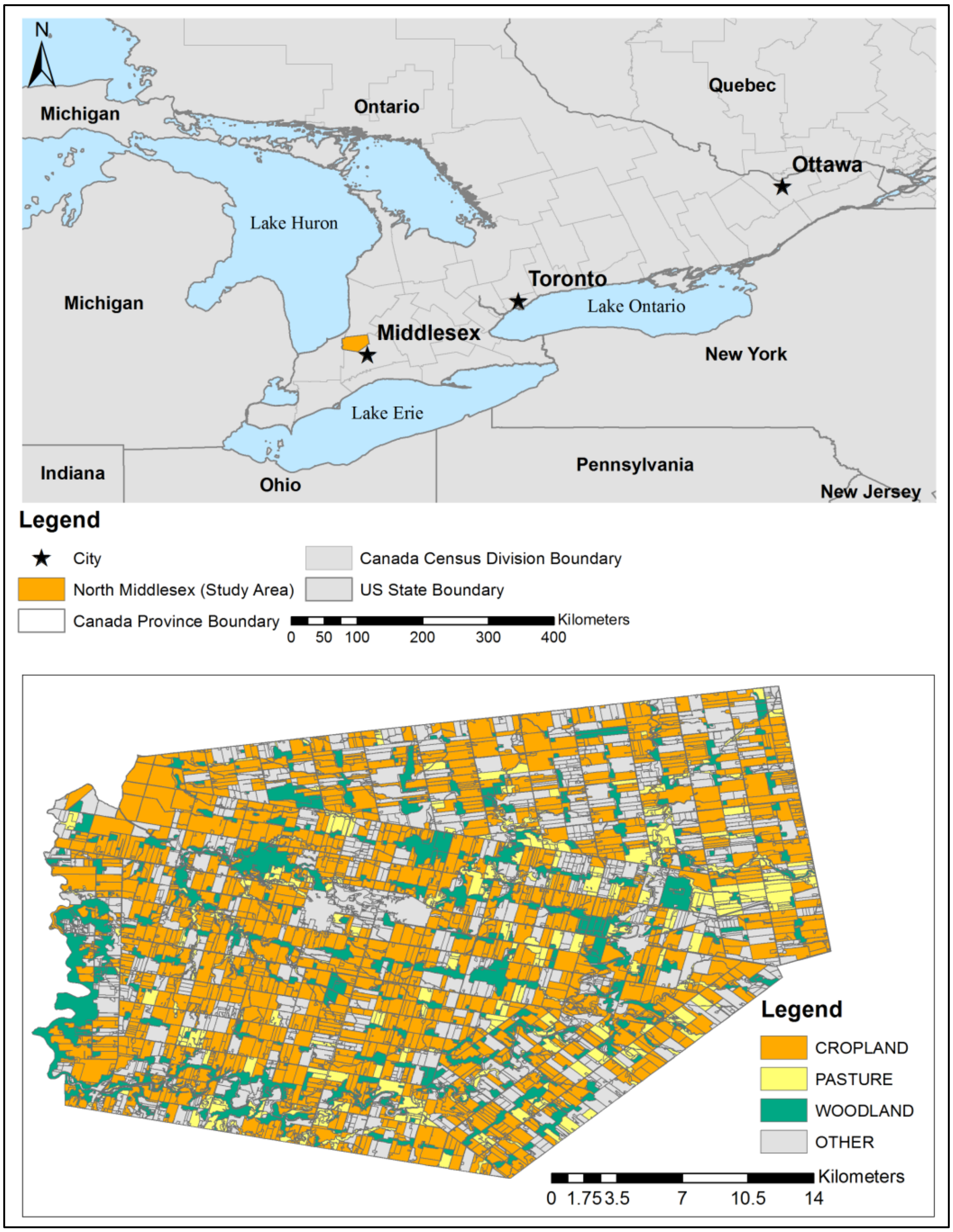


Figure 2-1 Map of Northern Middlesex location and land use (Data source: Southern Ontario Land Use and Agricultural Resource Inventory, See Appendix 1 for land use specification).

2.3 Conceptual Model (ODD Description)

This model is described following the ODD (Overview, Design concepts, Details) protocol, which is a *de facto* standard for describing individual- and agent-based models (Grimm et al. 2006; Grimm et al. 2010). The model Pseudo Code is provided in Appendix 2.

2.3.1 Overview

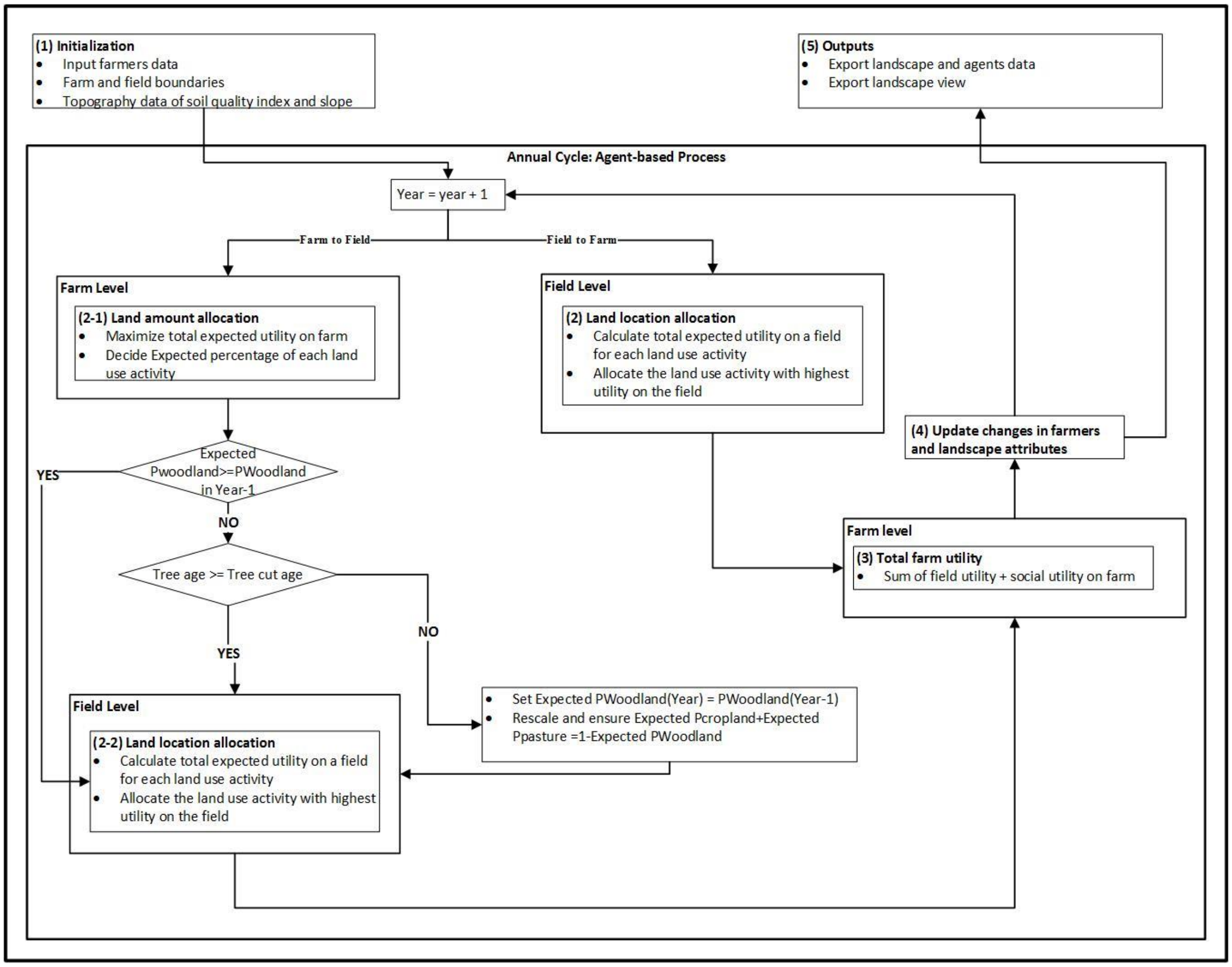


Figure 2-2 Flow Chart of main model process.

2.3.1.1 Purpose

The model was designed to investigate how farmers' decisions (taking environmental, social, and economic into account) affect land-use allocation. Farmer agents make on-farm decisions about 1) the proportion of their farm to allocate to among three land-use activities (cropland, pasture, or woodland (step 2-1 in Figure 2-2); and 2) which of the three land-use activities to allocate to each field (step 2-2 in Figure 2-2).

2.3.1.2 Entities, state variables, and scales

This model consisted of entities representing the landscape of farms and fields, farmer agents who own the farms, and the environmental variable of market prices for different land-use activities. The model was run at an annual time step for 31 years from 1982 to 2012 based on data availability.

2.3.1.2.1 Landscape

The landscape is composed of patches, fields, and farms (Table 2-1), covering a total area of approximately 603 km^2. The first layer consists of patches with site-specific variables representing spatial heterogeneity. The second layer consists of 2987 fields, which were a group of patches. Lastly, the third layer consists of 458 farms, which were a group of fields owned by the farm owner. Fields are the smallest unit where decisions are made in the model. The three layers have the variables of slope, Soil Quality Index (SQI), woodland age, and their associated identity number indicating field and farm they belong to. Patch and field also own the variable of land-use type.

2.3.1.2.2 Agents

Farmer agents were considered to be the only type of land manager, with each farmer agent owning a single farm; therefore, there were 458 farmers in total in this model. Farmer agents have a number of state variables that include a farmer agent identity number which is matched with farm identity number, preference weights of environmental, social, and economic factors, and knowledge about the extent to which slope affects productivity (Table 2-1).

2.3.1.2.3 Global Environment

The model includes global environment variables describing the average annual selling prices and expenses for general crops, pasture, and woodland. Detailed description is provided in Input Data section.

Table 2-1 State variables of landscape and agents

Entity		**State Variable**	**Description**
Landscape	Patch	pslope	Slope (no unit)
		psqi	Soil Quality Index (SQI) (no unit)
		planduse	Land use
		pfarmid	Identity number indicating farm the patch located on
		pfieldid	Identity number indicating field the patch located on
	Field	fieldid	Field identity
		farmid	Farm identity
		fieldslope	Mean slope of a field (no unit)
		fieldsqi	Mean SQI of a field (no unit)
		fieldtreeage	Age of woodland on a field (years)
		landuse	Land-use on a field
	Farm	farmno	Farm identity

		farmtreeage	Mean age of woodland on a farm (years)
Agent	Farmer	farmerno	Farmer agent identity
		alpha-env beta-soc gama-eco	Preference weights towards environmental, social, and economic variables (no unit)
		gama-slope	Farmer agents' belief about the extent to which slope affects productivity (no unit)

2.3.1.3 Process overview and scheduling

As illustrated in Figure 2-2, the model runs with an annual time step. Within each annual cycle, submodels of land-use allocation run in sequence. For Farm-To-Field strategy, the first submodel of Land Amount Allocation calculates an expected percentage for each land-use activity to maximize total farm utility. Then the submodel of Land Location Allocation chooses the land-use activity with the highest utility for each field on the farm. Lastly, the submodel of Total Utility calculates total utility on each farm based on land-use allocation results. For Field strategy, the submodels of Land Location Allocation and Total Utility were run in sequence. Detailed description of the submodels can be found in Submodels section. Following the submodels, the state variables of landscape and agents were updated and exported. In addition, the coverage of the three land-use activities of cropland, pasture, and woodland, average farm utility, and Gini Index were plotted at each time step and exported at the end of entire model run.

2.3.2 Design concepts

2.3.2.1 Basic principles

Farmer agents were considered to be rational and autonomous when making decisions. A utility function is adopted to quantify land suitability for a land-use activity at the farm or field level. The benefit of a utility-based approach comes from its ability to represent agents' preference towards an alternative action while maintaining the agents' goals with numeric values (Dillon, 1971). Farmer agents evaluate the utility of a potential decision using the following (Equation 2-1):

$$\begin{aligned} U_i &= U_i\left(LU_i \middle| Farmer_j, Farm_k\right) \\ &= \alpha_{Envi} Env_i + \alpha_{Soci} Soc_i + \alpha_{Ecoi} Eco_i \end{aligned} \qquad \text{Equation 2-1}$$

where U_i is the utility value when a $Farmer$ agent j on $Farm$ k applies land-use activity i, α_{Envi}, α_{Soci}, and α_{Ecoi} are the agent's preference weights of $Farmer$ agent j for environmental, social, and economic factors , respectively, that contribute to the decision making process. All these variables range from 0 to 1 without a unit.

2.3.2.1.1 Environmental and Social Factor

Ecosystem Service Indicators (ESSi) have been used to estimate the performance of a land-use activity from the perspective of environmental and social feedback (Brown and Robinson, 2006; Murray-Rust et al., 2014). In this study, ESSi of landscape aesthetics and soil loss were used to provide examples of indicators driving environmental and social factors affecting land-use utility scores.

Landscape aesthetics can be assessed with an objectivist (attributes of landscape) or subjectivist (perception of landscape viewers) paradigm (Lothian, 1999; Frank et al., 2013). In this study, an objective assessment approach was adopted. Landscape metrics have been used to describe the composition and configuration of land cover and various metrics have been combined to represent naturalness and landscape diversity (e.g., Frank et al. 2013). Using this work as a guide, Shannon’s Diversity Index (SHDI) was used as a proxy for landscape esthetic quality recognizing that this is a highly simplified representation of a complex concept, but it is one of few metrics used to describe landscape aesthetics that can be incorporated into the optimization algorithm to compute expected utility.

The aesthetic quality was therefore calculated based solely on the SHDI (McGarigal and Marks 1995), which is expressed in Equation 2-2:

$$A = w_{SHDI} L_{SHDI} = -w_{SHDI} \sum_{i=1}^{n} P_i ln(P_i) \qquad \text{Equation 2-2}$$

where A is the aesthetics quality index; w_{SHDI} is the weight for the landscape matrix, which equals 1 to because only one landscape matrix was included; L_{SHDI} is the SHDI of a farm; P_i is the proportion of land-use activity i; n is the number of land-use activity alternatives, which is 3 in this study (cropland, pasture, woodland). The calculated values of A were rescaled to a standard range [0, 1] with no unit that is consistent with other environmental and economic indicators.

The environmental indicator used in the presented model represents soil loss. Soil loss is frequently estimated using the Universal Soil Loss Equation (USLE) or the revised USLE (RUSLE). Comprising six factors, soil loss in RUSLE is a function of rainfall-runoff erosivity, soil erodibility, slope length, slop steepness, cover management, and supporting practices (Renard et al., 1991). Among the six factors, cover management is considered to be the most important factor because it can be managed the most easily to reduce soil erosion. Cover management is a function of prior land-use, canopy, surface cover, and surface roughness. Being the most important factor altering soil erosion, a simplified approach is taken that uses only surface cover (SC) to represent the impact of vegetation ground cover on reducing the impact of rainfall-runoff on soil loss (Robinson et al., 2014, unpublished manuscript). Surface cover is calculated using Equation Equation 2-3 and Equation 2-4:

$$SC = exp\left[-b \cdot S_p \left(\frac{0.24}{R_{LU}}\right)^{0.08}\right] \qquad \text{Equation 2-3}$$

$$S_p = [1 - exp(-\alpha \cdot \beta)] \cdot 100 \qquad \text{Equation 2-4}$$

where b is a coefficient representing the effectiveness of reducing soil loss (Table 2-2); R_{LU} is the surface roughness for a given land-use type (Table 2-2); S_p is the percent of land area covered by vegetation (assumed to be 30% in the presented research, Table 2-3); α is the ratio of area covered by a piece of residue to the mass of the residue (acre·lb^{-1}); and β is the dry weight of the residue on the surface (lb·acre^{-1}). The results of SC values fall within our standard indicator range [0, 1] and were inverted such that a value of 0 indicates exposed and unprotected soil and a value of 1 represents well-protected soil. It was assumed that woodland has a SC value of 1 due to little to no soil loss from woodland (Robinson et al., 2014, unpublished manuscript).

Table 2-2 Parameter value for b and R_{LU}

Parameter	b	Source	R_{LU}	Source
Bare soil	0.025	Kuenstler, 1998	0.7	
Crops	0.035		0.85	
Rangelands & Permanent pasture	0.039	Yoder et al., 1997	1.0	Kuenstler, 1998
long-term no-till cropping	0.05	Jones et al., 1996	0.9	

Table 2-3 Parameter value for α and β (Source: Yoder et al., 1997)

Parameter		α (acre·lb^{-1})	β(lb·acre^{-1})
Crops	Wheat	0.00059	600
	Corn	0.00038	950
	Soybeans	0.00059	600
Pasture		0.00055	650

2.3.2.1.2 Economic Factor

The economic factor *(Eco)* for cropland and pasture is estimated by subtracting the total costs from the total revenue. The functional approach was based on work by Kelly and Evans (2011), who evaluated land-use decision-making among land managers in Indiana, as described in Equation 2-5 to Equation 2-7. For woodland, the economic factor ($Eco_{woodland}$) is estimated based on the estimated carbon storage in the woodland, as shown in Equation 2-8:

$$Eco = \sum_{i=1}^{n}(P_i - c_i)Y_i \quad \text{Equation 2-5}$$

$$Y_i = A_i Per_i \quad \text{Equation 2-6}$$

$$A_k = soil_k/(1 + \gamma_{slope} \cdot slope_k) \quad \text{Equation 2-7}$$

$$Eco_{woodland} = P_{co2} \cdot BD \cdot Per_{woodland} \cdot 0.5 \quad \text{Equation 2-8}$$

$$f(t_i) = \frac{2}{1+exp(-t_i)} - 1 \quad \text{Equation 2-9}$$

where P_i is the selling price for land-use activity i per unit area; c_i is the operating cost of land-use activity i per unit area; Y_i is the productivity for land-use activity i; A_k is aggregated representations of productivity enhancement input at location k; Per_i is the area percentage of land-use activity i; $soil_k$ is soil quality index which is between 0 (lowest quality) and 1 (highest quality) for location k; γ_{slope} is an agent's belief about the extent to which slope affects productivity; $slope_k$ is the slope of land surface which is between 0 (flat) and 1 (landscape maximum); P_{co2} is the price for CO_2 (CAD$/kg); BD is the biomass density, which is total biomass per unit area; $Per_{woodland}$ is the area percentage of woodland; 0.5 is standard carbon fraction ratio (Whittaker 1975); t_i is the coefficient for land-use activity i. The calculated coefficient for each land-use activity was then rescaled to [0, 1] using sigmoid function (Han and Moraga, 1995), as shown in Equation 2-9, to ensure consistency with other environmental and social indicators.

2.3.2.2 Emergence

Coverage of the three land-use types of cropland, pasture, and woodland in each time step, average farm utility across study area, and Gini Index emerged based on land-use allocation by farmer agents.

2.3.2.3 Adaptation

The agents' preferences towards environmental, social, and economic factors were constant through the period of model run. In addition, although there is fluctuation in prices, agents do not adapt their decision-making strategies over time. Therefore, no adaptation was included in this model.

2.3.2.4 Objectives

There are two objectives for each agent at each time step. First, the agents need to maximize total expected utility on farms through determining proportion for each land-use activity. Then the agents need to maximize expected utility on each field by allocating one of the land-use activity on the field.

2.3.2.5 Learning and Prediction

Learning was not modeled as agents do not change their decision-making strategies in adaptation to environment change; therefore, prediction of environment changes was not necessary for this model.

2.3.2.6 Sensing

The agents were assumed to sense their own preference weights, identity number, farm and fields they own, site characteristics on their farms and fields, and historical prices for cropland, pasture, and woodland. The information from these variables was used in their decision-making processes.

2.3.2.7 Interaction

The agents make decisions independently without interacting with the others.

2.3.2.8 Stochasticity

In the absence of data on preference weights and the impact of slope, these variables were randomly generated[1] ensuring that the preference weights summed to 1. In addition, initial woodland ages on the fields were also randomly generated as integers due to the absence of real data.

2.3.2.9 Collectives

No collectives of agents were represented in this model.

2.3.2.10 Observation

The model was designed to observe how farmer agents' decision affect land-use allocation. Therefore, first, the view of the model (i.e. landscape) was exported at each time step for the visualization of land-use allocation. Second, the percentage of each of the three land-use activities was plotted and exported to analyze temporal changes in land-use.

2.3.3 Details

2.3.3.1 Initialization

The initialization includes setting up farm and field boundaries, initial state variable values for landscape (identity number, land-use, farm and field boundaries, soil quality index, and slope) and agents (identity number, preference weights and knowledge about slope impact), and initial year (1981).

Land-use data were acquired from the Southern Ontario Land Use and Agricultural Resource Inventory (ARI), which was developed in 1983 and used as the initial land-use composition and configuration in which agents are situated. The ARI land-use classes were aggregated into cropland, pasture, woodland, and other land-use types based on the detailed land-use categories in the dataset.

Field boundaries were obtained from the Ministry of Natural Resources for 2012 from their Agriculture Operation Inventory data. Then using the road network and orthographic imagery, farm boundaries (containing fields) were interpreted and digitized. Soil data were retrieved from the soil survey complex provided by the Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA) created in 1929 and revised in 2003. A soil capacity classification indicating the degree of soil limitation for agriculture provided under the Canada Land Inventory (CLI) was rescaled to a standard range [0, 1] to provide a soil quality index (SQI). In addition to these spatial data, the Canadian Digital Elevation Model (CDEM) was obtained from Natural Resources Canada (20 m resolution) to generate slope estimates across the study area. Slope was also rescaled to a standard range [0, 1].

[1] All variables were standardized to a range of 0 to 1 to ensure compatibility and to facilitate understanding the relative contributions of each variable or preference weight on individual decision outcomes.

In the absence of data on preference weights and the impact of slope, these variables were randomly generated with range between 0 and 1. The preference weights summed to 1 for normalization of utility function (Elster and Roemer 1991 in Brown and Robinson, 2006). In addition, initial woodland ages on the fields were also randomly generated as integers due to the absence of real data.

2.3.3.2 Input data

External input data in this model includes average annual selling prices and expenses for general cropland, pasture, and woodland from 1981-2011. First, annual crop prices for the three dominant crops in Middlesex County (winter wheat, grain corn, and soybeans) were acquired from OMAFRA and aggregated to a mean annual crop price. Price data for hay and yield per square meter were also acquired from OMAFRA and were used as a proxy for the revenue generated per area of pasture. Due to the lack of data and difficulty in consolidating data on the range of costs associated with cultivating crops and managing pasture (e.g., seed, fertilizer, herbicide, machinery maintenance and acquisition, insurance, land rent, labour, and others), it is assumed that production costs are linearly related to production activities and account for about 80% of the per unit price (implemented in a similar manner to Kelly and Evans, 2011).

The incorporation of woodland as an agricultural land-use required unique handling. The economic benefits from woodland were estimated based on the value of the carbon stored in forest cover. While different approaches to carbon valuation exist, one approach suggests that the optimal carbon price should depend on the marginal damage that carbon would cause to society at a certain time as a function of the stock of greenhouse gases in the atmosphere (Nordhaus, 1991; Mendelsohn, 2013). Using this approach, historical annual carbon prices were calculated using estimates of total carbon dioxide damage (in US$) in Canada divided by total carbon emissions in Canada (World Development Indicators, 2015), which was converted to Canada dollars using historical currency exchange rates. The carbon stored in woodland was estimated based on above-ground biomass on forest land by tree age classes based on Canada's National Forest Inventory datasets in 2013.

2.3.3.3 Submodels

2.3.3.3.1 Land Amount Allocation

When the farm-level model is run, it is assumed that farmer agents make decisions about the distribution of land-use activities to allocate on their land by selection the distribution that maximizes their total expected utility on the farm. To identify the optimum distribution a non-linear programming approach is used (Henseler et al., 2009) under the following two constraints: the total percent of land-use activity must add up to 100%; the percent of woodland in the current model year cannot be less than that of the previous year unless the trees were older than allowed cutting age. It means timber harvesting was only allowed at or beyond certain age (i.e. 40) in this model. The objectives are expressed mathematically as follows:

Maximize: $U = \sum_i U_i(LU_i|Farmer, Farm) + \lambda \cdot (1 - \sum_i LU_i)$

Objectives: 1) $\sum_i LU_i = 100\%$

2) if tree age < cut age, $P_{Woodland(j)} \geq P_{Woodland(j-1)}$

A Lagrange multiplier of λ (no unit) was add to constraint that total available land-use sum up to 100%. For each farm, the land-use activity allocation needs to satisfy the first order and Kuhn-Tucker conditions (see Guignard, 1969 for details):

$$\frac{\partial \mathrm{U}}{\partial \mathrm{LU}_i} = 0,\ \frac{\partial \mathrm{U}}{\partial \lambda} = 0, \lambda \geq 0$$

The calculated value of λ could provide solutions to a combination of percentage of each land-use activity that could maximize total on farm utility for each agent in each year run.

2.3.3.3.2 Land Location Allocation

When the field-level model is run, farmer agents calculate the total expected utility for each land-use activity for a given field and allocate the land-use with the highest utility. As social utility remains 0 at field level, only environmental and economic variables were considered at field level. When the farm-level model is run, the same approach is used; however, if the amount of one land-use activity allocated reaches that determined by the farm-level optimization then that land-use activity would no longer be considered for allocation in subsequent field evaluations.

2.3.3.3.3 Total Utility

The total utility on a farm was calculated by summing field utility on the farm plus the farm social utility, as represented in Equation 2-10:

$$TU = \sum_{Field} U_{Field} - \alpha_{Soci} \cdot w_{SHDI}/ln3 \cdot \sum_{i=1}^{n} P_i ln(P_i) \qquad \text{Equation 2-10}$$

2.4 Computational Experiments

Five computational experiments were conducted to explore how variance in farmer agents' preference weights impact land-use allocation using decision strategies of Farm-To-Field and Field. For each experiment, the model was run 20 times to account for stochasticity within the model and the mean percent of each land-use activity was computed. Each individual model run included 31 annual time steps, which represented modelling land-use decisions from 1982 to 2012. The experiments were designed to gain a better understanding of the behaviour of the model under both decision strategies and verify their behaviour rather than validate the performance of the model and predict future land-use outcomes.

First, it was assumed that all farmer agents have the same set of preference weights (i.e., the population is homogeneous). Experiment 1 was set to explore the land allocation with consideration of economic factor only, which is what farmers would usually consider. All farmer agents set their preference weight towards economic variable as 1 ($\alpha_{Env} = 0$, $\alpha_{Soc} = 0$, $\alpha_{Eco} = 1$). Then we explored land allocation results under the circumstance that farmer agents consider environmental or social factors only. In Experiment 2 all farmer agents value the environment factor only and the preference weight towards the environment was set as 1 ($\alpha_{Env} = 1$, $\alpha_{Soc} = 0$, $\alpha_{Eco} = 0$). In Experiment 3 all farmer agents value the social factor only and the preference weight towards social variable was set as 1 ($\alpha_{Env} = 0$ $\alpha_{Soc} = 1$, $\alpha_{Eco} = 0$). Then Experiment 4 assumes that all farmer agents have equal preferences towards the three variables ($\alpha_{Env} = 0.33$, $\alpha_{Soc} = 0.33$, $\alpha_{Eco} = 0.33$). Second, Experiment 5 assumes that the farmer agents are heterogeneous and the preference weights of each farmer agent were randomly generated.

The result from the five experiments were described and compared based on land use conversion, utility, and Gini Index. Gini index is a coefficient used to measure the inequality of family income or wealth within a region. It is usually calculated based on the Lorenz Curve[2] (blue line in Figure 2-3). The red line in Figure 2-3 at 45 degrees illustrates perfect equality of incomes. The Gini coefficient is represented as the ratio of the area between perfect equality and the Lorenz curve (A in Figure 2-3) to the total area under the perfect equality (A + B in Figure 2-3). It can be expressed mathematically as A/(A+B). Therefore, Gini Index does not have a unit and ranges from 0 to 1, where 0 means absolute equality and 1 means complete inequality (Measuring Inequality, 2016). In this chapter, we use Gini Index to quantify the distribution of total utility on each farm over the study area.

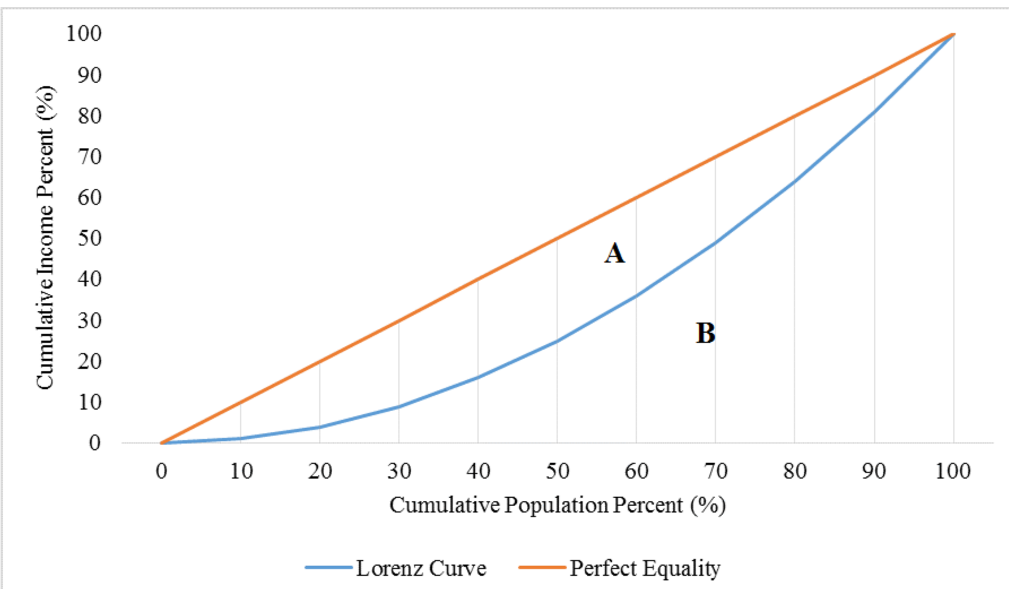


Figure 2-3 Lorenz Curve illustration (created from hypothetical data)

[2] Lorenz Curve plots cumulative income earned by percent of the population against the percent of the total income of the population.

2.5 Results

2.5.1 Experiment 1 (Economic Preference Only)

Table 2-4 Computational experiment outputs of average and standard deviation for cropland, pasture, and woodland coverage for Farm-To-Field and Field strategy

Experiment	Year	Farm-To-Field						Field					
		Cropland		Pasture		Woodland		Cropland		Pasture		Woodland	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
E1 Economic Preference Only	1981	61.9%	0.00	6.6%	0.00	2.4%	0.00	61.9%	0.00	6.6%	0.00	2.4%	0.00
	1982	99.4%	0.00	0.0%	0.00	0.6%	0.00	98.9%	0.00	0.0%	0.00	1.1%	0.00
	1992	99.5%	0.00	0.0%	0.00	0.5%	0.00	98.9%	0.00	0.0%	0.00	1.1%	0.00
	2002	99.6%	0.00	0.0%	0.00	0.4%	0.00	98.7%	0.00	0.0%	0.00	1.3%	0.00
	2012	99.7%	0.00	0.0%	0.00	0.3%	0.00	98.9%	0.00	0.0%	0.00	1.1%	0.00
E2 Environmental Preference Only	1981	61.9%	0.00	6.6%	0.00	2.4%	0.00	61.9%	0.00	6.6%	0.00	2.4%	0.00
	1982	0.0%	0.00	0.0%	0.00	100%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	1992	0.0%	0.00	0.0%	0.00	100%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	2002	0.0%	0.00	0.0%	0.00	100%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	2012	0.0%	0.00	0.0%	0.00	100%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
E3 Social Preference Only	1981	61.9%	0.00	6.6%	0.00	2.4%	0.00	61.9%	0.00	6.6%	0.00	2.4%	0.00
	1982	32.0%	0.00	3.1%	0.00	49.9%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	1992	5.3%	0.00	30.9%	0.00	61.3%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	2002	5.3%	0.00	30.9%	0.00	61.3%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
	2012	5.3%	0.00	30.9%	0.00	61.3%	0.00	0.0%	0.00	0.0%	0.00	100%	0.00
E4 Equal Preferences	1981	61.9%	0.00	6.6%	0.00	2.4%	0.00	61.9%	0.00	6.6%	0.00	2.4%	0.00
	1982	46.6%	0.00	6.9%	0.00	46.5%	0.00	51.8%	0.00	0.0%	0.00	48.2%	0.00
	1992	8.8%	0.00	2.1%	0.00	89.2%	0.00	0.6%	0.00	0.0%	0.00	99.4%	0.00
	2002	8.5%	0.00	1.6%	0.00	89.9%	0.00	0.6%	0.00	0.0%	0.00	99.4%	0.00
	2012	9.1%	0.00	0.9%	0.00	90.0%	0.00	0.7%	0.00	0.0%	0.00	99.3%	0.00
E5 Heterogeneous Preferences	1981	61.9%	0.00	6.6%	0.00	2.4%	0.00	61.9%	0.00	6.6%	0.00	2.4%	0.00
	1982	43.3%	0.01	15.5%	0.01	41.2%	0.01	47.4%	0.02	0.0%	0.00	52.6%	0.02
	1992	26.0%	0.01	14.4%	0.01	59.7%	0.02	37.9%	0.02	0.0%	0.00	62.1%	0.02
	2002	27.4%	0.01	7.4%	0.01	65.2%	0.02	37.7%	0.02	0.0%	0.00	62.3%	0.02
	2012	27.7%	0.01	5.3%	0.01	67.0%	0.02	37.8%	0.02	0.0%	0.00	62.2%	0.02

In Experiment 1, farmer agents consider economic variable only. For Farm-To-Field strategy, cropland increased to 99.7% and woodland decreased to 0.3% (Table 2-4). Cropland increased from 62% to 99.4% after the first model step and then increased by 0.1% every several years for the remainder of the model run. No pasture was allocated after the first model run. Woodland decreased from 2.4% to 0.6% after the first model run and then decreased by 0.1% every several years (Figure 2-4). Conversions from pasture and woodland to cropland were the dominant conversion types. The average farm utility across the study area was positively related to cropland price (Figure 2-6). The Gini Index for the study area was approximately between 0.03 and 0.05 for the 31 years.

Similarly for Field Strategy, cropland increased to 99.7% and woodland decreased to 0.3% (Table 2-4). Cropland increased to 98.9% after the first model step and remained stable for the remainder of the model run. No pasture was allocated after the first model run. Woodland decreased from 2.4% to 1.1% after the first model run and then remained stable until 2012 (Figure 2-5). Conversions from pasture and woodland to cropland were the dominant conversion types. The average farm utility across the study area and Gini Index were both identical to that of Farm-To-Field strategy. The average farm utility across the study area was positively related to cropland price (Figure 2-6). The Gini Index for the study area was approximately between 0.03 and 0.05.

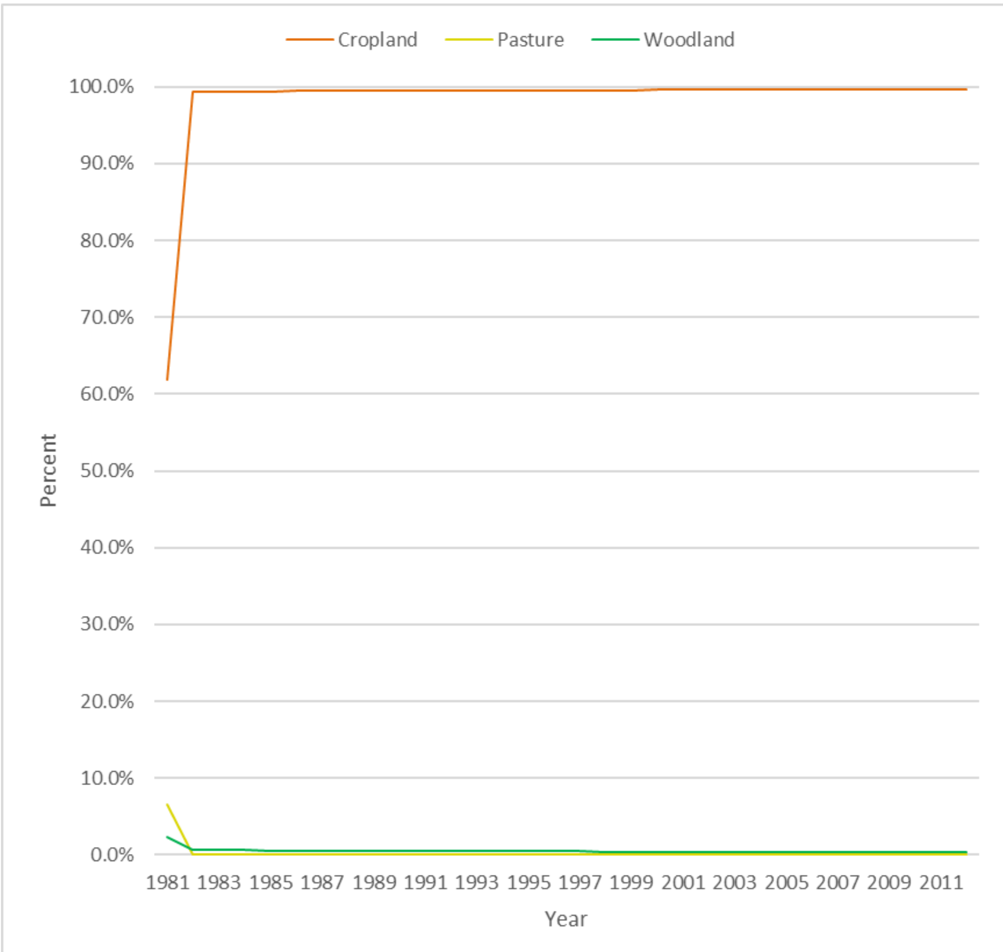


Figure 2-4 Average cropland, pasture, and woodland coverage from Experiment 1 with Farm-To-Field strategy.

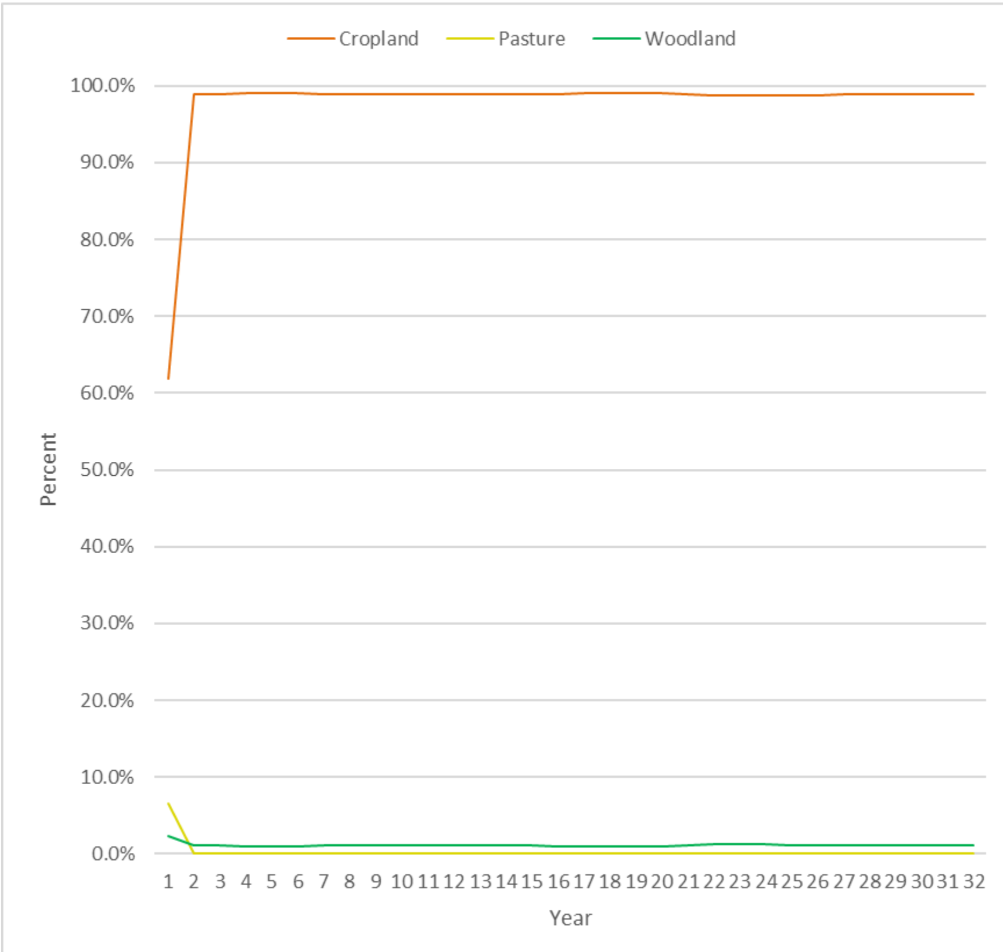


Figure 2-5 Average cropland, pasture, and woodland coverage from Experiment 1 with Field strategy.

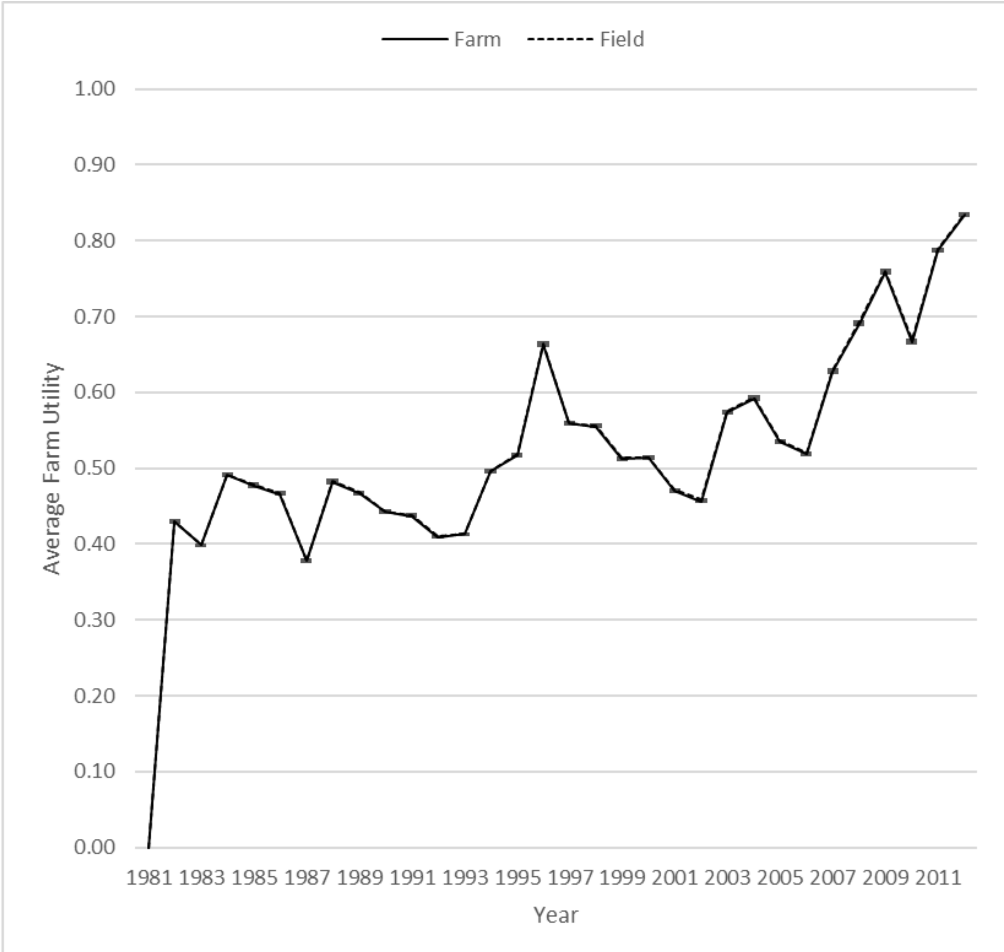


Figure 2-6 Annual average utility across study area from Experiment 1 with Farm-To-Field and Field strategy (Error bars represented range of experiment results).

2.5.2 Experiment 2 (Environmental Preference Only)

In Experiment 2, all the farmer agents consider environmental factor only. For both strategies, all the cropland and woodland were converted to woodland after the first model step and the model reached a steady state afterwards (Table 2-4, Figure 2-7). The average farm utility across the study area remained to be 1 and the Gini Index remained to be 0 for the 31 years. Woodland have a surface cover value of 1, cropland and pasture have surface cover values of 0.61 and 0.65, respectively. Therefore, choosing woodland could result in the highest utility for farms.

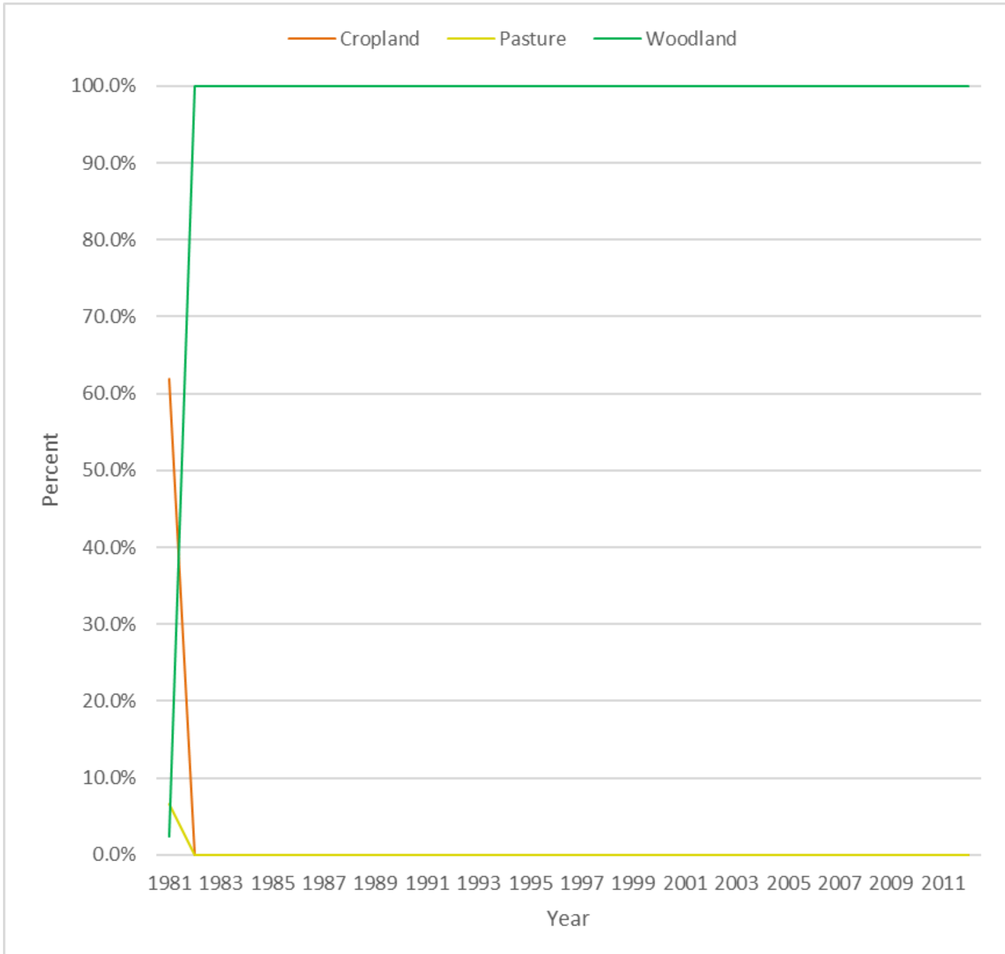


Figure 2-7 Average cropland, pasture, and woodland coverage from Experiment 2 with Farm-To-Field and Field strategy.

2.5.3 Experiment 3 (Social Preference Only)

In Experiment 3, farmer agents consider social variable only. For Farm-To-Field strategy, cropland decreased to 5.3%, pasture increased to 30.9%, and woodland increased to 61.3% (Table 2-4). Cropland decreased from 62% to 5.3% between 1981 and 1983 and then remained steady afterwards. Conversions from cropland to pasture and woodland were the dominant conversion types, with pasture increasing from 6.6% to 30.9% and woodland increasing from 2.4% to 61.3% between 1981 and 1983 (Figure 2-8). The coverage remained steady after 1983. In this experiment, farmer agents would like to achieve an equal amount of land for each land-use activities. However, due to the fact that fields are not allowed to be subdivided and woodland can only be harvested at certain age, it was not realistic for farmer agents to allocate the three land-use activities equally on farms. As a result, cropland, pasture, and woodland accounted for about 5.3%, 30.9%, and 61.3% of the total farm area, respectively. The average farm utility across the study area was 0.88 in 1982 and remained 0.59 afterwards. The Gini Index for the study area was 0.1 in 1982 and remained 0.4 for the remaining 30 years.

Field Strategy had a different outcome from Farm-To-Field strategy as the social variable is 0 on the field level regardless of the preference weight. All the land use of cropland and pasture are converted to woodland after the first model step and remained steady afterwards (Figure 2-9). The average farm utility across the study area remained 0 and the Gini Index remained 1 for the 31 years.

Comparing the two strategies, it was evident that Farm-To-Field strategy resulted in a significantly higher average utility than that of Field strategy. Farm-To-Field strategy resulted in an absolute equality across the study area, while Field strategy resulted in an absolute inequality.

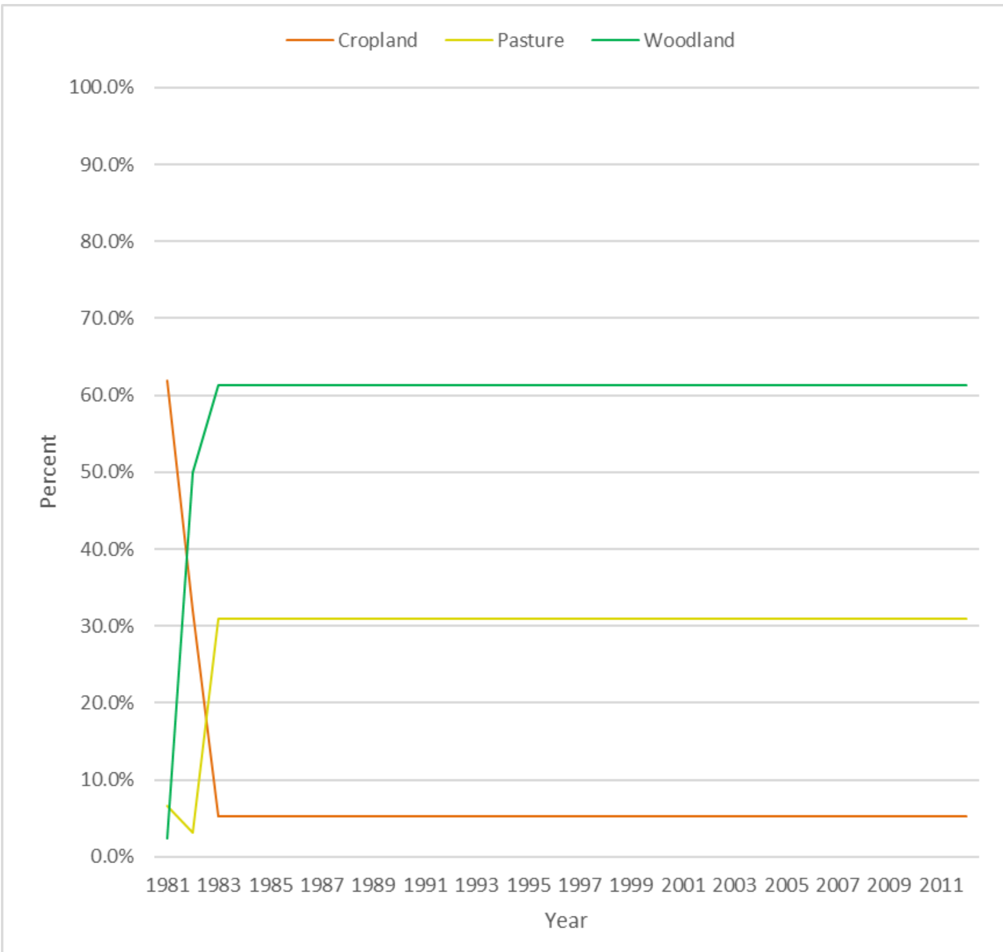


Figure 2-8 Average cropland, pasture, and woodland coverage from Experiment 3 with Farm-To-Field strategy.

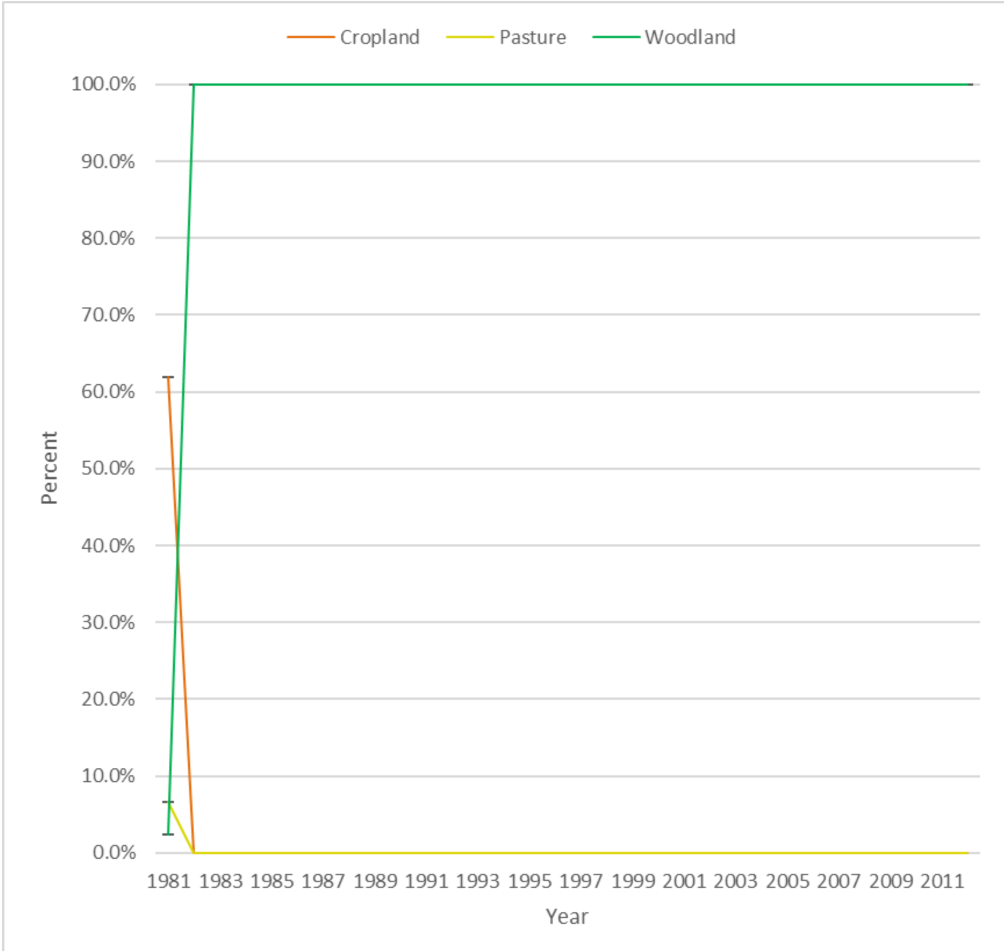


Figure 2-9 Average cropland, pasture, and woodland coverage from Experiment 3 with Field strategy.

2.5.4 Experiment 4 (Equal Preferences)

In Experiment 4, farmer agents have even preference weights toward environmental, social, and economic variables. For Farm-To-Field strategy, cropland decreased to 9% and woodland increased to 90% (Table 2-4). Cropland decreased from 62% to 9% between 1981 and 1988 and then fluctuated between 8% and 9% afterwards. Pasture decreased from 6.6% to 1.6% between 1981 and 1988 and then fluctuated between 1% and 2% until 2012. Woodland rapidly increased from 2.4% to 89% between 1981 and 1988 and remained relatively stable until 2012 (Figure 2-10). Conversion from cropland and pasture to woodland were the dominant conversion types. The average farm utility across the study area was between 0.4 and 0.5, and the Gini Index for was between 0.09 and 0.13 for the 31 years.

Outcome from Field Strategy was similar to Farm-To-Field strategy. Cropland decreased to 0.7% and woodland increased to 99.3%. No pasture was allocated after the first model step. Therefore, the conversions from cropland and pasture to woodland were the dominant conversion type (Table 2-4). Cropland area decreased from 62% to 0.6% between 1981 and 1987 and remained stable afterwards. Woodland area increased from 2.4% to 99.4% between 1981 and 1987, and remained the stable until 2012. The model reached a stable state after 1987 (Figure 2-11). The average farm utility across the study area was between 0.35 and 0.42 for the 31 years. The Gini Index was ranging between 0.00 and 0.02.

The average annual on-farm utility obtained from the Farm-To-Field strategy was higher than that obtained by the Field strategy (Figure 2-12). The Gini Index indicates that Farm-To-Field strategy resulted in more inequality in the study area than that of Field strategy.

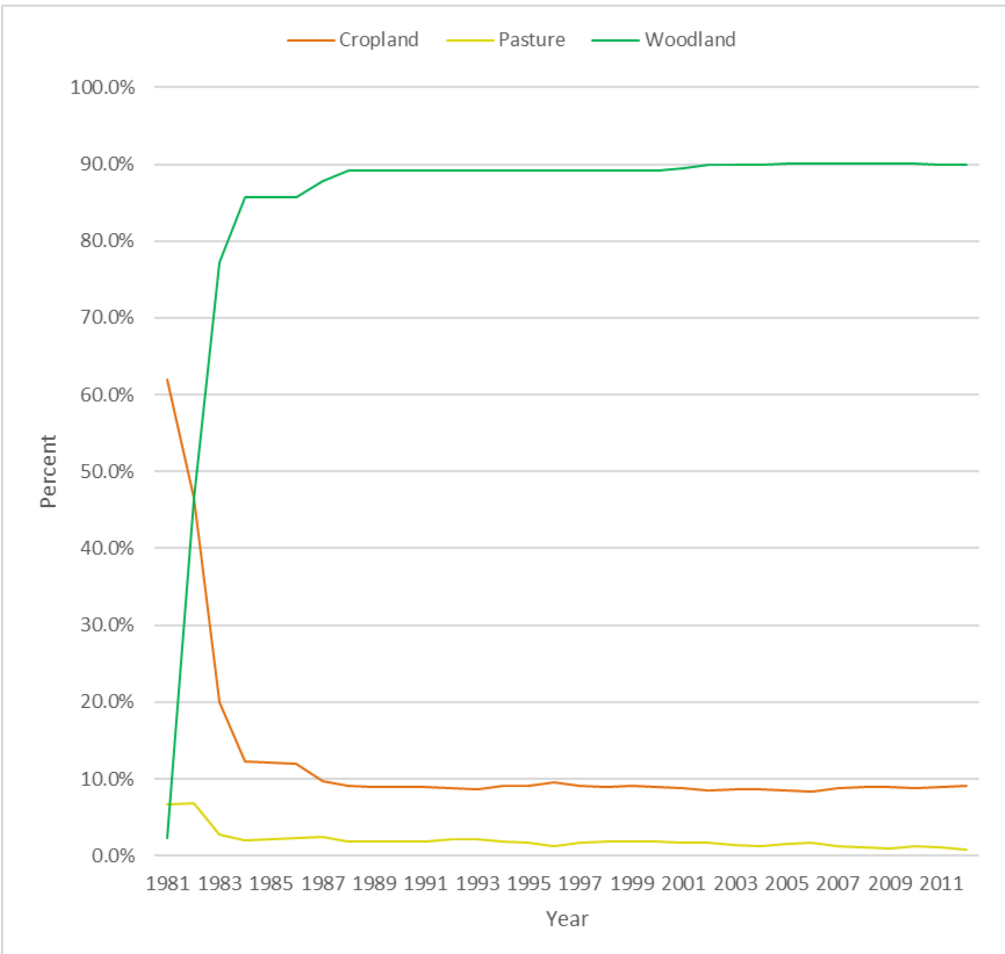


Figure 2-10 Average cropland, pasture, and woodland coverage from Experiment 4 with Farm-To-Field strategy.

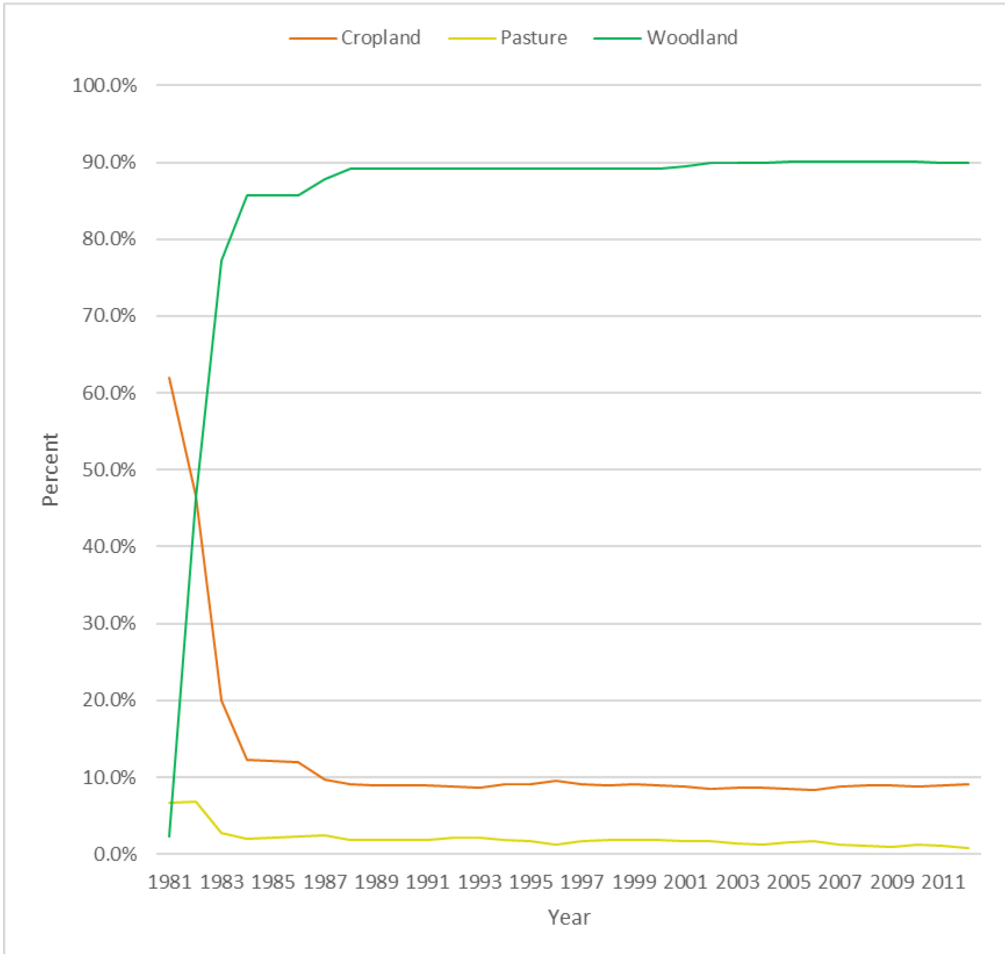


Figure 2-11 Average cropland, pasture, and woodland coverage from Experiment 4 with Field strategy.

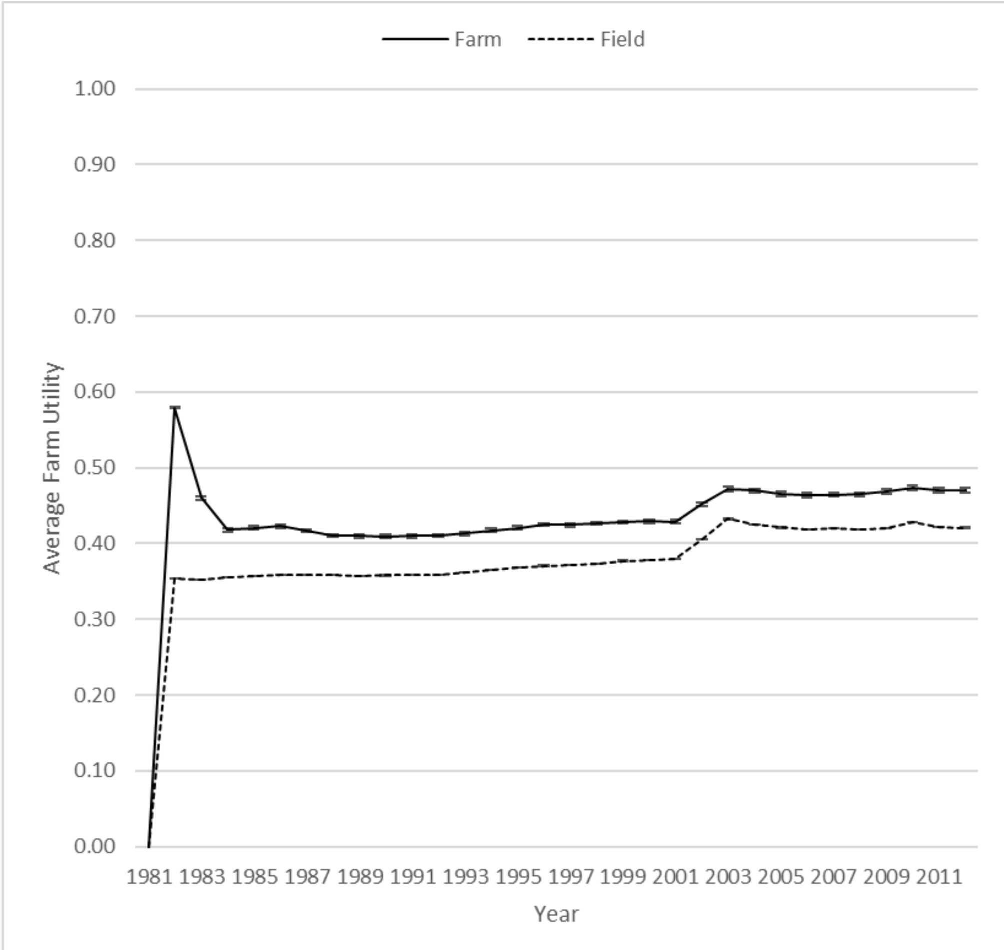


Figure 2-12 Annual Gini Index across study area from Experiment 4 with Farm-To-Field and Field strategy (Error bars represented range of experiment results).

2.5.5 Experiment 5 (Heterogeneous Preferences)

In Experiment 5, farmer agents are heterogeneous in terms of their preference weights towards environmental, social, and economic variables across the study area. Initially (in 1981), cropland, pasture, and woodland accounted for 61.9%, 6.6% and 2.4% of the total farm area (Table 2-4, Figure 2-17-A). After 31 years land use allocation using Farm-To-Field strategy, cropland decreased to 27.7% and woodland increased to 67.0% (Figure 2-17-E1). The changes in land use occurred relatively quickly as cropland decreased from 62% to 25% between 1981 and 1987 and then fluctuated between 25% and 30% for the remainder of the model run (Figure 2-13). Cropland to woodland was the dominant conversion type, with woodland rapidly increasing from 2.4% to 59% between 1981 and 1987 and remaining relatively stable until 2001. Afterward, woodland increased to 67% in 2003 and remained stable until 2012. When woodland remained stable, conversion between cropland and pasture was the dominant conversion type. Therefore, pasture coverage was negatively related to cropland coverage (Figure 2-13). The average farm utility across the study area (Figure 2-15) was between 0.5 and 0.6 for the 31 years. The Gini Index for the study area was between 0.1 and 0.16 (Figure 2-16).

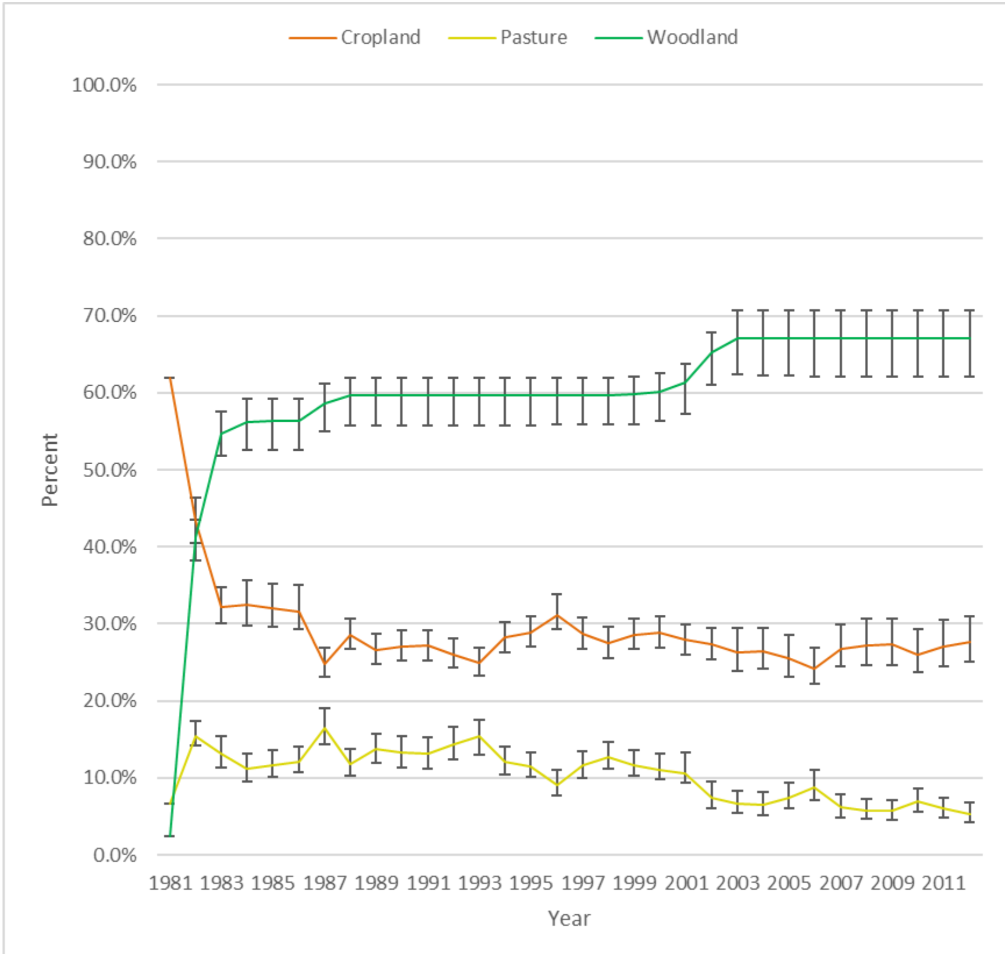


Figure 2-13 Average cropland, pasture, and woodland coverage from Experiment 5 with Farm-To-Field strategy (Error bars represented range of experiment results).

For land use allocation using the Field Strategy a similar outcome occurred. Cropland decreased to 37.8% and woodland increased to 62.2%. The conversion from cropland to woodland was also dominant (Table 2-4, Figure 2-17-E2). Cropland area decreased from 62% to 38% between 1981 and 1987 and remained stable afterwards. Woodland area increased from 2.4% to 62% between 1981 and 1987, and remained stable until 2012. Unlike the Farm-to-Field Strategy, no pasture was allocated after the first model step and the model reached a steady state after 1987 (Figure 2-14). The average farm utility across the study area (Figure 2-15) was between 0.4 and 0.5 for the 31 years. The Gini Index for the study area was between 0.15 and 0.2 (Figure 2-16).

Figure 2-14 Average cropland, pasture, and woodland coverage from Experiment 5 with Field strategy (Error bars represented range of experiment results).

Obvious similarities and differences existed in the two decision-making strategies. Both strategies resulted in a decrease in cropland and pasture, but an increase in woodland over time (Table 2-4, Figure 2-13, Figure 2-14, and Figure 2-17). Differently, for Farm-To-Field strategy, the proportion of each land-use activity was fluctuating over time more than that of Field strategy. Land-use proportion generated from the Field strategy became stable after 1987. The average annual on-farm utility obtained from the Farm-To-Field strategy was higher than that obtained by the Field strategy (Figure 2-15). The Gini Index indicates that Farm-To-Field strategy resulted in a more stable equality status than that of Field strategy; and it resulted in less inequality of utility among the farmer agents in this study area (Figure 2-16). Therefore, the agent population is better off with Farm-to-Field strategy because they have a higher utility with less utility disparity than with Field strategy.

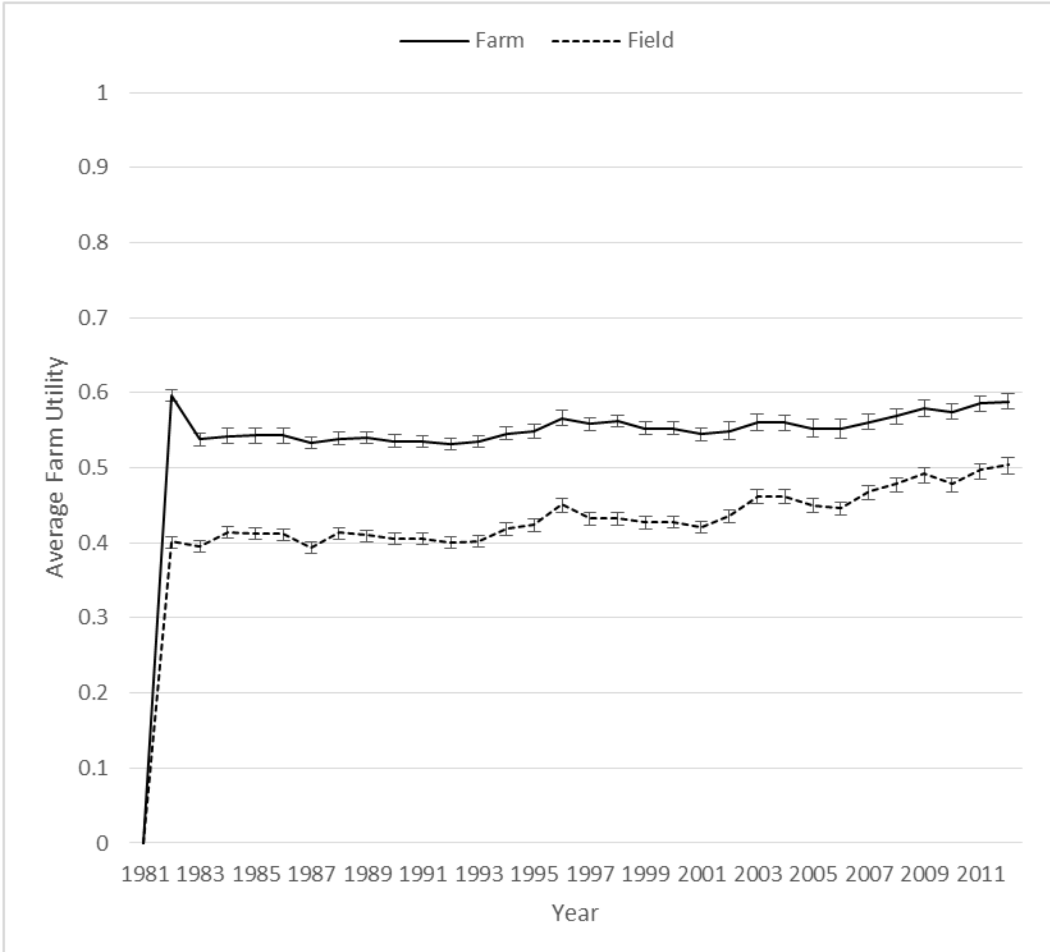


Figure 2-15 Average annual farm utility from Experiment 5 with Farm-To-Field and Field strategy (Error bars represented range of experiment results).

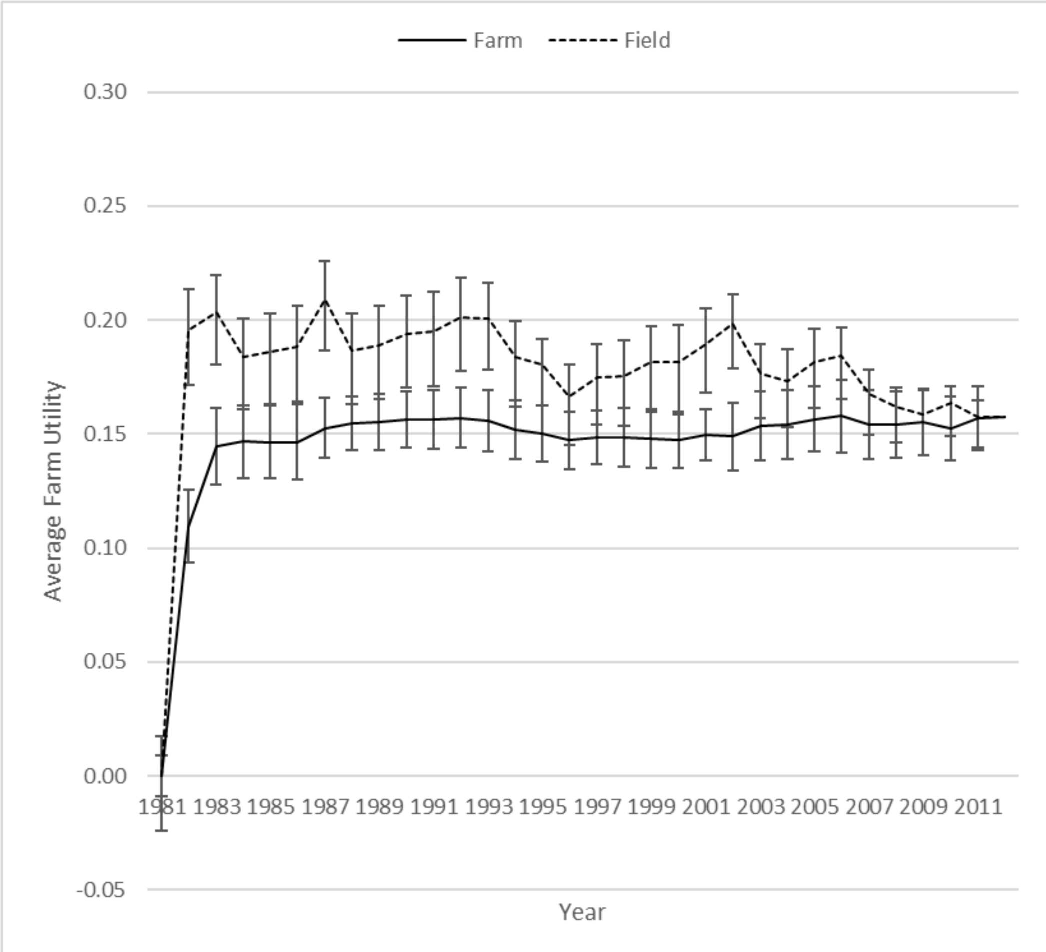
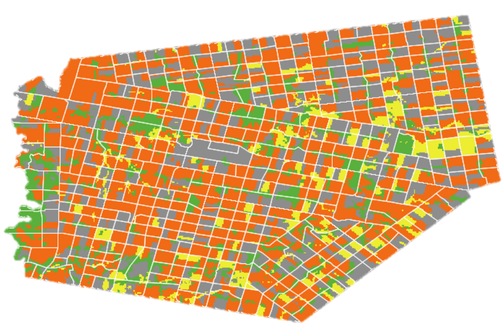
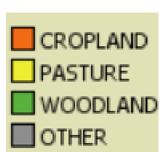


Figure 2-16 Annual Gini Index across study area from Experiment 5 with Farm-To-Field and Field strategy (Error bars represented range of experiment results).

Year	**Initial Conditions**	
1981	**A** 	Legend 
1982	**B1 Farm to Field**	**B2 Field**

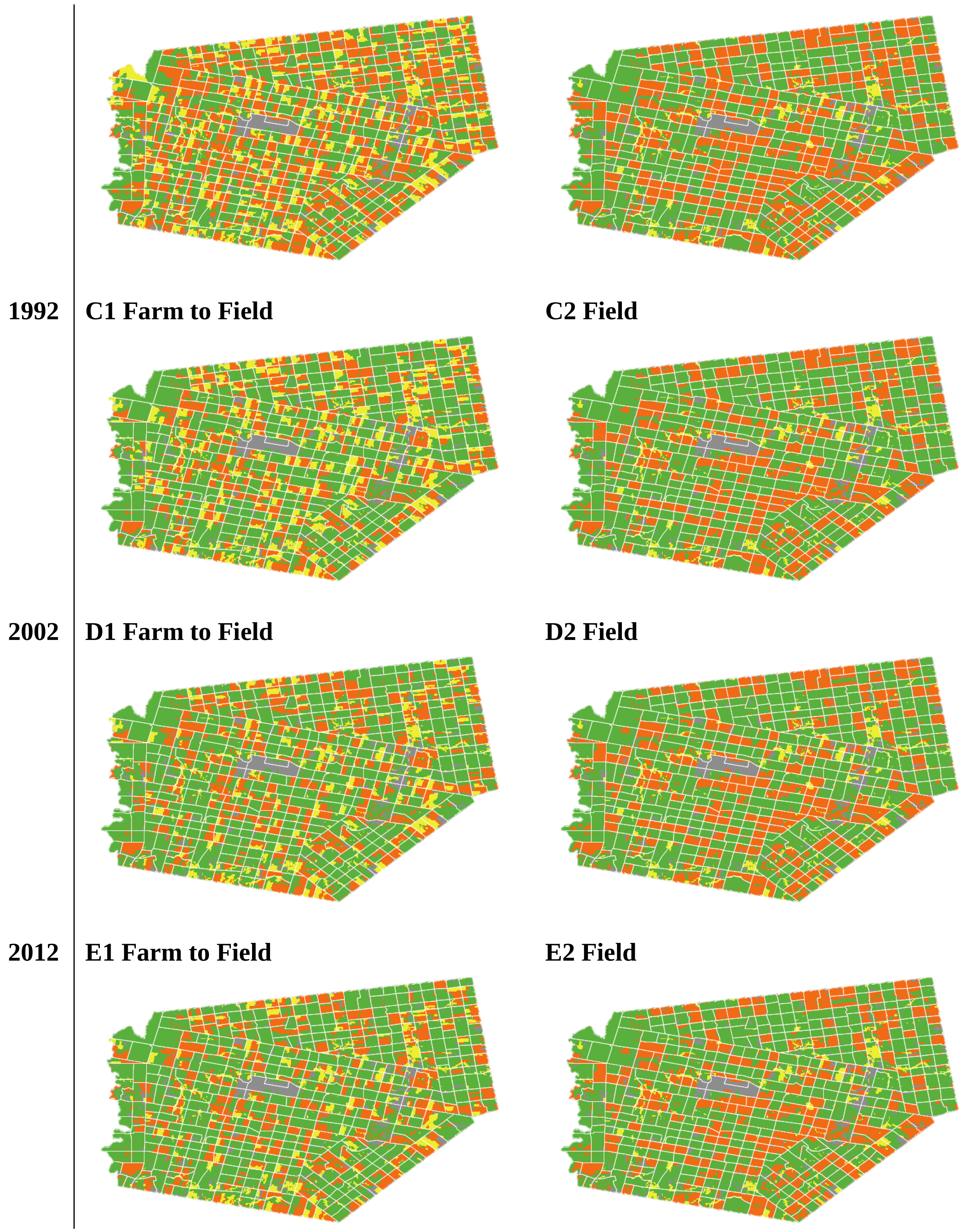


Figure 2-17 Maps of land-use in Year 1981 (initial, A), 1982 (B1, B2), 1992 (C1, C2), 2002 (D1, D2), and 2012 (final, E1, E2) from model Experiment 5 (1 stands for Farm-To-Field strategy; 2 stands for Field strategy).

2.5.6 Experiments Comparison

The five experiments were compared regarding land use conversion type (Table 2-5), average farm utility (Figure 2-18 and Figure 2-19) and Gini Index (Figure 2-20 and Figure 2-21).

Although the land-use conversion amount varies between Farm-to-Field and Field strategy, the general land-use conversion types showed some consistence between the two strategies. When the farmer agents valued economic factor only, they all chose cropland over the other two land use activities. For the other four experiments, woodland was preferred (Table 2-5).

Table 2-5 Land use conversion type from Farm-To-Field and Field strategy

Experiment	Conversion type	
	Farm-To-Field	Field
E1 (Economic Preference Only)	Pasture & Woodland -> Cropland	
E2(Environmental Preference Only)	Cropland & Pasture -> Woodland	
E3 (Social Preference Only)	Cropland -> Pasture &Woodland	Cropland & Pasture -> Woodland
E4 (Equal Preferences)	Cropland & Pasture -> Woodland	
E5 (Heterogeneous Preferences)	Cropland -> Woodland	

2.5.6.1 Average Utility

For Farm-To-Field strategy, Experiment 1 generated a more variable result with the average farm utilities fluctuating over time, which were positively related to cropland price over time. The average farm utility from Experiments 2-5 achieved relative stability with Experiment 2 achieving the highest utility, followed by Experiment 3, Experiment 5, and Experiment 4 (Figure 2-18).

For Field strategy, the average farm utility from Experiments 2-5 also achieved relative stability. Experiment 2 achieved the highest utility, followed by Experiment 5, Experiment 4, and Experiment 3 (Figure 2-19). Experiment 1 had the same utility tendency as that of Farm-To-Field strategy.

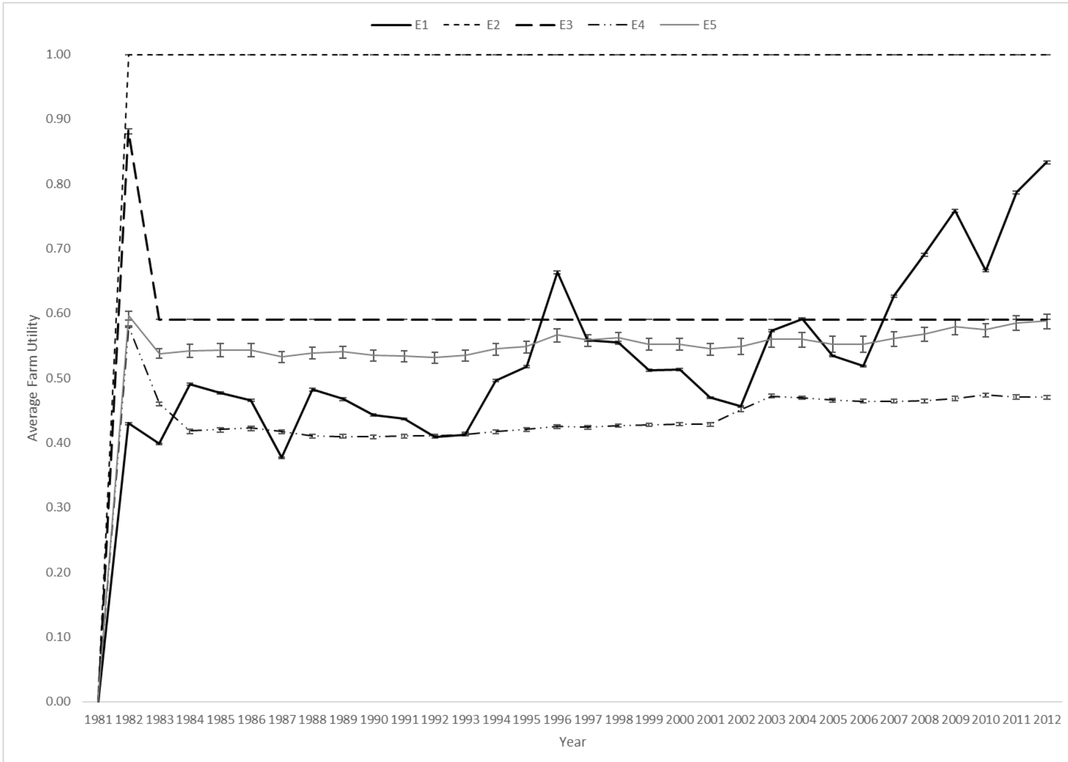


Figure 2-18 Average farm utility from Experiment 1- 5 with Farm-To-Field strategy showing (Error bars represented range of experiment results)

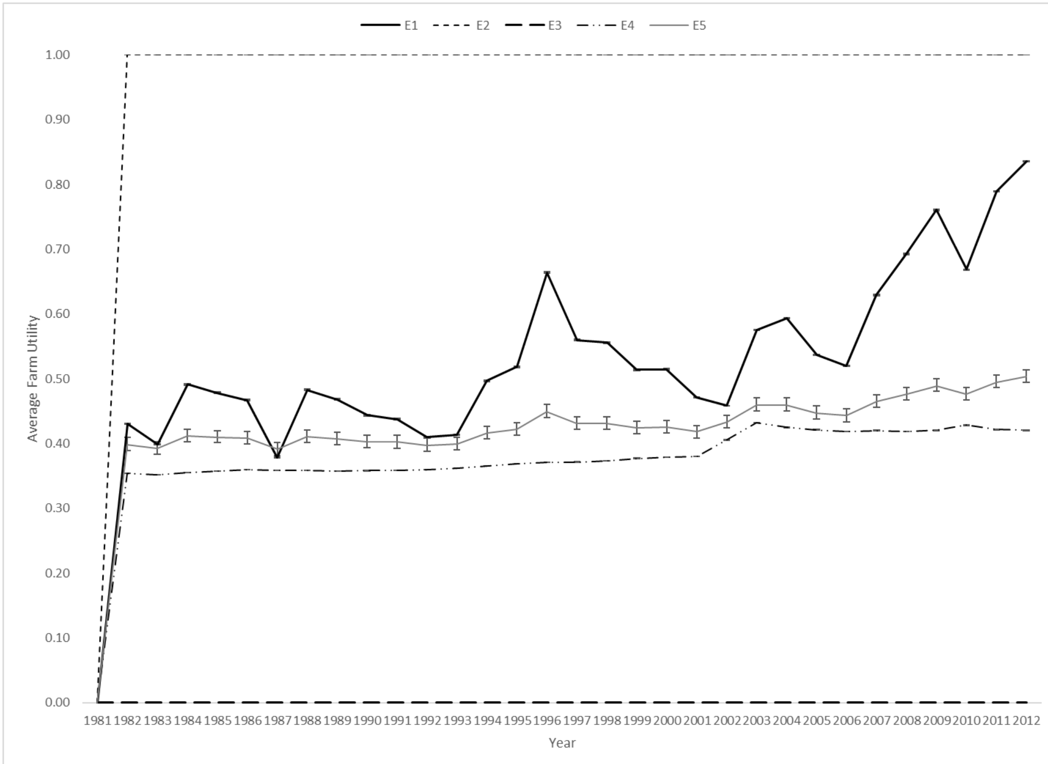


Figure 2-19 Average farm utility from Experiment 1- 5 with Field strategy showing (Error bars represented range of experiment results)

2.5.6.2 Gini Index

For Farm-To-Field strategy, the Gini Index from Experiments 1-5 are relative stable with Experiment 3 achieving the highest Gini Index, followed by Experiment 5, Experiment 4, Experiment 1, and Experiment 2 (Figure 2-20).

For Field strategy, the Gini Index from Experiments 1 has more variation than that of Farm-To-Field strategy. With this strategy, Experiment 3 achieved the highest Gini Index, followed by Experiment 5, Experiment 1, Experiment 4, and Experiment 2 (Figure 2-20). Experiment 2 resulted in an absolute equality for both strategies, because all farmer agents chose woodland after the first model run, then the environmental indicator was constant and would not affect the utility outcomes. Therefore, Gini Index of 0 was given by both strategies in Experiment 2.

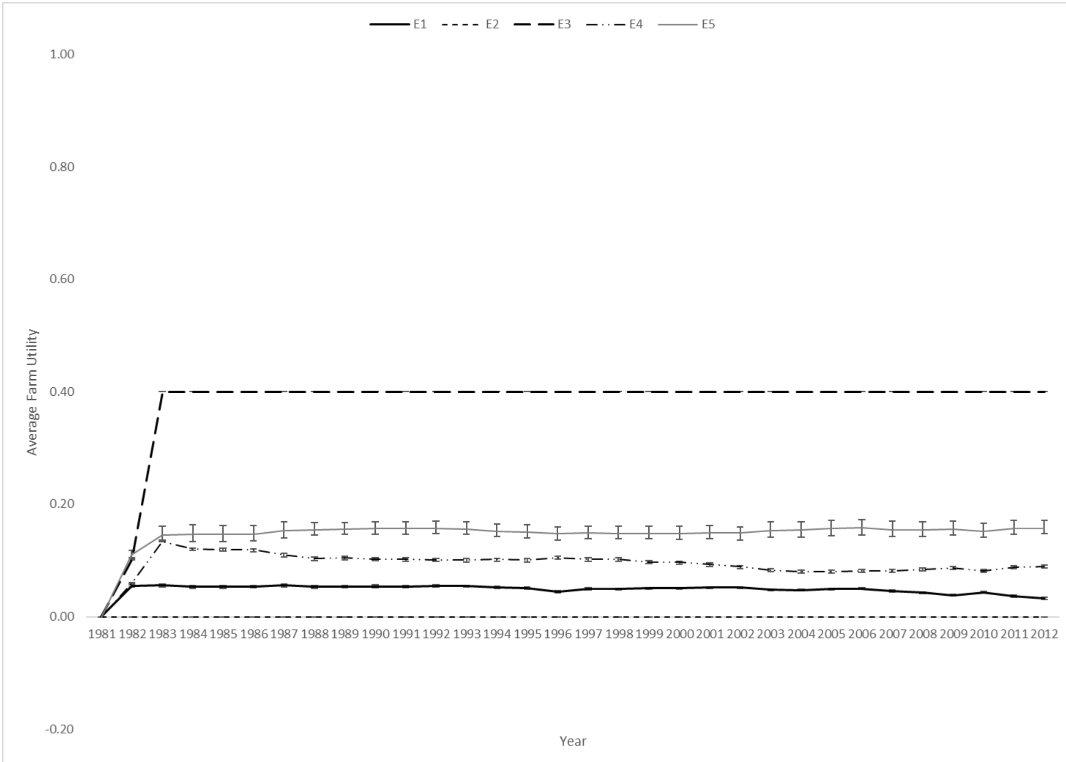


Figure 2-20 Gini Index from Experiment 1- 5 with Farm-To-Field strategy (Error bars represented range of experiment results)

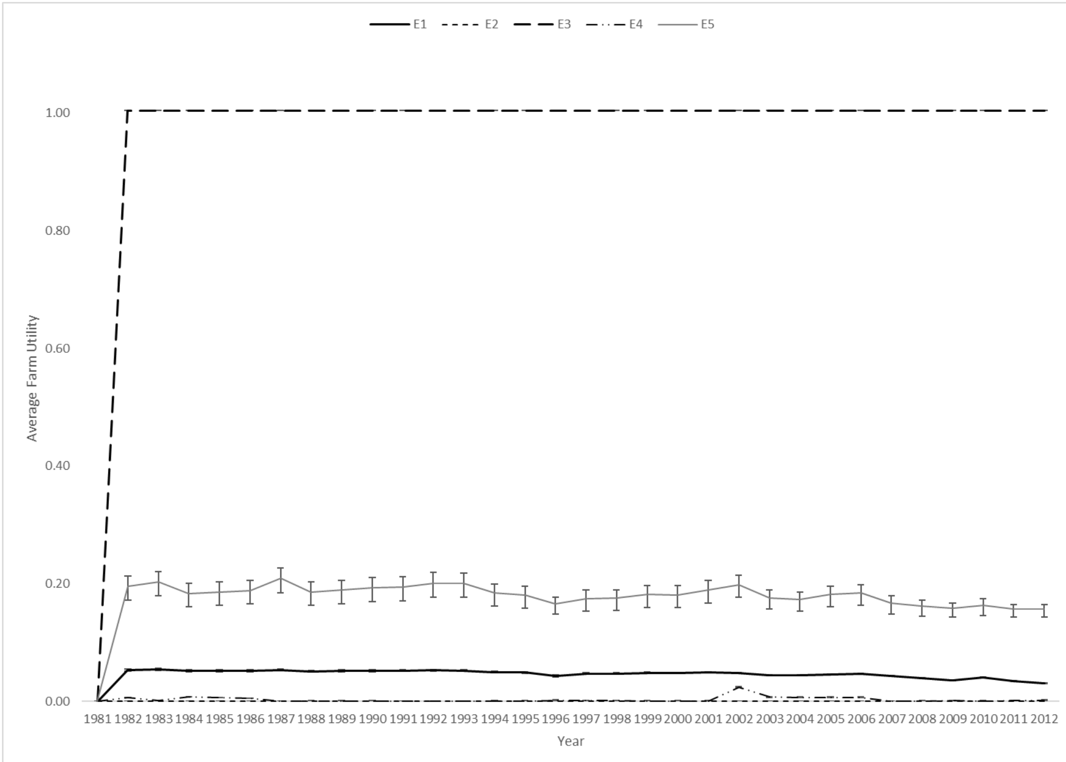


Figure 2-21 Gini Index from Experiment 1- 5 with Field strategy (Error bars represented range of experiment results)

2.6 Discussion

2.6.1 Farm-To-Field versus Field Decision Making Strategy

Experiment 5 (Heterogeneous Preferences) and Experiment 4 (Equal Preferences) resulted in similar land use allocation tendencies for Farm-To-Field and Field strategies. Farm-To-Field strategy resulted in less extreme land-use allocation results and higher average utilities than Field strategy. Farm level utility maximization is the main reason accounting for it. As Farm-To-Field strategy integrated a step of land amount allocation with multi-objective optimization, it allowed farmer agents to determine how much land they expected to allocate for each land-use activity before deciding where to allocate the land-use activities. Therefore, farmer agents' final land location allocation on the fields must be consistent with the results from the farm level decision-making.

When farmer agents employed the Field strategy, farmer agents only need to determine which land use activity could bring them the highest environmental and economic utility on each field, as social utility remains 0 at field level. Under this circumstance, land use allocation decision was stable over time as cropland and woodland could always result in higher environmental and economic utilities. Taking the example of Farmer agent 200 ($\alpha_{Env} = 0.46$ $\alpha_{Soc} = 0.36$, $\alpha_{Eco} = 0.18$, $\gamma_{slope} = 0.78$) in 2005, based on farm level optimization, the farmer agent expected to allocate 21.2%, 20.4%, and 58.4% of the land for cropland, pasture, and woodland, respectively. In his final decision, 58.4% and 41.6% of the land was allocated for cropland and woodland, as subdividing fields was not allowed in this model and the allocation takes place on a per field basis. However, with the Field strategy, he simply chose to allocate all the land for woodland because this could derive the highest per-field utility, but not necessarily the highest aggregate farm utility. As a result, his total farm utility in 2005 was approximately 0.60 and 0.46 for Farm-To-Field and Field strategies, respectively. To summarize, farm level optimization integrating environmental, social, and economic variables allow farmer agents to have higher diversity of land use types on farms. It can reduce the risk resulted by unitary land use type.

Land use coverage tendencies for Farm-To-Field and Field strategies are almost identical in Experiment 1 (Economic Preference Only) and Experiment 2 (Environmental Preference Only). In these two experiments, extreme land-use allocation results were achieved for both strategies. When only economic variable is included, farmer agents simply determine which land use activity could result in the highest economic utility, which could only be cropland or woodland older than 60 years old (Figure 2-22). It was set by the model that only woodland older than 40 years old is allowed to be harvest, when the growth rate starts to decrease. Therefore, cropland became the dominate land use type resulting in the highest utility, with woodland accounting for a small portion. When only environmental variable is included, 100% of woodland would be allocated on both farm and field level as woodland has a surface cover value of 1, while cropland and pasture have surface cover values of 0.61 and 0.65, respectively. It reveals that converting cropland and pasture into woodland could bring farmer agents with the highest environmental benefits, while converting woodland and pasture into cropland could bring the farmer agents with the highest economic benefits. This is consistent with what the land use had be changing over the last 300 years, where there is a net loss of about 7 to 11 million km^2 of forest due to agriculture and timber harvesting activities over the previous 300 years (F.A.O., 2004).

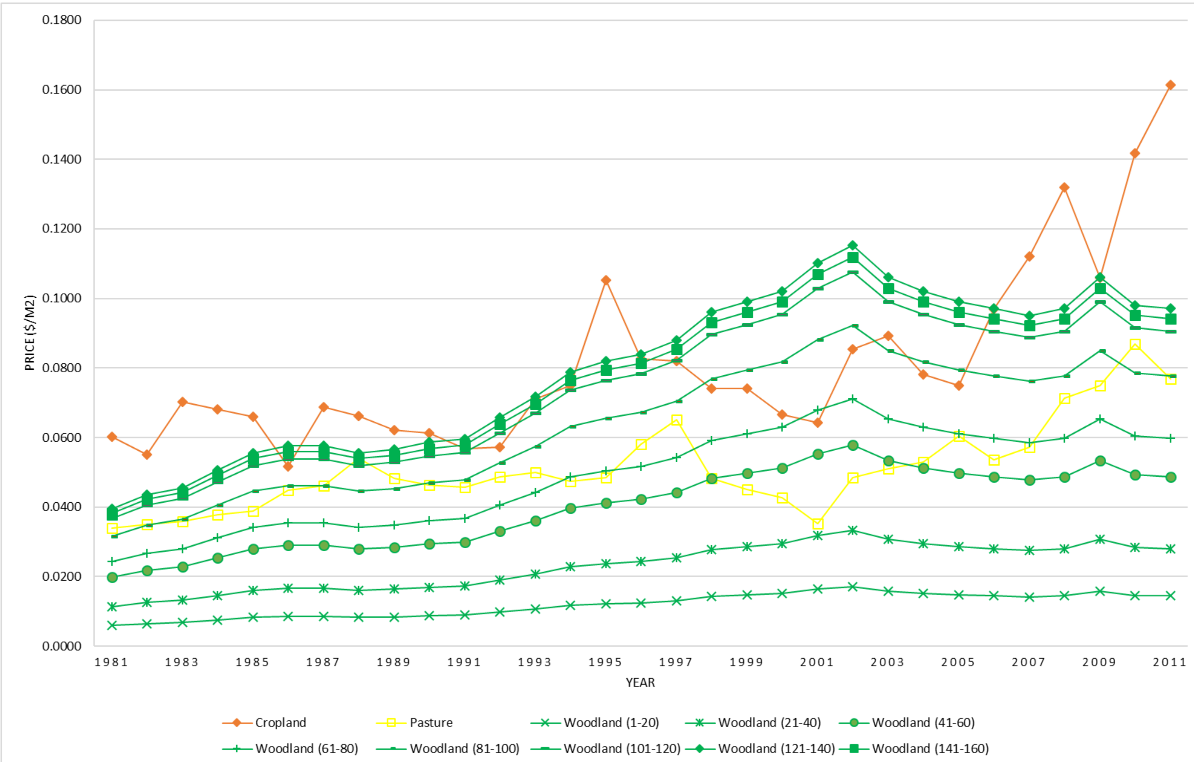


Figure 2-22 Unit revenue for cropland, pasture, and woodland from 1981 to 2011

Experiment 3 (Social Preference Only) resulted in different land use allocation tendencies for Farm-To-Field and Field strategies. As discussed above, social factor remains 0 on field level regardless of the preference weight as field cannot be subdivided. Therefore, social factor has a more significant impact on farm level optimization than field level optimization. It requires farmers to ensure land use diversity on farms.

The results from computational experiments with two decision-making strategies indicate that integrating a farm level optimization with consideration of social variable could increase diversity of land-use types on farms without taking the risk of unitary land use type. It also resulted in relatively high utilities for farmers.

2.6.2 Limitations

2.6.2.1 Model Calibration

Although some real world data (e.g. slope, SQI, and prices) were used in this study, this model has limited ability to support real land-use planning practices. Results from the presented computational experiments had significantly higher proportions and coverage of woodland than occurred historically. The results indicated a movement towards woodland dominance for both decision-making strategies, partly because woodland more frequently resulted in a higher environment utility than cropland and pasture. In addition, woodland had higher economic utility than pasture at all times and tended to have a slightly higher economic utility at older ages than cropland, but a lower utility at younger ages. For these reasons, woodland typically yielded higher utility and therefore a greater proportion of adoption by farmer agents. This indicates that using only one indicator for one factor (e.g. use soil loss to represent environment factor) is not sufficient and could result in under or over estimate to a great degree.

Given the unrealistic results generated by the model in this study, it is necessary to collect more data to calibrate model variables (e.g. Berger 2001; Kelley and Evans, 2011). Sample surveys, participant observations, field and laboratory experiments, companion modeling, and GIS and remotely sensed spatial data are widely used approaches to collect required data at decision making agent level (see Robinson et al., 2007 for details). In this study, in the absence of farmer characteristics data, computational experiments were performed to understand how farmers' knowledge impact land-use allocation decisions. For more comprehensive representation of farmer agents, sample surveys among farmers can provide detailed data representing human heterogeneity regarding farmers' knowledge. Alternatively, spatial analysis using GIS and remotely sensed data has the ability to provide information about quantitative relationship between farmers' decision-making and relevant variables (e.g. Plantinga, 1996; Verburg et al., 1999). In addition to farmer characteristics data, the social interaction among farmers can also be captured with participant observations or companion modeling (Robinson et al., 2007). Detailed discussion about advantages and limitations of these data collection approaches is beyond the scope of this study.

Static data of slope and SQI were used in this model. In reality, they tend to change over time due to land-use activity applied on the land. For example, the land-use activity performed on a farm or field tends to change soil quality differently (forest re-growth increases soil quality while farming degrades soil quality in the long term) and soil quality in return affects the decision making process (Lal, 2003). Including a feedback loop between agents and the landscape could be one approach to solving this problem. By including temporal variance in site conditions, land-use allocation on farms will be less stable than the results presented in this study. For example, with cropland allocated on a field continuously, the soil quality will be degraded and the expected economic utility for cropland would decrease (Equation 2-7). Therefore, it will be less likely that the farmer will continue to allocate cropland on the same field and more temporal variance of land-use allocation will occur.

Woodland usually involves a relatively long-term commitment to achieve an economic return. However, the monetary value of woodland in the future was represented with historical price directly. In reality, woodland price in the future needs to be discounted to a present value with a reasonable discount rate (Row et al., 1981). For example, if the revenue 50 year in the future is \$1000, its present value will be \$87 ($\frac{1000}{(1+0.05)^{50}}$) at a discount rate of 5%. Applying a discount rate on woodland price could reduce the revenue on woodland in the short term relative to the way it was implemented in the model, which would make it less appealing to farmers. In addition, policy requirements for land use composition and subsidies are also factors that need to be integrated for land-use allocation.

Experiment 4 with Field strategy resulted in Gini Index values close to 0 for the majority of the years because all agents have equal preference weights toward environmental, social, and economic factors and the preference weights dominated the utility outcome. It indicated that the indicators had little effect on the individual environmental, social, and economic factors based on site conditions. As local area has only a little amount of spatial heterogeneity (as represented in the model), with identical agents the landscape alone has little effects on the outcome. This suggests the necessity of the inclusion of more indicators.

Parameter uncertainty is another important issue for this study. For stochastic data, the model was run 20 times to account for stochasticity. However, for the data obtained directly from existing datasets, the impact of their uncertainty on model output was not considered. First, the model landscape was initialized based on ARI data in 1983. Second, slope, SQI, and price data were used based on existing data directly. To explore how uncertainty in these data could alter model output, sensitivity analysis on each parameter at one time can be conducted.

2.6.2.2 Model Design

Interaction is one of the key capabilities for ABMs. It can be categorized into interaction between agents and spatial objects, spatial objects and agents, agents and agents, and spatial objects and spatial objects (Ligtenberg et al., 2001). In this model, it was assumed that farmer agents make decisions independently without interacting with the others. In addition, interaction between farmer agents and landscape was limited to farmer agents sensing site physical characteristics; however, how the agents' decisions alter landscape was not included.

The interaction between agents and spatial objects can be represented by including feedback loops into an ABM. Le et al. (2012) proposed a methodology to integrate two feedback loops and adaptations in modelling land-use decision-making. They suggested that in an adaptive situation, an ABM should include a primary and secondary feedback loop (Figure 2-23). For the primary loop, agents sense the environment and respond to it. An agent can alter the environment, which could in turn affect the decision-making process of the agent itself and others in the short term. The secondary feedback loop indicates accumulative changes in environmental, social, and economic conditions at a larger scale over a longer term, which could result in agents changing their behaviour and adapting to use a new decision-making process. Le et al. also mentioned that the feedback loops can exist on different scales. For example, in this study, the field level decision making was based on the farm level decision-making. However, "*not all locations in a spatial environment are equally suitable for the various types of spatial functions (i.e. a defined activity at a location during an uncertain or certain time). A location may show restrictions, opportunities or threats to a specific spatial function*" (Ligtenberg et al., 2001, p.1). Therefore, the farm level decision-making should interact with field characteristics as well. To sum up, feedback loops between human and nature across various scales can be included for a more comprehensive simulation.

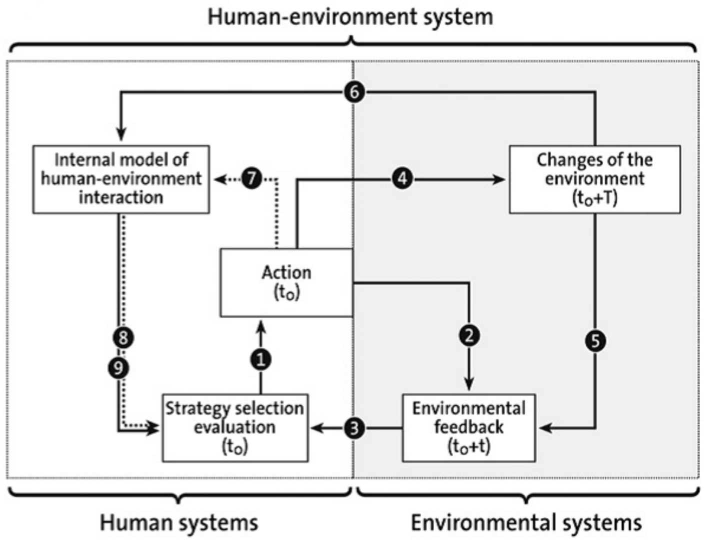


Figure 2-23 Primary ($(\overrightarrow{\mathbf{1},\mathbf{2},\mathbf{3}})$) and various types of secondary feedback loops (e.g. $(\overrightarrow{\mathbf{1},\mathbf{4},\mathbf{6},\mathbf{9}})$) in human-environment interaction (Source: Scholz et al., 2011cited in Le et al., 2012)

2.6.2.3 Optimization Method

The process of farm level land-amount allocation was represented as a MODA and the first order Kuhn-Tucker conditions were satisfied to determine the proportion of the farm to allocate to each land-use activity (Kelly and Evans, 2011). However, applying this method within the Netlogo platform is challenging. Instead, this study adopted the approach of rescaling optimization results. In agricultural modelling, linear (e.g. Chuvieco, 1993; Becu et al., 2003; Sante-Riveira et al., 2008) and non-linear programming (e.g. Henseler et al., 2009) are widely used. For linear programing, the objective function and constraints are required to be strictly linear (Dykstra, 1983). For this study, it is possible to represent the utility function with a linear function approximating to the real function. However, as the utility function was not a linear function, non-linear programming was assumed to be more accurate conceptual representation.

Ye (1987) proposed a general non-linear programming approach implementing the augmented Lagrange Multiplier method. The approach was operationalized by integrating the R package "Rsolnp" with Netlogo. A comparison among the method used in this study and linear and non-linear programming alternatives demonstrated that the results of this study and the non-linear programming approach were not significantly different. However, due to the low efficiency of interacting between R results and Netlogo entities, the non-linear programming package was not used directly. Instead, the optimization problem was solved by hard coding in Netlogo using the similar approach if implementing the augmented Lagrange Multiplier.

Table 2-6 Comparison of optimization method of this study, linear programming, and non-linear programming

Optimization Method	Cropland	Pasture	Woodland
This study	29.8%	29.8%	40.4%
Linear-programming	36.8%	26.4%	36.8%
Non-linear programming	30.5%	29.5%	40.0%

2.6.3 Broad Implication

Despite the limitations of data availability and model design, this study could provide some useful information for agricultural land use modelling. This model is an initial version that will contribute to a larger grant project. A typical ABM process is an iterative cycle (Figure 2-24). A conceptual model is constructed initially with basic theories and knowledge. The conceptual model could result in new findings through expert communications, which could help adjust and revise the conceptual model. With more external findings, theories, literature, and data, the model can be improved continuously (Rounsevell et al., 2012).

The main focus of this model is to provide a comparison between implementing decision-making on farm level with heterogeneity versus on field level. The result showed that obvious differences did exist between Farm-to-Field and Field strategies. This could suggest further exploration about land use decision making on land with heterogeneity. The land use conversions under different decision-making strategies could be integrated with other models (e.g. ecosystem models, climate models) to explore how different decision-making strategies could impact ecosystem services (Robinson et al., 2013), hydrology, and climate (Bithell and Brasington, 2009).

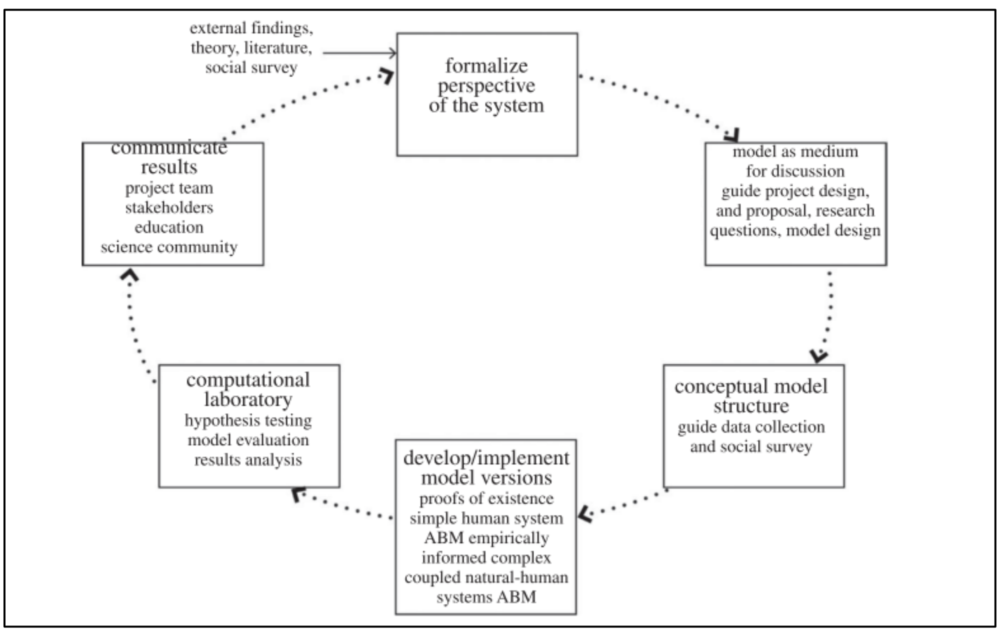


Figure 2-24 The agent-based modelling process as an approach to scientific enquiry (Rounsevell et al., 2012)

2.6.4 Future Directions

Empirical data collection from farmers has been identified to be necessary for model validation. Given the variation in farmers' preference weights towards environmental, social, and economic factors, it can be useful to collect more demographic data related to farmers to identify the reasons accounting for this variation. Studies have proven that farmers tend to act autonomously based on personal knowledge, education attainment, income, policy support, and other sources (Lambin et al., 1999; Le 2005). Therefore, study about the relationship between farmers' decision-making and the aforementioned factors can be conducted for more comprehensive understanding about farmers' behaviours.

In addition to non-spatial data, spatial data is another important factor impacting the ability of ABMs to simulate human-nature interaction. This requires updated and detailed data within the study area including historical land use, soil quality, and detailed forest inventory information. Given limited data resources, it is possible to obtain historical remote sensing imageries and produce spatial data such as soil resources (e.g. Seelan et al., 2003), land cover (e.g. Lambin and Strahler, 1994), crop types (e.g. Jakubauskas et al., 2002), and crop area and grain yield (e.g. Tennakoon et al., 1992).

With more data availability, more interactions can be integrated in the model. For example, to integrate interaction between ecosystem and human decision-making in ABMs, ecological processes of water flow, nutrition transit, and vegetation growth can be represented with hydrological or vegetation models (e.g. Monticino et al., 2007; Bithell and Brasington, 2009). In addition, as aforementioned, this model has limited ability to represent real world land use as farmers' behaviours are autonomous and independent without interacting with the others. Agents' interaction of resource exchange, competition, and technology diffusion can also be incorporated in ABMs (e.g. Berger, 2001). More types of agents can be added into the model, including individual farmer, farmer household, neighborhoods (e.g. Zvoleff, 2014), land developer, and government agents (e.g. Monticino et al., 2007).

2.7 Conclusion

This study presented an initial version of ABM to simulate land-use allocation with two decision-making strategies: from farm level to individual fields on a farm (Farm-To-Field), and direct land-use allocation to individual fields (Field). From computational experiments, we gained a better understanding of how model behaves with the two strategies. It suggests that Farm-To-Field decision-making strategy allowed farmers to evaluate land allocation at a higher level and resulted in higher total utilities on farms compared to Field strategy. Farmers with various preferences toward different factors would perform differently. Farmers preferring environmental factors chose to allocate substantially higher amount of land to woodland than the other two land-use activities; farmers preferring social factors tried to ensure a balance among the three land-use activities; and farmers preferring economic factors always allocate more land to the activity resulting in more economic utility. Although the model was able to provide useful information about farmers' decision-making and LUCC patterns, it has limited ability to support real world decision-making due to lacking empirical data. The model can be substantially improved with calibrating variables, integrating interactions and feedback loops, and adding agent types. It also provides meaningful information about decision making on land with heterogeneity, which could be further integrated with other models. With the aforementioned improvements, it could provide more comprehensive understanding about the impact of farmers' decision on LUCC and support land-use planning more effectively.

Chapter 3

Multi-criteria suitability analysis for corn growth in Southern Ontario

3.1 Introduction

Due to the rapid growth of global populations, especially in developing countries, and competition among different land-uses for arable land, there is a demand for higher food productivity (Fischer et al., 1996). While food productivity has generally increased, some of the technologies driving this increase (e.g., pesticide and fertilizer) are also concerns related to human health and environmental degradation (Prakash, 2003). To ameliorate these concerns effective land-use planning and resource evaluation is needed and is a research focus (e.g. Ceballos-Silva & López-Blanco, 2003; Elsheikh et al., 2013; Akinci et al, 2013).

Land-use suitability analysis provides one approach for identifying the level of fitness of a location for a land-use activity. By integrating land-use requirements, farmer preferences, and predictors of a land-use output, suitability analysis synthesizes our understanding of the drivers of a particular process into a single suitability score (Hopkins, 1977; Joerin et al., 2001; Collins et al., 2001; Malczewski, 2004; Akinci et al., 2013). In the agricultural context, land-use suitability is a complex approach that brings together multiple disciplines, such as biophysics, climate science, social science, economics, and geography. Drivers of suitability are represented as criteria, which are not necessarily equally important to a particular agricultural land-use activity (Prakash, 2003).

Multi-criteria decision analysis (MCDA) provides an overarching framework for the integration of different suitability criteria and their relative degree of importance (i.e., weights) (e.g. Ceballos-Silva and López-Blanco, 2003; Phua and Minowa, 2005; Mendas and Delali, 2012). Conceptually, MCDA can be achieved through either a multi-objective decision analysis (MODA) (e.g. Wang et al., 2004) or a multi-attribute decision analysis (MADA) (e.g. Phua and Minowa, 2005). In a MODA, the potential evaluation sites are not predefined. Instead, a decision rule, constituting what sites should be evaluated, is defined based on multiple objectives and constraints (e.g. shape, size, and boundary) using the suitability criteria. Linear programming, heuristic algorithms, or another optimization method is applied to the decision rule to determine suitable sites. In contrast, a MADA uses potentially suitable sites that are predefined and then ranks those sites based on the criteria and weights with the most suitable sites achieving the highest suitability scores (Malczewski, 2004).

Land suitability Analysis (i.e., MCDA) research frequently uses a MADA approach in combination with a Geography Information System (GIS), due to its ability to store, manage, and visualize spatial and aspatial data (Malczewski, 2004). A number of studies have generated agricultural land-use suitability maps (e.g. Mendas & Delali, 2012; Akinci et al., 2013; Elsheikh et al., 2013) with an emphasis on presenting MCDA methods and technologies to improve the development of suitability scores. Typically, the presentation and interpretation of suitability results are limited to the proportion of different suitability levels (e.g., high, medium, and low) and a general description of where those suitability levels are located. However, the quantification of the spatial distribution the suitability scores, the explicit description of their pattern, and insight into the reasons accounting for the patterns, and the contribution of suitability mapping to land-use planning have been rarely presented or discussed.

The research presented in this chapter describes the generation of a suitability map for corn growth in Southern Ontario and a spatial analysis of the distribution and pattern of suitability scores. To achieve this goal, the following objectives are achieved: 1) determine criteria and their corresponding weights for suitability score calculation; 2) perform a MADA to score and map suitability across Southern Ontario; 3) analyze the suitability scores to quantify the spatial distribution and patterns of suitable corn growing locations.

3.2 Study Area

Southern Ontario is located in the southernmost area of Canada consisting of 10 census divisions (CDs, Figure 3-1) that comprise a total area of 21,520 km^2. Southern Ontario has a climate condition (Table 3-1) suitable for crops intolerant to frost (e.g. corn, bean, and squash) with warm summer and mild winter (Fecteau, 1985). The region has an adequate number of frost-free days and growing-season days for crops, ranging from 138 to 177 days and 193 to 219 days respectively. The mean monthly precipitation in Southern Ontario during corn growth season ranges from 6.2 cm to 7.6 cm. It can provide adequate water for corn growth, which requires 30 cm to 60 cm of precipitation during growing season (Fecteau, 1985). In addition to climate suitability constraints, soil texture and drainage also play critical roles in agricultural performance in Southern Ontario agriculture. Well-drained soils with texture of loamy sand to clay and clay loams make it suitable for agriculture.

Table 3-1 Summary of Climatic Values in Southern Ontario Related to Suitability for Corn Growth (Fecteau, 1895)

Climate elements		Range
Temperature	Mean May-September (°C)	16.5 – 19.4
Average length of growing season (days)		193 – 219
Average number of frost-free days		138 – 177
Heat units for corn (CHU)		2500 – 3500
Precipitation	Mean Monthly May-September (cm)	6.2 – 7.6
Photoperiod	Mean Monthly May-September (hours)	219 – 251
	Mean Daily May-September (hours)	7.2 – 8.2

Southern Ontario is an ideal agricultural area with about 4 million acres of farmland in 2011, occupying approximately 74% of the total land area. Farms primarily cultivating corn account for 25.5% of the total farmland area and have the second largest area of all farm types following soybean farms (Statistics Canada, 2011). Corn farms are widely distributed across Southern Ontario, with more corn farms in the west and center than that in the east of Southern Ontario (Figure 3-2A). The census divisions of Middlesex, Chatham-Kent, Oxford, and Elgin have the largest area of corn farms among the census divisions that comprise Southern Ontario (Figure 3-2B).

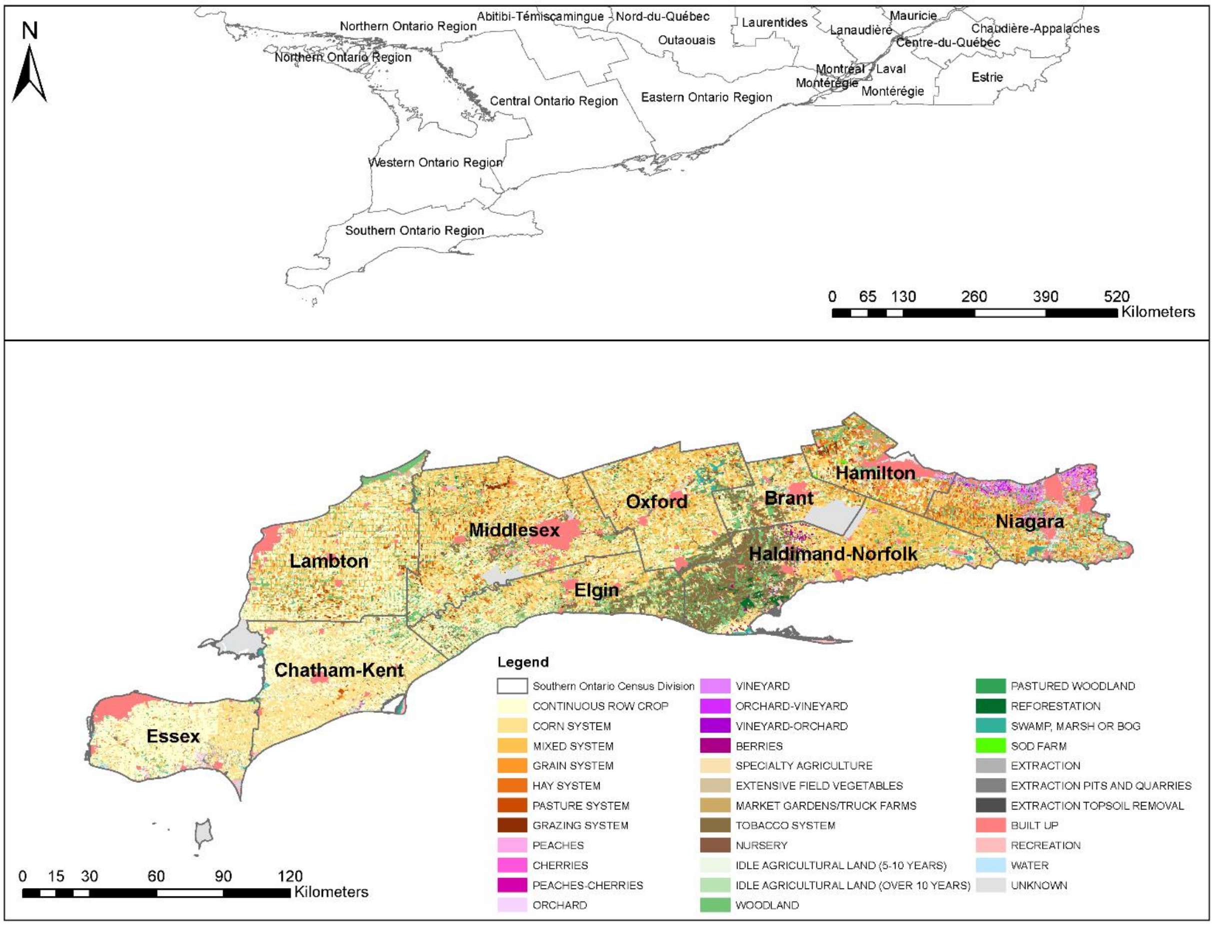


Figure 3-1 Map of Southern Ontario Land-use (Data source: Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA), 2010)

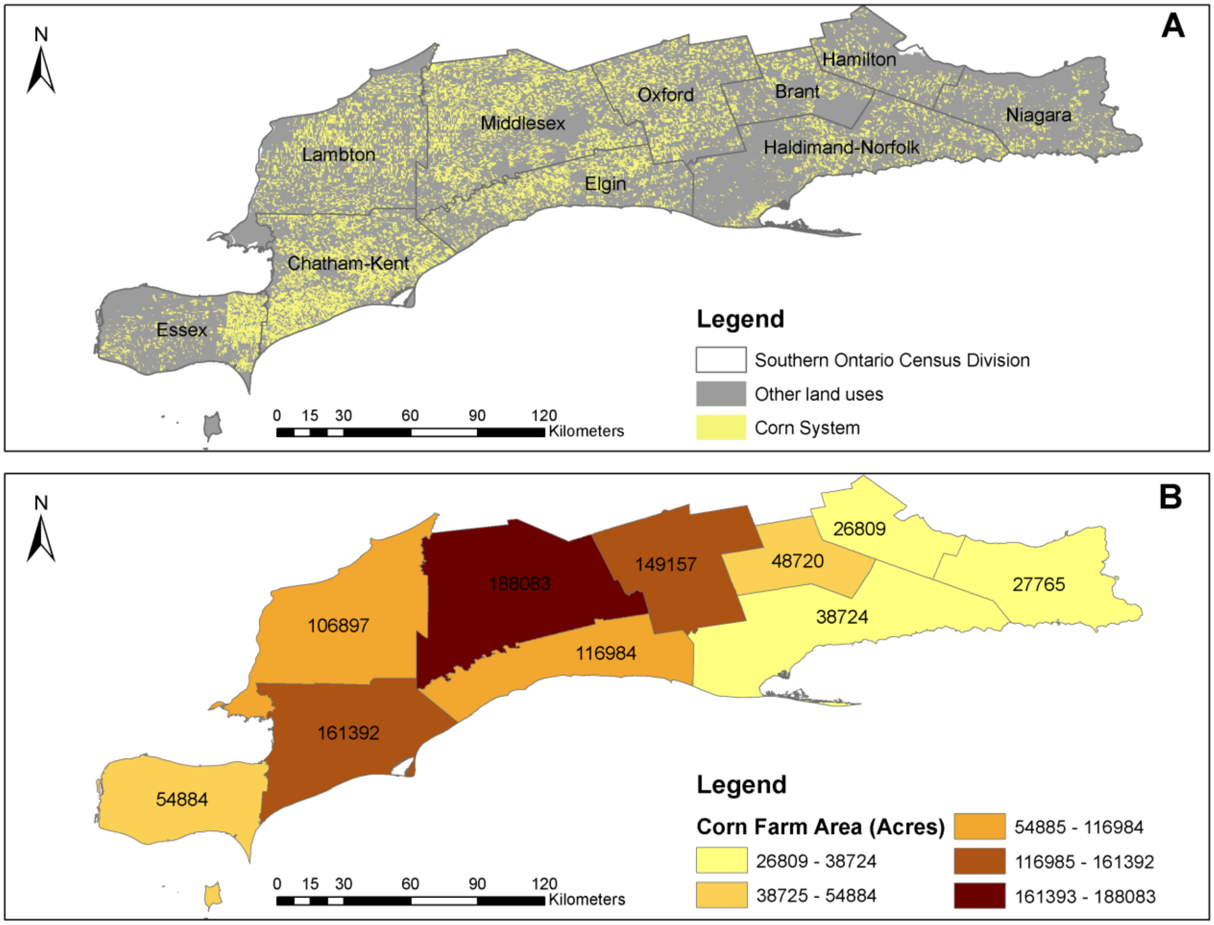


Figure 3-2 Map of corn system distribution in Southern Ontario: A) corn system distribution, data source: OMAFRA, 2010; B) corn farm area in census division, data source: Statistics Canada, 2011.

3.3 Methods

The typical seven-step methodology to MADA was employed to create a map of suitable locations for growing corn across Southern Ontario. Having defined the problem at the outset of the paper, the second step involved identifying the criteria for inclusion (Figure 3-3). Data were collected for each criterion (step three) and then each criterion was scored and standardized to a common numerical scale (step four). The relative importance of each criterion was obtained based on farmers' knowledge through a survey questionnaire, which provided a weighting mechanism for the suitability criteria (step five). The overall suitability scores at each location were calculated using a weighted linear combination of the criteria and corresponding weights to create a suitability map (step six). Lastly, spatial and non-spatial analysis were performed to quantify the distribution of suitability scores and their spatial pattern at multiple census geographical levels, which could be used in combination with a decision rule to decide where corn should be planted (step seven).

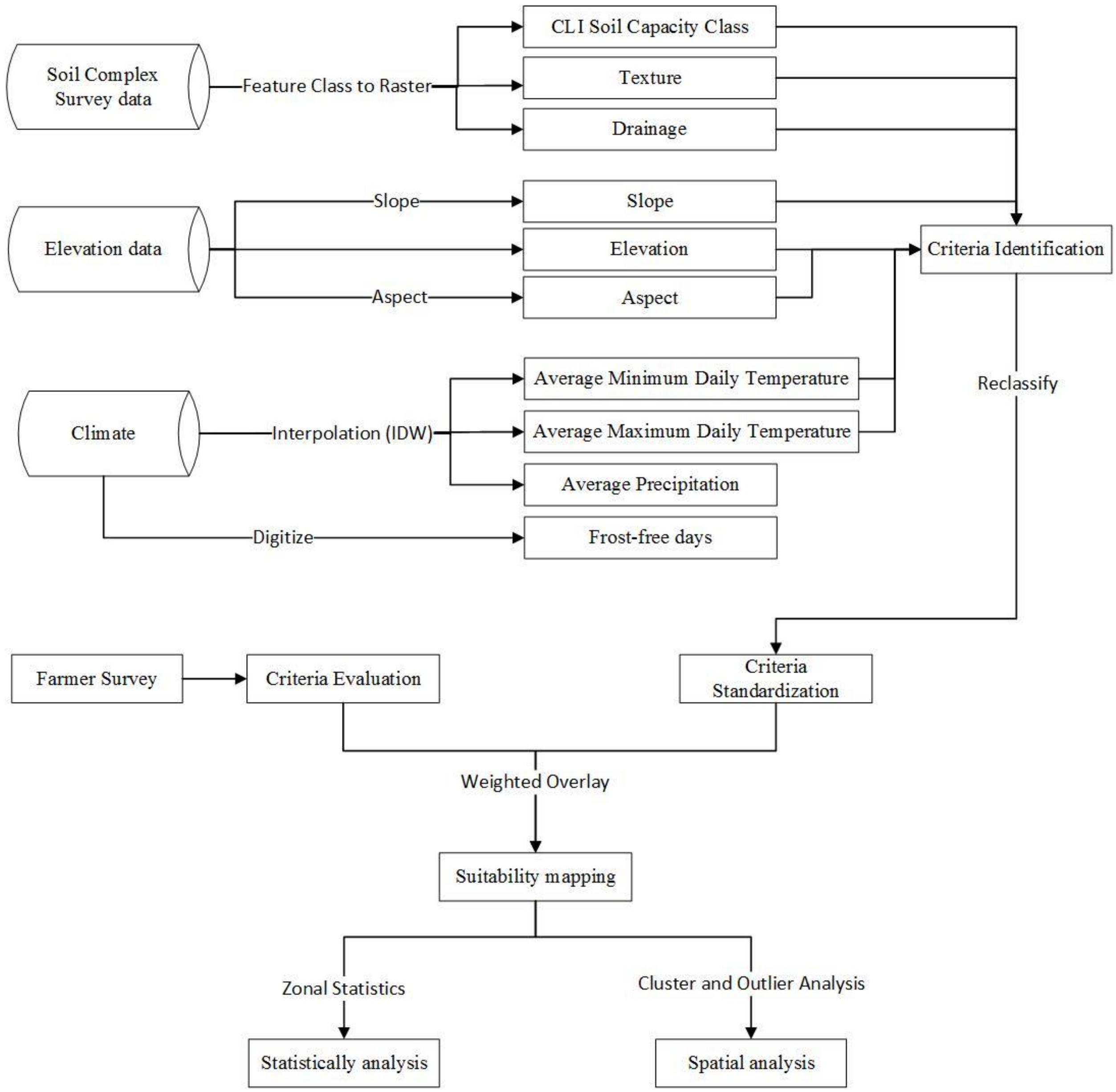


Figure 3-3 Flowchart of methodology (Texts in the boxes represent methodology steps, and texts on the lines represent tools used for data processing)

3.3.1 Criteria Identification and Mapping

There are no standards for identifying criteria for agricultural land suitability (Akinci et al., 2013); hence, criteria selected in this study were based on previous research (Ceballos-Silva and López-Blanco, 2003; Fecteau, 1985) and available data. Examples of criteria included in suitability analysis for agricultural land include soil group, land-use capability class and sub-class, soil depth, slope, elevation, erosion level, and other soil properties (Akinci et al. 2013). Others have included climate (maximum and minimum temperature and precipitation/evaporation index), soil (pH, texture, and depth), and relief (altitude and slope) characteristics for suitability analysis of maize (Ceballos-Silva and López-Blanco 2003). Similar criteria were used to identify the suitability of land for rice, sugarcane, maize, vegetables, horticulture, and pulses (Prakash 2003). These criteria included soil (pH, organic carbon, fertility, texture, drainage, and depth), climate (temperature and rainfall), irrigation (canal irrigation and ground water), market and infrastructure (roads, and markets and processing industries), and socio-economic variables (population, Prakash 2003). In addition to criteria related to soil, drainage, fertility, texture, and pH, Fecteau (1985) described criteria related to climate conditions required for corn growth as *"[f]rost free days, length of growing season, temperature of soil and air, photoperiod, and the amount of rainfall*" (Fecteau, 1985, p.24). Given available data for our study area, criteria describing characteristics of soil, topography, and climate were used (Table 3-2).

3.3.2 Data Description

The data used to score each criterion were acquired from a number of government sources (Table 3-2) and represented as raster cells with cell size of 20m×20m. Soil data were obtained from Soil Complex Survey conducted by Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA), which was published in 1929 and revised in 2003. Canada Land Inventory (CLI) soil capacity class, texture, and drainage were extracted from this dataset. Elevation data in the form of the Canadian Digital Elevation Model (CDEM) were acquired from Natural Resource Canada. The CDEM was used to compute slope and aspect for the study area. Climate data (temperature and precipitation) were obtained from the Environment Canada with historical data available at 286 climate stations within Southern Ontario from 1840 to 2015. The variables taken from the dataset include minimum daily temperature, maximum daily temperature, and total precipitation during growing season (i.e. May to September). To prepare spatial maps of the three variables, values within growing season were averaged for all the available recorded years. Then inverse distance-weighted (IDW) interpolation was applied to generate a surface map based on point data. Data of frost-free days were obtained from OMAFRA where climate zones of average frost-free period from 1976 to 2005 were identified.

Table 3-2 Evaluation criteria

Criteria		Data Source	Year
Soil	CLI Soil Capacity Class	OMAFRA	2003
	Texture		
	Drainage		
Topography	Slope (%)	Natural Resources Canada	2012
	Elevation (m)		
	Aspect		
Climate (during growing season)	Mean Minimum Daily Temperature (℃)	Environment Canada	2015
	Mean Maximum Daily Temperature (℃)		
	Mean Total Precipitation (mm)		
	Total Frost-free days	OMAFRA	2013

3.3.3 Criteria Standardization

After the criteria were identified and data were collected, each criterion was reclassified into several classes based on its suitability for corn growth. According to previous studies, each class was provided with a score within the range of 0-10, with 0 being the least suitable class and 10 being the most suitable class (Akinci et al., 2013; Table A-2).

3.3.4 Criteria Evaluation and Scoring

The weights for criteria were obtained from farmers. A questionnaire-based survey (Appendix 4) was designed with one question asking farmers to rank the 10 identified criteria from 1 to 10 (1 being the most important, and 10 being the least important) based on their relative importance to corn growth. The questionnaire along with information letter and a self-addressed stamped envelope were dropped at farmers' mailboxes when the author was driving randomly around farms in Southern Ontario. The participants who were willing to participate the survey only need to fill in the survey, put it in the envelope, and mail it back. As a result, 150 surveys were sent out and 6 responses were returned. The rank for each criterion was then represented by the mean rank from all the respondents. Standard deviation of the ranks provided by farmers was also provided to show the variation of ranks for each variable. Criterion weights were calculated using the rank reciprocal method by dividing the reciprocal individual rank by the sum of all reciprocal ranks (Carr and Zwick, 2007):

$$w_j = \frac{(1/r_j)}{\sum(1/r_j)}$$

Table 3-3 Ranking and weights of criteria

Criteria	Mean rank	Recipocal ranking	Weights	Standard Deviation
CLI Soil Capacity Class	5.67	0.18	0.08	4.08
Texture	4.50	0.22	0.10	2.51
Slope (%)	7.17	0.14	0.06	2.64
Elevation	8.50	0.12	0.05	1.05
Aspect	8.50	0.12	0.05	1.38
Drainage	3.33	0.30	0.13	1.51
Minimum Daily Temperature (℃)	4.67	0.21	0.09	1.51
Maximum Daily Temperature (℃)	4.17	0.24	0.10	1.60
Precipitation	2.50	0.40	0.17	0.57
Frost-free days	2.67	0.38	0.16	2.07
		Sum	1.00	

Before suitability scoring took place, areas deemed unsuitable were identified and excluded from subsequent analysis. These areas included those with a land-use designation of built up, recreation, water, woodland, Indian Reserve, swamp, marsh or bog in the Agricultural Resource

Inventory data (2013). Following these exclusions, a suitability score was calculated for each remaining location as a weighted sum of the standardized criteria using the following equation:

$$\mathrm{S} = \sum \mathrm{Score}_i * \mathrm{w}_i$$

where S is the suitability score, Score_i is the score for criteria i, and w_i is the ranking weight of criteria i as identified in Table 3-3.

3.3.5 Suitability Score Analysis

To describe the distribution of suitability scores and their spatial pattern a number of summary and spatial statistics were used. First, mean, maximum, minimum, and the standard deviation of suitability scores were summarized at four spatial levels, which comprised the entire study area of Southern Ontario, Census Divisions (CD), Census Subdivisions (CSD), and Areas (DA). It is essential to conduct the analysis on various spatial aggregation levels as analysis results could be different even if the input data are the same under different analysis scales or zoning systems, which is named Modifiable Area Unit Problem (MAUP) (Parenteau and Sawada, 2011). MAUP considers two effects on spatial analysis, namely scale effect (impact of unit size due to spatial aggregation) and zoning effect (impact of unit boundary and shape) (Dark and Bram, 2007). In this study, the scale effect is the main concern as the data were aggregated at different census levels with different analysis unit area.

Second, to investigate the spatial pattern of suitability scores, spatial autocorrelation and a local indicator of spatial association (Anselin Local Morna's I), to identify clustering of suitability scores, were computed using the aggregated suitability scores at the DA level.

3.4 Results

3.4.1 Suitability Score Mapping and Statistics

When suitability scores were calculated across Southern Ontario (Figure 3-4), 26.89% of the area was found to be unsuitable for corn growth, and more than 70% of the total study area has a suitability score greater than 7. Among the suitable areas, scores ranged from 5.7 to 9.7, with the highest score located in Middlesex County. The CSDs of East Zorra-Tavistock, Lucan Biddulph, Zorra, South-West Oxford, and Norwich are the five CSDs that have the highest mean suitability score and they all fell in the central area of the study area.

To explore the impact of MUAP on the spatial pattern of suitability scores, suitability scores were averaged at three census levels, with a decreasing level of aggregation (i.e., CD, CSD, and DA; Figure 3-5). At CD level, the mean suitability scores range from 4.8 to 6.9. This range is a marked reduction from the Southern Ontario region range, which suggests that high suitability values are concentrated in one or two CDs and lower suitability scores dominate the majority of CDs. Among the 10 CDs comprising the study region, Chatham-Kent and Oxford have the highest mean suitability score, and Hamilton and Niagara have the lowest.

At the CSD level, the mean suitability score range widens to 0 to 7.6. There were 15 CSDs that have very little suitable land and therefore attain a value of about zero. East Zorra-Tavistock, Lucan Biddulph, Zorra, South-West Oxford, and Norwich are the five CSDs that have a mean suitability score greater than 7. About 50% of the CSDs have a mean suitability score between 5 and 7. At DA level, the mean suitability score ranges from 0 to 9, and approximately 62% of the DAs are not suitable for corn growth.

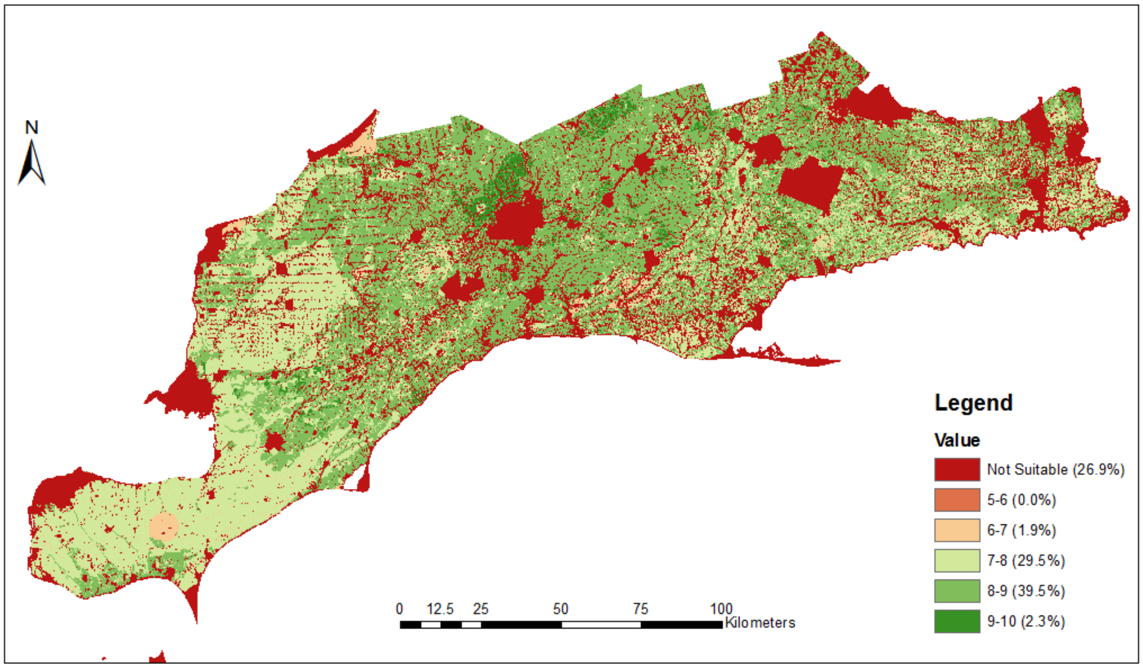


Figure 3-4 Suitability map for corn growth in Southern Ontario.

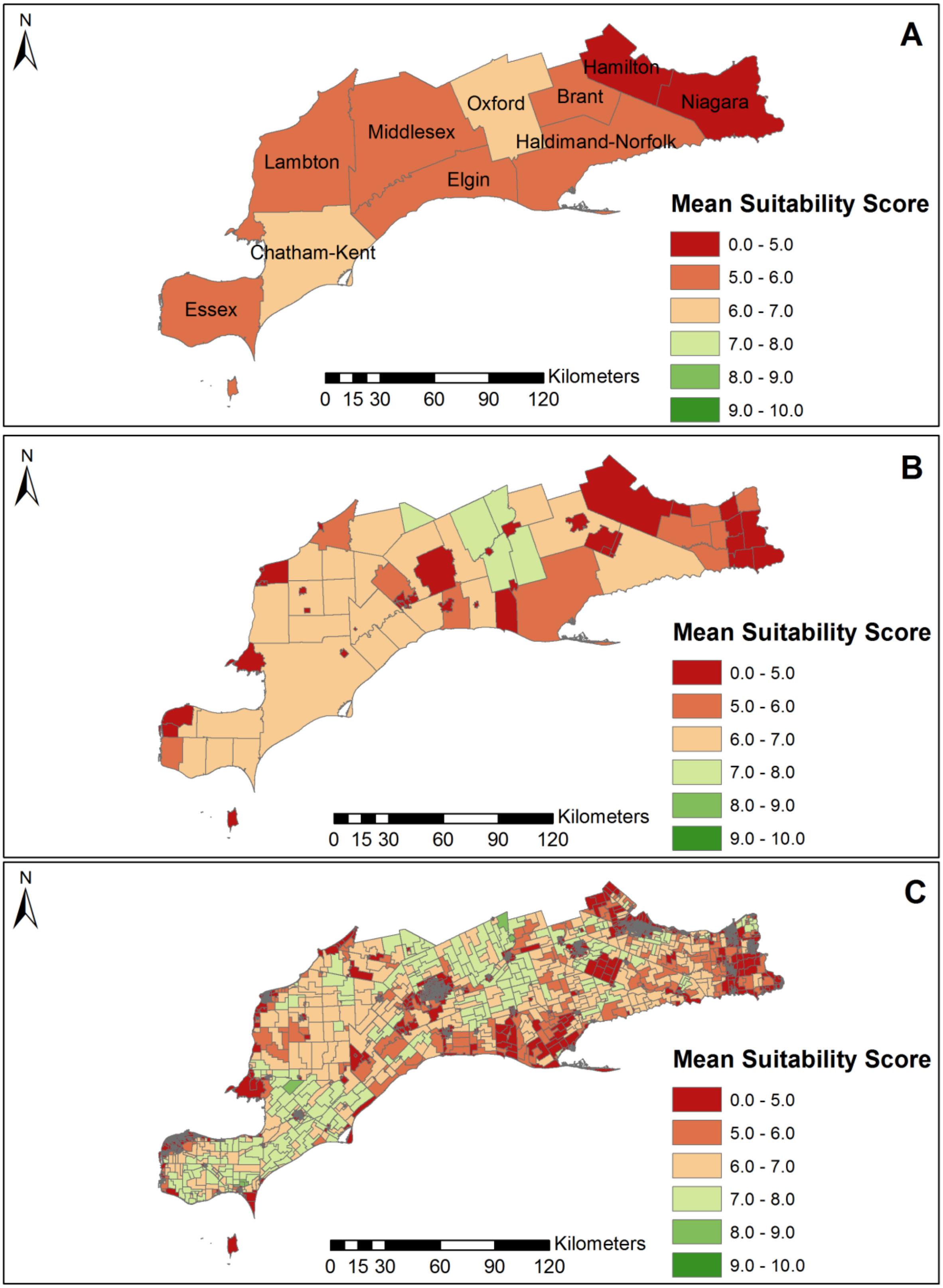


Figure 3-5 Mean suitability score at census level: A) CD; B) CSD; C) DA.

3.4.2 Suitability Score Analysis

The spatial autocorrelation analysis generated a Global Moran's I of 0.213 and z-score of 130.57 with a p-value of 0, indicating that there is a more than 99% likelihood that the mean suitability score is spatially clustered instead of randomly distributed. Furthermore, the cluster and outlier analysis using Anselin Local Moran's I at the DA level provided information about how the suitability scores are spatially clustered (Figure 3-6). Using a p-value < 5% to determine statistical significance, four types of spatial clusters were identified, including high scores surrounded by high scores (high/high), high scores surrounded by low scores (high/low), low scores surrounded by low scores (low/low), and low scores surrounded by high scores (low/high), with 56.1%, 12.8%, 1.4%, and 7.9% of the total area respectively. The remaining 21.7% of the total area did not appear to have any significant cluster patterns. As illustrated in Figure 3-6, significant high/high clusters are mostly located in non-CMAs (Census Metropolitan Area). Non-high-high clusters occupied about 1,005,569 hectares, and approximately 77% of them are located within CMAs.

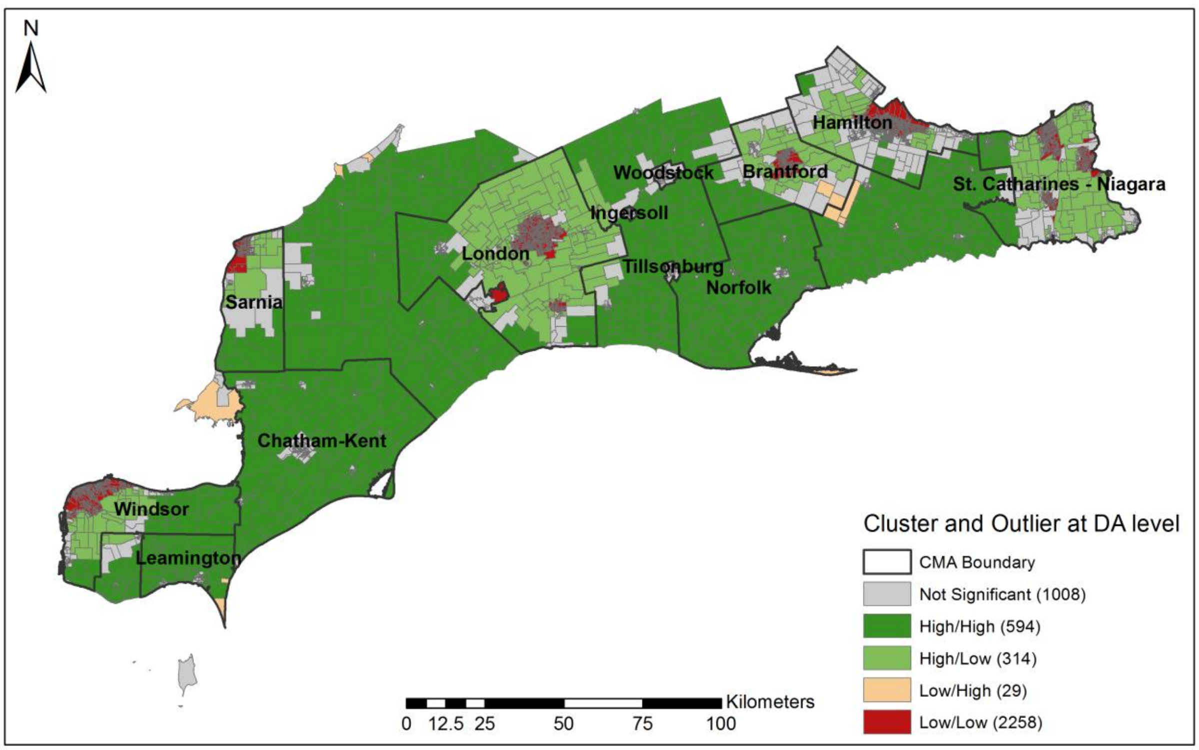


Figure 3-6 Cluster and outlier mapping of suitability score at DA level.

3.4.3 Impact of MAUP(Scale Effect) on Suitability Interpretation

Scales, including resolution (i.e. area represented by data unit or time frequency) and extent (total size of study area or total duration of temporal data), tend to have significant impact on land-use patterns, as data at finer resolutions are able to capture more landscape heterogeneity than coarse resolution data, which tends to smooth and generalize information but is typically able to cover larger spatial extents (Turner et al., 1989). In the interpretation of suitability spatial distribution, obvious impact of scales, both resolution and extent was discovered.

First, in the calculated raster of suitability scores (Figure 3-4), values are higher in the central area than the other areas. However, when the scores were aggregated at CD level (Figure 3-5A), the central area appeared to have lower mean suitability scores than surrounding area. CD of Chatham-Kent and Oxford had higher mean suitability score than Middlesex, which is not consistent with the original suitability result. This is primarily due to the spatial extent effect, which is the effect of including or excluding aforementioned constrained land-uses. Taking Middlesex for example, for suitability raster of Figure 3-4, the description of “values are higher in the central area than the other areas” did not take the white area (London) into consideration, which was identified as not suitable for corn growth with a suitability score of 0. Therefore, even though the suitable areas in Middlesex have high suitability scores, the mean suitability score was ultimately dragged down due to the inclusion of unsuitable area. In this case, a second suitability map excluding unsuitable areas was generated and mean suitability scores were also aggregated at CD level. Comparing the mean suitability scores at CD level generated with different spatial extent in Table 3-4, aggregated suitability score at CD level with restricted areas excluded has a higher mean and a lower standard deviation. Oxford, Hamilton, and Middlesex have the highest mean suitability score. The new spatial distribution of mean suitability scores at CD level is more consistent with the original raster data.

Second, it is notable that obvious variance exists among the suitability spatial distribution at the four spatial levels of CD, CSD, DA, and 20m×20m raster with increasing resolutions, which can be observed from Figure 3-4 and Figure 3-5. Indexes of diversity, dominance, and contagion, although commonly used as landscape measures, can also be used here to quantify the spatial differences among results based on the four scales (Turner et al., 1989). Statistically, the value range and standard deviation are positively related to the resolution. The relevant statistics are plotted and compared in Figure 3-7.

The comparison between various spatial extent and resolution emphasized the importance of selecting an appropriate scale for land-use analysis to ensure sufficient and accurate analysis. In addition, quantifying the scale effects can help understand and predict land-use analysis results to some extend (Turner et al., 1989).

Table 3-4 Comparison of aggregated suitability statistics at CD level between including and excluding restricted area

CD	Mean		STD			
	Include	Exclude	Include	Exclude	SUM	Not suitable
Essex	5.96	7.46	3.02	0.47	28039760.59	20.18%
Middlesex	5.95	8.41	3.85	0.47	49817523.39	29.30%
Haldimand-Norfolk	5.81	8.01	3.60	0.52	42641862.90	27.45%
Brant	5.07	8.29	4.07	0.54	14076488.14	38.89%
Hamilton	4.93	8.43	4.16	0.40	14207265.81	41.48%
Oxford	6.79	8.54	3.46	0.36	34983673.02	20.51%
Lambton	5.74	7.70	3.39	0.53	44163087.51	25.44%
Chatham-Kent	6.92	7.88	2.62	0.54	43321821.88	12.14%
Elgin	5.91	8.27	3.77	0.60	28050092.46	28.56%
Niagara	4.83	8.00	3.94	0.56	22828969.81	39.69%

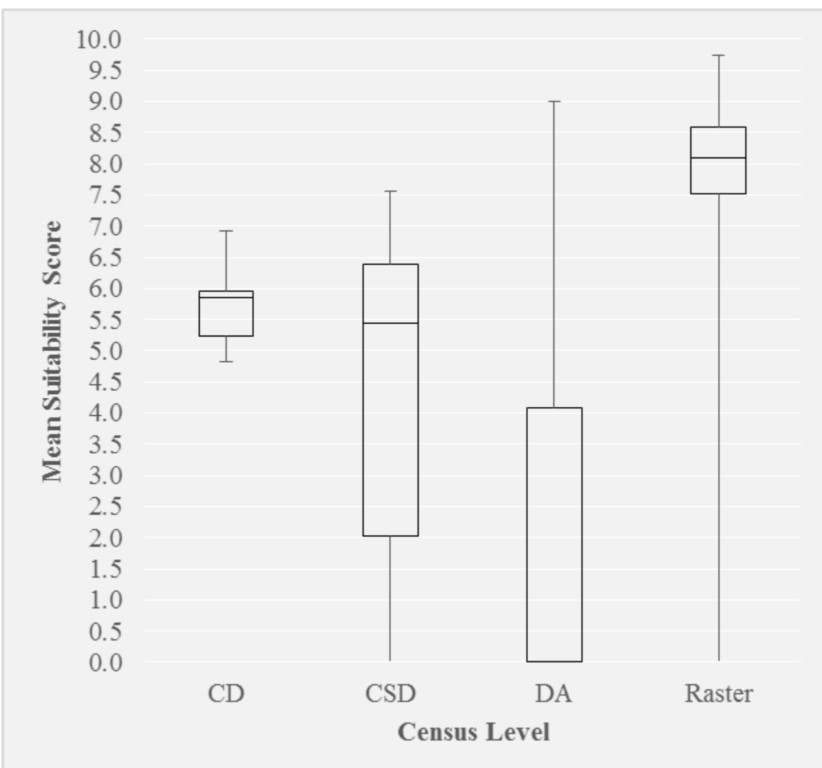


Figure 3-7 Boxplot of mean suitability score at different scales.

3.5 Discussion

3.5.1 Result Interpretation

3.5.1.1 Relationship between yield and suitability

Previous studies have proved that corn yield is a function of fertilizer input, weather conditions, technology adoption (Dumanski et al., 1986); elevation, slope, and curvature (Kaspar et al., 2003); some of which were selected in this study to be suitability criteria. Under this circumstance, corn yield is expected to be positively related to the calculated suitability scores. Therefore, an Ordinary Least Squares (OLS) regression of mean corn yield (bushels/acre) on mean suitability score. Due to the data availability, CD level corn yield from Statistics Canada in 2011 was used. The mean suitability scores used excluded unsuitable areas to be consistent with census data. However, no significant correlation was discovered and only 1.5% of the total variance in corn yield can be explained by suitability scores. Lacking data at a finer resolution could be one of the reasons accounting for this result. Potential reasons could be factors that were not included in suitability calculation such as fertilizer use and technology adoption.

3.5.1.2 Suitability Mapping Validation

To further validate the overall accuracy of suitability mapping, the result was compared to census of agriculture data in 2011 regarding total area of corm farms at CSD level. OLS Regression of the sum of suitability scores in CSD against total area of corn farm was performed. The result indicated a significant positive correlation between total suitability score and corn farm area, which means that the area with higher overall suitability level had larger area of corn farms in 2011 and the estimated suitability score is consistent with real world situation.

3.5.2 Method Limitations

3.5.2.1 Data Availability and Accuracy

As aforementioned, agricultural land-use suitability assessment does not have a common requirement for criteria that need to be included. As summarized in Table 3-5, studies of cropland suitability analysis can involve various criteria from aspects of soil, topography, climate, irrigation, and social factors depending on data availability and research focus. Therefore, this study tried to include as many criteria as possible to ensure adequate representation of corn growth requirements. However, due to the spatial extent of the study area, detailed soil data of soil nutrition and fertility could not be obtained. Also, for the obtained soil data, missing data of CLI soil capacity class, texture, and drainage exist in the dataset. To resolve this problem, it is possible to conduct fieldwork to collect detailed soil data for validation (e.g. Sicat et al., 2005). Alternatively, soil classification with updated remotely sensed images is also possible (e.g. Bugden et al., 2009).

Second, climate data were generated based on average daily climate data at 286 climate stations within Southern Ontario from 1840 to 2015. Therefore, the impact of temporal variance of climate and missing data were not considered or quantified. Furthermore, the climate data over the entire study area were created based on point data with interpolation approach, of which the accuracy is challenging to quantify.

Lastly, as discussed before, integration of various scales of data can introduce uncertainty for the overall suitability calculation. In this study, soil data came in a vector format with homogeneous areas ranging from 0.01 m^2 to 830 km^2; topography data were in a raster format with a 20 m resolution; and climate data were generated using point data. To ensure a consistent spatial resolution for calculation and avoid information lost due to aggregation, the finest spatial resolution of 20m×20m was chosen for data process. However, it is arguable whether it is the most suitable spatial resolution. According to Statistics Canada, the average farm size of Ontario in 2011 is about 1 km^2 and a spatial resolution of 1km×1km might be more reasonable to represent potential corn growth sites.

Therefore, the calculated suitability scores have a high dependency on the existing data and can be improved substantially if more datasets with higher accuracy are available.

Table 3-5 Criteria used for cropland suitability analysis in literature

Criteria category		Criteria	Akinci et al., 2013	Ceballos-Silva & Lo´pez-Blanco, 2003	Elsheikh et al., 2013	Kalogirou, 2002	Mendas & Delali, 2012	Nisar Ahamed et al., 2000	Prakash, 2003
Soil	Toxicities	pH		√	√	√			√
		H_2O				√	√		
		Depth to sulphate			√	√			
		Organic matter			√	√	√		√
		Sodicity			√		√		
		Salinity			√		√		
		Cation exchange capacity			√	√	√	√	
		Base saturation			√	√		√	
		Active limestone			√		√		
	Rooting condition	Depth	√	√	√	√	√		√
		Coarse fragment				√			
		Gravel			√			√	
		Erosion	√		√				
		Soil Mechanics			√				
	Workability	Great soil group	√						
		Land use capacity class	√						
		Texture		√		√		√	√
	Oxygen soil drainage	Oxygen soil				√			
		Drainage			√		√	√	√
Topography		Slope	√	√	√	√	√	√	
		Elevation	√		√				
		Aspect	√						
		Altitude		√					
Climate		Minimum temperature		√			√		√
		Maximum temperature		√			√		√
		Precipitation		√	√		√		√
		Length of dry season			√				
		Flood hazard				√			
Social		Population							√
		Availability of labour					√		
		Markets and Processing industries							√
		Proximity to roads					√		√
Irrigation		Canal irrigation							√
		Ground water							√
		Water level				√			

3.5.2.2 Criteria Weights

To acknowledge farmers’ knowledge about importance of corn growth criteria, which has proved to be important for agricultural suitability analysis (Sicat et al., 2005), the weights used in this study were completely based on a mail-out survey questionnaire among farmers. However, uncertainties of weights from farmers' understanding about the criteria, rating methods, and response rate could be introduced.

First, although definitions of the criteria were provided in the survey, it is still uncertain to what extend farmers could understand the criteria correctly. For example, one of the farmers wrote that he/she was "not sure what CLI soil capacity class means" in the comments. Therefore, an in-person interview might provide slightly different results that better capture the ranking of criteria affecting crop choices and the decision to cultivate corn.

Second, the designed survey simply listed 10 criteria and asked farmers to rank them from 1-10 based on importance, with 1 being the most important and 10 being the least important. Two of the farmers expressed that they thought some of the criteria were of equal importance and difficult to be ranked differently. This is an understandable issue, as it has been proven that it is challenging for humans to compare more than three items at a time (Prakash, 2003). In this case, the Analytic Hierarchy Process (AHP) could be an alternative for weights calculation. With AHP, the criteria need be organized hierarchically and compared to each other (pairwise comparison) at their own level. In this study, criteria can be organized at two hierarchies with the first level being soil, topography, and climate, and second level are the criteria under each of the three categories. Then at each level, pairwise comparison matrix is created to determine the importance of one criterion to the other quantitatively based on the scale developed by Saaty (1987). The weights can then be calculated by normalizing the pairwise comparison matrix (Akinci et al., 2013). This method enables easier comparison when there are a large number of criteria with the ability to quantify comparison consistency (Saaty, 1987). However, it can be difficult to implement among farmers due to its complex comparison. Farmers may find it difficult to provide a numeric value to determine the relative importance between two criteria.

Third, to collect survey data, 150 surveys were sent out in Southern Ontario and only 6 responses were received, which is a relative low response rate of 4%. Although, as displayed in Table 3-3, the ranks for the criteria were consistent to a moderate degree except CLI soil capacity class, the survey process could be improved with larger sample size, better sampling method, and appropriate follow-up methods. Morse (2000, p.3) summarized that sample size of a study is dependent on "*the quality of data, the scope of the study, the nature of the topic, the amount of useful information obtained from each participant, the number of interviews per participant, the use of shadowed data, and the qualitative method and study design used*". Although this study did not intend to use the sample data to represent the farmer population within Southern Ontario, it wanted to learn farmers' opinion about criteria importance. Therefore, participants can be randomly selected in each CD. To receive more responses, more surveys should be sent out. Additionally, this study can be cooperated with some agriculture organizations which have farmer members. It could enable more effective follow-up with farmers. Moreover, for a quantitative assessment of how the weight of each criterion affects suitability results, sensitivity analysis can always be conducted as a supplement.

As criteria weights can contribute significantly to the suitability uncertainty, sensitivity analysis of criteria weights is always necessary for a land-use suitability analysis. It is able to qualitatively or quantitatively estimate to what degree the suitability result can be impacted by changes in weights and the robustness of suitability result with changes in weights (Chen et al., 2010). Daniel (1973) proposed a One-At-a-Time (OAT) method to change one criteria at a time incrementally (e.g. 1%) within a range (e.g. ±20%). The other criteria are adjusted proportionally to ensure that all the weights sum up to 1. With this approach, sensitivity of suitability to each criterion can be quantified and compared.

3.5.2.3 Criteria Inclusion and Class Scores

In the determination of what criteria should be included and their individual suitability score for corn growth for each class, relevant studies were referred. To provide a rational for including certain criteria and class suitability score, regression of corn yield against relevant criteria can be performed. It can help determine which criteria are significantly related to suitability and how they are correlated. For example, a multi-linear regression performed by Dumanski et al. (1986) proved that grain corn yield was significantly related to temperature and precipitation.

3.5.3 Future Direction

Studies proved that corn yield is related to weather conditions such as temperature and precipitation (Dumanski et al., 1986; Smit et al., 1989). This study had an emphasis on the spatial variation of the factors while ignored how the suitability changed temporally due to climate change. In this situation, a continuous suitability mapping over time can be obtained to investigate the temporal variation of suitability scores, and may be able to help predict land suitability in the future, as defined by FAO as potential suitability (FAO, 1976).

3.6 Conclusion

This study presented a GIS-based multi-criteria suitability mapping and analysis for corn growth in Southern Ontario integrating farmers' knowledge with criteria about soil, topography, and climate. Based on the analysis, about 73% of the total area was identified as suitable for corn growth with suitability score ranging from 5.6 to 9.7. Highly suitable climate condition with adequate frost free days, warm temperature, and adequate rainfall is the main reason accounting for the high suitability. Spatially, CD of Chatham-Kent and Oxford have the highest mean suitability, but Middlesex and Lambton have the highest total suitability. Although the suitability scores indicated a consistent with Census of Agriculture data, uncertainties exist in many aspects including data accuracy, criteria rating, and scale effects. It is essential to acknowledge and try to eliminate sources of these uncertainties through improved data collection and method design. Despite the limitations of this study, it provides an effective method to quantify spatial distribution of land suitability for corn growth based on farmers' knowledge. In the light of future studies, temporal dimension can be integrated to help predict land potential suitability besides current suitability.

Chapter 4

Conclusion

4.1 MCDA overview

This thesis intended to gain insight into the application of MCDA for agricultural land-use decision-making and presented two studies emphasizing on MODA and MADA, respectively. Chapter 2 presented an ABM prototype involving a multi-objective optimization to determine the proportion of each land-use activity and location for land-use activities on farms integrating environmental, social, and economic factors. Chapter 3 applied a GIS-based multi-attribute suitability analysis for corn growth based on soil, topography, and climate characteristics on potential sites, and farmers' opinions about relative importance of these criteria.

Similarity and differences exist between MODA and MADA. A general MCDA problem involves selecting decision process (options formulation and criteria selection), evaluating performance, deciding decision parameters, applying the method, and evaluating results (Pohekar & Ramachandran, 2004). It provides a clear and transparent representation of decision process to various stakeholders, especially for problems that are difficult to be quantified (Giove et al., 2009). Mathematical programming, multi-attribute/value utility theory, outranking, or a combination of multiple methods are widely used to solve MCDA problems (Figure 1-1). All the methods need to deal with criteria conflicts, incomparable units, and selecting alternatives (Pohekar & Ramachandran, 2004).

Detailed comparison between MODA and MADA is displayed in Table 4-1 regarding criteria, objective, constraints, alternatives, and decision-making. The major difference between MODA and MADA is whether decision alternatives are defined before making decisions. In a MODA problem, decision makers need to optimize multiple objective functions under set of constraints and obtain the best solution, which is essentially a trade-off among multiple criteria. Therefore, improving performance of one objective will be at the sacrifice of the performance of one or several other objectives (Pohekar & Ramachandran, 2004). MODA is widely used in portfolio optimization. For example, in Chapter 2, the farmer agents did not know the proportion of land that they wanted to allocate for each land use activity or where to allocate them, but they were aware of their objectives. Under this circumstance, MODA is the method that can help solve this problem, while MADA cannot. During the decision making process, farmer agents have control over their decisions and can adjust their behaviors over time (although not included in the model in Chapter 2).

While in a MADA problem, decision alternatives are predetermined before making decisions and the best alternative that satisfies decision maker's objective is selected by comparing it with the other alternatives. In Chapter 3, potential sites for corn growth were predefined and the decision-making process only involved evaluating the potential sites and determining what were the best sites based on the evaluation scores. In this case, MADA is the the proper choice to solve this problem as it did not require any portfolio optimization.

The choice of MODA and MADA depends on problem definition. Despite the differences between MODA and MADA, there could also be a combination of the two approaches. For example, in Chapter 2, a farm level utility maximization was an application of a MODA, while on the field level, the farmer agents need to evaluate each land use activity on each field to choose the land use activity with the highest utility. This is then a MADA problem.

Table 4-1 Comparison of MODA and MADA approaches (Malczewski, 1999 in Mendoza and Martins, 2006)

Criteria for comparison	MODA	MADA
Criteria defined by	Objectives	Attributes
Objectives defined	Explicitly	Implicitly
Attributes defined	Implicitly	Explicitly
Constraints defined	Explicitly	Implicitly
Alternatives defined	Implicitly	Explicitly
Number of alternatives	Infinite (large)	Finite (small)
Decision maker's control	Significant	Limited
Decision modelling paradigm	Process-oriented	Outcome-oriented
Relevant to	Design/search	Evaluation/choice

4.2 ABM versus Suitability Analysis

This thesis adopted two different approaches to solving MODA and MADA problems. In Chapter 2, an ABM was developed, while in Chapter 3, a suitability analysis was conducted. In Chapter 2, it was expected to explore farmers' decision-making on farms, which involves individual human (i.e. farmers), landscape (farms and fields), and their interaction over time. In addition, it had a path dependency indicating future decisions need to be based on previous decisions (e.g. woodland ages). Therefore, it will be difficult for other types of models (such as statistical models) to represent individuals with different behaviours and model the behaviors continuously. In addition, this ABM prototype will enable integration of more complexity in the future. Although the great opportunity brought by ABM can contribute to land use science in many aspects, there are some drawbacks that constraints ABMs' ability to be more effectively applied. Sullivan et al. (2016) believe that the key drawback is that most ABMs were developed specifically for a certain study to answer the related research question, making it challenging for others to learn from and make progress on top of the existing models. As ABM is usually data hungry, data availability is one of the biggest challenges to enable empirical calibration, verification, and validation of the models. In addition, land use is usually a complex system with a lot of processes and data requirement. It is the researchers' responsibility to ensure a balance between a detailed ABM representing real world situation and a simplified model based on ground theories. Furthermore, ABM participatory is another major issue. Many models were developed by researchers to address scientific question, but not too many of them were actually used by relevant stakeholders. It is important to make the models easier for the general public to understand and use rather than for the scientific community to conduct researches only (Sullivan et al., 2016).

In Chapter 3, the decision-making did not involve any interactions between human and landscape, though farmers' opinions on criteria were used to calculate weights. In addition, no temporal dimension was included for analysis. A suitability analysis, which usually deals with "location, development plans, and environment elements" (Collins et al., 2001) is sufficient for this Chapter. The methods adopted in this Chapter, MADA, is simple, which is a weighted sum of 10 criteria and their corresponding weights from farmers. However, there are more advanced methods existing, such as artificial intelligence, fuzzy logic, neural networks, evolutionary (genetic) algorithms, and cellular automata. These methods could have the possibility of improving criteria weights determination, which is one of the main challenges for land suitability analysis (Malczewski, 2004).

It has been discussed that the allocation of land by humans for different activities (i.e., land-use) consists of a land suitability assessment, land demand estimation, and land location allocation (Karimi et al., 2012). Chapter 3 could then be a significant component for Chapter 2. If the land use activities in Chapter 2 were crop selections rather than general land use type determination, the result in Chapter 3 could help determine whether a field is suitable for a specific crop. Therefore, the selection between a complex ABM and a simple suitability analysis largely depends on the research objective.

To conclude, it is not possible to conclude whether ABM is better than a suitability analysis or suitability analysis is better than ABM directly. The choice of method for land use planning is subjective to research objectives. Understanding the strength and weakness of both methods is essential for method determination.

4.3 Recommendations and Future Directions

Recommendations regarding steps of MCDA process are provided. The selecting decision process consists of options formulation and criteria selection. The criteria selected in this study were based on previous literature and data availability as there are no standards for criteria determination. Alternatively, expert knowledge can be consulted and integrated. In addition, statistical analysis, such as regressions can be conducted to gain knowledge about the relationship between decisions and potential criteria with accurate spatial and temporal data. For example, in Chapter 3, a regression of corn yield against soil data, climate data, and other potential criteria can be performed to learn how corn yield is correlated to these criteria and the significance of correlation.

When evaluating performance, this study adopted a Simple Additive Weighting (SAW) approach to integrate multiple criteria. However, in reality, human opinions are too complex to be represented as a simple numeric value; instead, it might involve complex interactions with the others, self-learning, and continuous adaptations to temporal factors. Therefore, integrating more complex interactions among different types of land managers and between ecosystem and human in land use evaluation could be a future direction for more comprehensive simulation of human-nature systems.

Data calibration, result verification and validation have always been challenging for land use modeling. Commonly, a sensitivity analysis is conducted to explore to what degree changes in criteria and preferences toward these criteria can affect modelling results. However, beyond using sensitivity analysis to account for impacts from parameter variance, the model structure validity is another raised problem, which have not been well addressed. The question of “does the model represent appropriate system elements in the most appropriate ways” needs to be answered through further studies (Sullivan et al., 2016, p180).

Furthermore, as LUCC is a complex process involving years of changes, including the impacts of temporal variation in a land-use evaluation is essential. For example, acknowledging the temporal changes in soil quality and including it in both MADA of corn growth and MODA of land allocation could be beneficial to better representation of LUCC.

References

Akinci, H., Özalp, A. Y., & Turgut, B. (2013). Agricultural land use suitability analysis using GIS and AHP technique. *Computers and Electronics in Agriculture*, *97*, 71–82. doi:10.1016/j.compag.2013.07.006

Ananda, J., & Herath, G. (2009). A critical review of multi-criteria decision making methods with special reference to forest management and planning. *Ecological Economics*, *68*(10), 2535–2548. doi:10.1016/j.ecolecon.2009.05.010

Becu, N., Perez, P., Walker, A., Barreteau, O., & Page, C. L. (2003). Agent based simulation of a small catchment water management in northern Thailand. *Ecological Modelling*, *170*(2-3), 319–331. doi:10.1016/S0304-3800(03)00236-9

Beinat, E., & Nijkamp, P. (1998). Land-use management and the path towards sustainability. In E. Beinat & P. Nijkamp (Eds.), *Multicriteria analysis for land-use management (Vol. 9, pp. 1-13)*. Norwell, MA: Kluwer Academic Publishers

Belton, S., Stewart, T.S. (2002). Multiple Criteria Decision Analysis. An Integrated Approach. Kluwer Academic Publishers, Massachusetts.

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, *25*(2-3), 245–260. doi:10.1111/j.1574-0862.2001.tb00205.x

Bithell, M., & Brasington, J. (2009). Coupling agent-based models of subsistence farming with individual-based forest models and dynamic models of water distribution. *Environmental Modelling and Software*, *24*(2), 173–190. doi:10.1016/j.envsoft.2008.06.016

Brent. R. J. (1996). *Applied cost-benefit analysis*, Edward Elgar, Cheltenham

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and Society*, *11*(1). doi:10.2337/dc11-1153

Bugden, J. L., Pattey, E., & McNairn, H. (2009). Classification of crop and soil homogenous zones using multipolarization C-band SAR. *Canadian Journal of Remote Sensing*, *35*(2), 130–140. doi:10.5589/m09-001

Carr, M. H., & Zwick, P. D. (2007). *Smart land-use analysis: the LUCIS model land-use conflict identification strategy*. ESRI, Inc..

Carsjens, G. J., & Van Der Knaap, W. (2002). Strategic land-use allocation: Dealing with spatial relationships and fragmentation of agriculture. *Landscape and Urban Planning*, *58*, 171–179. doi:10.1016/S0169-2046(01)00219-5

Ceballos-Silva, A., & López-Blanco, J. (2003). Delineation of suitable areas for crops using a Multi-Criteria Evaluation approach and land use/cover mapping: A case study in Central Mexico. *Agricultural Systems*, *77*(2), 117–136. doi:10.1016/S0308-521X(02)00103-8

Cerri, C. C., Maia, S. M. F., Galdos, M. V., Cerri, C. E. P., Feigl, B. J., & Bernoux, M. (2009). Brazilian greenhouse gas emissions: the importance of agriculture and livestock. *Scientia Agricola*, *66*(6), 831–843. doi:10.1590/S0103-90162009000600017

Chen, Y., Yu, J., & Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environmental Modelling and Software*, *25*(12), 1582–1591. doi:10.1016/j.envsoft.2010.06.001

Chuvieco, E. (1993). Integration of linear programming and GIS for land-use modelling. *International Journal of Geographical Information Systems*, *7*(1), 71–83. doi:10.1080/02693799308901940

Collins, M. G., Steiner, F. R., & Rushman, M. J. (2001). Land-use suitability analysis in the United States: Historical development and promising technological achievements. *Environmental Management*, *28*(5), 611–621. doi:10.1007/s002670010247

Daniel, C. (1973). One-at-a-Time Plans. *Journal of the American Statistical Association*, *68*(342), 353–360.

Dark, S. J., & Bram, D. (2007). The modifiable areal unit problem (MAUP) in physical geography. *Progress in Physical Geography*, *31*(5), 471–479. doi:10.1177/0309133307083294

Dillon, J. L. (1971). An expository review of Bernoullian Decision Theory in agriculture: Is utility futility? *Review of Marketing and Agricultural Economics, 39*(1), 3-80.

Dumanski, J., Bootsma, A., & Kirkwood, V. (1986). A geographic analysis of grain corn yield trends in Ontario using a computerized land information base. *Canadian Journal of Soil Science*, *66*(3), 481–497. doi:10.4141/cjss86-049

Dykstra, D. P. (1983). Mathematical Programming for Natural Resource Management (New York: McGraw Hill).

Elsheikh, R., Mohamed Shariff, A. R. B., Amiri, F., Ahmad, N. B., Balasundram, S. K., & Soom, M. A. M. (2013). Agriculture Land Suitability Evaluator (ALSE): A decision and planning support tool for tropical and subtropical crops. *Computers and Electronics in Agriculture*, *93*, 98–110. doi:10.1016/j.compag.2013.02.003

Elster, J., and Roemer, J. E. (1991). *Interpersonal comparisons of well-being*. Cambridge University Press, Cambridge, UK.

F.A.O. (1976). A framework for land evaluation, F.A.O soils bulletin, Pb No 32. Rome.

Fecteau, R. D. (1985). *The introduction and diffusion of cultivated plants in Southern Ontario*. York University.

Fischer, G., Makowski, M., & Antoine, J. (1996). *Multiple criteria land use analysis* (No. WP-96-006). *Multiple criteria land use analysis*. Laxenburg.

Foley, J. A., Defries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., … Snyder, P. K. (2005). Global consequences of land use. *Science (New York, N.Y.)*, *309*(5734), 570–574. doi:10.1126/science.1111772

Food and Agriculture Organization, FAOSTAT Forestry Database (2004). http://faostat.fao.org.

Frank, S., Fürst, C., Koschke, L., Witt, A., & Makeschin, F. (2013). Assessment of landscape aesthetics - Validation of a landscape metrics-based assessment by visual estimation of the scenic beauty. *Ecological Indicators*, *32*, 222–231. doi:10.1016/j.ecolind.2013.03.026

Giove, S., Brancia, A., Satterstrom, F. K., & Linkov, I. (2009). Decision support systems and environment: Role of MCDA. In A. Marcomini, G. W. Suter, & A. Critto (Eds.), *Decision Support Systems for Risk-Based Management of Contaminated Sites* (pp. 53–73). New York: (Springer Science Business Media). doi:10.1007/978-0-387-09722-0

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., … DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*(1-2), 115–126. doi:10.1016/j.ecolmodel.2006.04.023

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling*, *221*(23), 2760–2768. doi:10.1016/j.ecolmodel.2010.08.019

Guignard, M. (1969). Generalized Kuhn–Tucker Conditions for Mathematical Programming Problems in a Banach Space. *SIAM Journal on Control*, *7*(2), 232–241. doi:10.1137/0308037

Hagerty, T., & Kingston, M. (1992). *The soils of Middlesex County* (Vol. 1). Guelph. Retrieved from http://sis.agr.gc.ca/cansis/publications/surveys/on/on56/index.html

Han, J., & Moraga, C. (1995). The influence of the sigmoid function parameters on the speed of backpropagation learning. *From Natural to Artificial Neural Computation*, *930*, 195–201. doi:10.1007/3-540-59497-3_175

Hannam, R., Ferguson, M., Stoddart, H., & Mussell, A. (2015). *County of Middlesex: Agriculture Strategy Report and Recommendations 2015-2020*. London. Retrieved from https://www.middlesex.ca/council/2015/may/12/B 1 b - CW - May 12 - County of Middlesex Agriculture Strategy Report and Recommendations_For County of Middlesex Council.pdf

Henseler, M., Wirsig, A., Herrmann, S., Krimly, T., & Dabbert, S. (2009). Modeling the impact of global change on regional agricultural land use through an activity-based non-linear programming approach. *Agricultural Systems*, *100*(1-3), 31–42. doi:10.1016/j.agsy.2008.12.002

Historical Climate Data. (2015, November 18). Retrieved December 10, 2015, from Government of Canada: http://climate.weather.gc.ca/

Hopkins, L. D. (1977). Methods for Generating Land Suitability Maps: A Comparative Evaluation. *Journal of the American Institute of Planners*, *43*(4), 386–400. doi:10.1080/01944367708977903

Houghton, R. A., and J. L. Hackler. (2001). Carbon flux to the atmosphere from land-use changes: 1850 to 1990. ORNL/CDIAC-131, NDP-050/R1. Carbon Dioxide Information Analysis Center, U.S. Department of Energy, Oak Ridge National Laboratory, Oak Ridge, Tennessee, U.S.A. doi: 10.3334/CDIAC/lue.ndp050

Jakubauskas, M. E., Legates, D. R., & Kastens, J. H. (2002). Crop identification using harmonic analysis oftime-series AVHRR NDVI data. *Computers and Electronics in Agriculture, 37*, 127–139.

Joerin, F., Thériault, M., & Musy, A. (2001). Using GIS and outranking multicriteria analysis for land-use suitability assessment. *International Journal of Geographical Information Science*, *15*(March 2015), 153–174. doi:10.1080/13658810051030487

Jones, D. S., Kowalski, D. G., & Shaw, R. B. (1996). Calculating Revised Universal Soil Loss Equation (RUSLE) Estimates on Department of Defense Lands: A Review of RUSLE Factors and U.S. Army Land Condition-Trend Analysis (LCTA) Data Gaps. Colorado State University, Center for Environmental Management of Military Lands, Technical Publication Series TPS 96-8.

Kalogirou, S. (2002). Expert systems and GIS: An application of land suitability evaluation. *Computers, Environment and Urban Systems*, *26*(2-3), 89–112. doi:10.1016/S0198-9715(01)00031-X

Karimi, M., Sharifi, M. A., & Mesgari, M. S. (2012). Modeling land use interaction using linguistic variables. *International Journal of Applied Earth Observation and Geoinformation*, *16*, 42–53. doi:10.1016/j.jag.2011.11.005

Kaspar, T. C., Colvin, T. S., Jaynes, D. B., Karlen, D. L., James, D. E., Meek, D. W., … Butler, H. (2003). Relationship between six years of corn yields and terrain attributes. *Precision Agriculture*, *4*(1), 87–101. doi:10.1023/A:1021867123125

Kelley, H., & Evans, T. (2011). The relative influences of land-owner and landscape heterogeneity in an agent-based model of land-use. *Ecological Economics*, *70*(6), 1075–1087. doi:10.1016/j.ecolecon.2010.12.009

Kuenstler, W. (1998) C factor: Cover-Management. In T.J. Toy, & G.R. Foster (Eds), *Guidelines for the Use of the Revised Universal Soil Loss Equation (RUSLE) Version 1.06 on Mined Lands, Construction Sites, and Reclaimed Lands* (pp.5-1-5-20). Denver, CO: Office of Surface Mining.

Lal, R. (2003). Soil erosion and the global carbon budget. *Environment International*, *29*(4), 437–450. doi:10.1016/S0160-4120(02)00192-7

Lambin, E. F., Rounsevell, M. D. ., & Geist, H. (2000). Are agricultural land-use models able to predict changes in land-use intensity? *Agriculture, Ecosystems & Environment*, *82*(1-3), 321–331. doi:10.1016/S0167-8809(00)00235-8

Lambin, E. F., Baulies, X., Bockstael, N., Fischer, G., Krug, T., Leemans, R., Moran, E. F., Rindfuss, R. R., Sato, Y., Skole, D., Turner II, B. L., Vogel, C., Nunes, C., & Augé, J. I. (1999). *Land-use and land-cover change implementation strategy*. IGBP Report No. 48, Stockholm, Sweden.

Lambin, E. F., & Strahler, A. H. (1994). Change-vector analysis in multitemporal space: A tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. *Remote Sensing of Environment*, *48*(2), 231–244. doi:10.1016/0034-4257(94)90144-9

Le, Q. B., Seidl, R., & Scholz, R. W. (2012). Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. *Environmental Modelling & Software*, *27-28*, 83–96. doi:10.1016/j.envsoft.2011.09.002

Le, Q.B. (2005). Multi-agent System for Simulation of Land-use and Land-cover Change: A Theoretical Framework and Its First Implementation for An Upland Watershed in the Central Coast of Vietnam. Cuvillier Verlag, Göttingen, Germany, 292.

Ligtenberg, A., Bregt, A. K., & van Lammeren, R. (2001). Multi-actor-based land use modelling: spatial planning using agents. *Landscape and Urban Planning*, *56*(1-2), 21–33. doi:10.1016/S0169-2046(01)00162-1

Lothian, A. (1999). Landscape and the philosophy of aesthetics: Is landscape quality inherent in the landscape or in the eye of the beholder? *Landscape and Urban Planning*, *44*(4), 177–198. doi:10.1016/S0169-2046(99)00019-5

Malczewski, J. (2004). GIS-based land-use suitability analysis: A critical overview. *Progress in Planning*, *62*(1), 3–65. doi:10.1016/j.progress.2003.09.002

Marshall, E. (2004). Open-space amenities, interacting agents, and equilibrium landscape structure. *Land Economics*, *80*(2), 272–293. doi:10.2307/3654743

Martin, W. E., Bender, H. W., & Shields, D. J. (2000). Stakeholder objectives for public lands : Rankings of forest management alternatives. *Journal of Environmental Management*, *58*(1), 21–32. doi:10.1006/jema.1999.0313

McGarial, K., & Marks, B. J. (1995). FRAGSTAT: Spatial pattern analysis program for quantifying landscape structure. United States Department of Agriculture, Pacific Northwest Research Station. (p. 120 pages).

Measuring Inequality. (2016). Retrieved August 1, 2016, from The World Bank website: https://www.cia.gov/library/publications/the-world-factbook/fields/2172.html

Mendas, A., & Delali, A. (2012). Integration of MultiCriteria Decision Analysis in GIS to develop land suitability for agriculture: Application to durum wheat cultivation in the region of Mleta in Algeria. *Computers and Electronics in Agriculture*, *83*, 117–126. doi:10.1016/j.compag.2012.02.003

Mendas, A., & Delali, A. (2012). Support system based on GIS and weighted sum method for drawing up of land suitability map for agriculture. Application to durum wheat cultivation in the area of Mleta (Algeria). *Spanish Journal of Agricultural Research*, *10*(1), 34–43.

Mendelsohn, R. (2013). An economic analysis of the effect of land use on terrestrial carbon storage. In D. G. Brown, D. T. Robinson, N. H. F. French, & B. C. Reed (Eds.), *Land use and the carbon cycle* (pp. 77-91). New York: Cambridge University Press.

Mendoza, G. A., & Martins, H. (2006). Multi-criteria decision analysis in natural resource management : A critical review of methods and new modelling paradigms. *Forest Ecology and Management*, *230*, 1–22. doi:10.1016/j.foreco.2006.03.023

Monticino, M., Acevedo, M., Callicott, B., Cogdill, T., & Lindquist, C. (2007). Coupled human and natural systems: A multi-agent-based approach. *Environmental Modelling and Software*, *22*(5), 656–663. doi:10.1016/j.envsoft.2005.12.017

Morse, J. M. (2000). Determining sample size. *Qualitative Health Research, 10*(1), 3–5. doi:10.1177/104973200129118183

Murray-Rust, D., Robinson, D. T., Guillem, E., Karali, E., & Rounsevell, M. (2014). An open framework for agent based modelling of agricultural land use change. *Environmental Modelling & Software*, *61*, 19–38. doi:10.1016/j.envsoft.2014.06.027

NetLogo 5.0.5 User Manual. (2013, December 19).

Nguyen, T. T., Verdoodt, A., Van Y, T., Delbecque, N., Tran, T. C., & Van Ranst, E. (2015). Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level. *Agriculture, Ecosystems & Environment*, *200*, 1–11. doi:10.1016/j.agee.2014.10.015

Nisar Ahamed, T. R., Gopal Rao, K., & Murthy, J. S. R. (2000). GIS-based fuzzy membership model for crop-land suitability analysis. *Agricultural Systems*, *63*(2), 75–95. doi:10.1016/S0308-521X(99)00036-0

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The Economic Journal*, *101*(407), 920–937.

Parenteau, M.-P., & Sawada, M. C. (2011). The modifiable areal unit problem (MAUP) in the relationship between exposure to NO_2 and respiratory health.*International Journal of Health Geographics*, *10*, 58. http://doi.org/10.1186/1476-072X-10-58

Parker, D. C., Berger, T., Manson, S. M., Mcconnell, W. J., Editor, M., Brown, D. G., … Thompson, R. (2001). Agent-Based Models Of Land-Use and Land-Cover Change Proceedings of an International Workshop (p. 131). California, USA: Center for Spatially Integrated Social Science.

Parker, D. C., Manson, S. M., Janssen, M. a., Hoffmann, M. J., & Deadman, P. (2003). Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. *Annals of the Association of American Geographers*, *93*(2), 314–337. doi:10.1111/1467-8306.9302004

Phua, M. H., & Minowa, M. (2005). A GIS-based multi-criteria decision making approach to forest conservation planning at a landscape scale: A case study in the Kinabalu Area, Sabah, Malaysia. *Landscape and Urban Planning*, *71*(2-4), 207–222. doi:10.1016/j.landurbplan.2004.03.004

Pilehforooshha, P., Karimi, M., & Taleai, M. (2014). A GIS-based agricultural land-use allocation model coupling increase and decrease in land demand. *Agricultural Systems*, *130*, 116–125. doi:10.1016/j.agsy.2014.07.001

Plantinga, A. J. (1996). The effect of agricultural policies on land use and environmental quality. *American Journal of Agricultural Economics*, *78*(4), 1082–1091. doi:10.1016/j.landusepol.2015.05.020

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning - A review. *Renewable and Sustainable Energy Reviews*, *8*(4), 365–381. doi:10.1016/j.rser.2003.12.007

Prakash, T. N. (2003). Land Suitability Analysis for Agricultural Crops : A Fuzzy Multicriteria Decision Making Approach. *Geo-Information Science*.

Pykäläinen,J., Kangas,J., & Loikkanen, T. (1999). Interactive decision analysis in participatory strategic forest planning: experiences fromstate owned boreal forests. J*ournal of Forest Economics 5*(3), 341–364.

Railsback, S. F., & Grimm, V. (2012). Models, agent-based models, and the modelling cycle. In S. F. Railsback, & V. Grimm, *Agent-based and individual-based modelling: A practical introduction* (pp. 3-13). Princeton, New Jersey, The United Kingdon: Princeton University Press.

Railsback, S. F., Lytinen, S. L., & Jackson, S. K. (2006). Agent-based Simulation Platforms: Review and Development Recommendations. *Simulation*, *82*(9), 609–623. doi:10.1177/0037549706073695

Renard, K. G., Foster, G. R., Weesies, G. a., & Porter, J. P. (1991). RUSLE: Revised universal soil loss equation. *Journal of Soil and Water Conservation*, *46*(1), 30–33. Retrieved from http://www.jswconline.org/content/46/1/30.extract

Rindfuss, R. R., Walsh, S. J., Turner, B. L., Fox, J., & Mishra, V. (2004). Developing a science of land change: challenges and methodological issues. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(39), 13976–81. doi:10.1073/pnas.0401545101

Robinson, D. T., Brown, D. G., French, N. H. F., & Reed, B. C. (2013). Linking land use and carbon cycle. In D. G. Brown, D. T. Robinson, N. H. F. French, & B. C. Reed (Eds.), *Land use and the carbon cycle* (pp. 3-23). New York: Cambridge University Press.

Robinson, D. T., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. a., Huigen, M., … Barnaud, C. (2007). Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science*, *2*(1), 31–55. doi:10.1080/17474230701201349

Robinson, D. T., Murray-Rust, D., Karali, E., Rounsevell, M. D. A., Hersperger, A., M., & Guillem, E. E. (2014). Impacts of agricultural land management on human well-being and ecosystem services. Unpublished manuscript.

Rounsevell, M. D. A, Robinson, D. T., & Murray-Rust, D. (2012). From actors to agents in socio-ecological systems models. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *367*(1586), 259–69. doi:10.1098/rstb.2011.0187

Row, C., Kaiser, H. F., & Sessions, J. (1981). Discount Rate for Long-Term Forest Service Investments. *Journal of Forestry*, *79*(6), 367–376.

Saaty, R. W. (1987). The analytic hierarchy process-what it is and how it is used. *Mathematical Modelling*, *9*(3-5), 161–176. doi:10.1016/0270-0255(87)90473-8

Sante-Riveira, I., Crecente-Maseda, R., & Miranda-Barros, D. (2008). GIS-based planning support system for rural land-use allocation. *Computers and Electronics in Agriculture*, *63*(2), 257–273. doi:10.1016/j.compag.2008.03.007

Scholten, H. & Stilwell, J. C. H. (1990, Eds.). Geographical Information Systems and urban and reginal planning, Kluwer, Dordrecht.

Scholz, R.W. (2011). Environmental Literacy in Science and Society: From Knowledge to Decisions. Cambridge University Press, Cambridge, UK.

Seelan, S. K., Laguette, S., Casady, G. M., & Seielstad, G. a. (2003). Remote sensing applications for precision agriculture: A learning community approach. *Remote Sensing of Environment*, *88*(1-2), 157–169. doi:10.1016/j.rse.2003.04.007

Sicat, R. S., Carranza, E. J. M., & Nidumolu, U. B. (2005). Fuzzy modeling of farmers' knowledge for land suitability classification. *Agricultural Systems*, *83*(1), 49–75. doi:10.1016/j.agsy.2004.03.002

Smit, B., Brklacich, M., Steward, R. B., McBride, R., Brown, M., & Bond, D. (1989). Sensitivity of crop yields and land resource potential to climatic change in Ontario, Canada. *Climatic Change*, *14*, 153–174.

Smith P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N. H., Rice, C. W., Robledo Abad, C., Romanovskaya, A., Sperling, F., & Tubiello, F. (2014). Agriculture, Forestry and Other Land Use (AFOLU). In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel & J.C. Minx (Eds.), *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Statistics Canada. (2012). *North Middlesex, Ontario (Code 3539041) and Middlesex, Ontario (Code 3539)* (table).*Census Profile*. 2011 Census. Statistics Canada Catalogue no. 98-316-XWE. Ottawa. Released October 24, 2012. http://www12.statcan.gc.ca/census-recensement/2011/dp-pd/prof/index.cfm?Lang=E (accessed February 4th, 2016).

Statistics Canada. *Table 004-0200 - Census of Agriculture, farms classified by the North American Industry Classification System (NAICS), every 5 years (number), 2011*, CANSIM (database). (accessed: October 6th, 2015)

Statistics Canada. *Table 004-0213 - Census of Agriculture, hay and field crops, every 5 years,* CANSIM (database). (accessed: February 4th, 2016)

Statistics Canada. *Table 004-0234 - Census of Agriculture, farm capital (farm machinery and equipment, livestock and poultry, land and buildings), every 5 years,* CANSIM (database). (accessed: October 6th, 2015)

Statistics Canada. *Table 004-0235 - Census of Agriculture, farm business operating expenses in the year prior to the census, every 5 years (number),* CANSIM (database). (accessed: February 4th, 2016)

Statistics Canada. *Table 004-0237 - Census of Agriculture, total number of farms and farm operators, every 5 years (number),* CANSIM (database). (accessed: October 5th, 2015)

Stewart, T. J., Janssen, R., & Herwijnen, M. Van. (2004). A genetic algorithm approach to multiobjective land use planning. *Computers & Operations Research*, *31*(14), 2293–2313. doi:10.1016/S0305-0548(03)00188-6

Sullivan, D. O., Evans, T., Manson, S., Metcalf, S., Ligmann- Zielinska, A., Bone, C., … Metcalf, S. (2016). Strategic directions for agent-based modeling : avoiding the YAAWN

syndrome. *Journal of Land Use Science*, *11*(2), 177–187. doi:10.1080/1747423X.2015.1030463
Tennakoon, S. B., Murty, V. V. N., & Eiumnoh, a. (1992). Estimation of cropped area and grain yield of rice using remote sensing data. *International Journal of Remote Sensing*, *13*(3), 427–439. doi:10.1080/01431169208904047
Turner, M. G., Neill, R. V. O., Gardner, R. H., & Milne, B. T. (1989). Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology*, *3*(3), 153–162. doi:10.1007/BF00131534
Van der Heijden, K. (1996). *Scenarios: the art of strategic conversion*, Wiley, London
Verburg, P. H., De Koning, G. H. J., Kok, K., Veldkamp, a., & Bouma, J. (1999). A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. *Ecological Modelling*, *116*(1), 45–61. doi:10.1016/S0304-3800(98)00156-2
Vitousek, P. M. (1997). Human Domination of Earth's Ecosystems. *Science*, *277*(5325), 494–499. doi:10.1126/science.277.5325.494
Wang, X., Yu, S., & Huang, G. H. (2004). Land allocation based on integrated GIS-optimization modeling at a watershed level. *Landscape and Urban Planning*, *66*, 61–74. doi:10.1016/S0169-2046(03)00095-1
Wathern, P. (1988). *Environmental Assessment*, Routledge, London
Whittaker, R.H. (1975). *Communities and Ecosystems*. Macmillan, New York, 385 pp.
World Development Indicators. (2015, October 14). Retrieved October 19, 2015, from The World Bank: http://data.worldbank.org/data-catalog/world-development-indicators
Wu, J., A, R. M., & Plantinga, A. J. (2004). Amenities in an Urban Equilibrium Model : Residential Development in Portland, Oregon. *Land Economics*, *80*(1), 19–32.
Ye, Y. (1987). Interior algorithms for linear, quadratic, and linearly constrained non linear programming, PhD Thesis, Department of EES Stanford University, Stanford CA.
Yoder, D. C., Porter, J. P., Laflen, J. M., Simanton, J. R., Renard, K. G., McCool, D. K., Foster, G. R. (1997). Chapter 5. Cover-management factor in predicting soil erosion by water: A guide to conservation planning with the revised universal soil loss equation (RUSLE). In K. G. Renard, G. R. Foster, G. A. Weesies, D. K. McCool, and D.C. Yoder (Eds). *Agriculture Handbook Number 703*, Springfield, VA: United States Department of Agriculture.
Zheng, X, Xia, T, Yang, X, Yuan, T, &Hu, Y. (2013). The Land Gini Coefficient and Its Application for Land Use Structure Analysis in China. *PLoS ONE 8*(10): e76165. doi:10.1371/journal.pone.0076165
Zvoleff, A. (2014). "Land Use in the Chitwan Valley" (Version 1).*CoMSES Computational Model Library*. Retrieved from: https://www.openabm.org/m odel/3640/version/1

Appendix 1

Table A- 1 Aggregated land use type and corresponding categories in Southern Ontario Land Use and Agricultural Resource Inventory (ARI)

Aggregated land use	Land use category ARI
Cropland	CONTINUOUS ROW CROP
	CORN SYSTEM
	EXTENSIVE FIELD VEGETABLES
	GRAIN SYSTEM
Pasture	GRAZING SYSTEM
	HAY SYSTEM
	PASTURE SYSTEM
Woodland	WOODLAND
Other	BUILT UP
	EXTRACTION PITS AND QUARRIES
	EXTRACTION TOPSOIL REMOVAL
	IDLE AGRICULTURAL LAND (5-10 YEARS)
	IDLE AGRICULTURAL LAND (OVER 10 YEARS)
	MARKET GARDENS/TRUCK FARMS
	MIXED SYSTEM
	NURSERY
	ORCHARD
	PASTURED WOODLAND
	RECREATION
	REFORESTATION
	SWAMP, MARSH OR BOG
	TOBACCO SYSTEM
	WATER

Appendix 2

Model Pseudo Code

INITIALIZATION

Import farm and field boundaries, land-use, slope, and soil quality index data
Create farms, fields, and farmer agents and assign values to state variables
Generate preference weights, impact of slope, and tree ages

EACH TIME STEP

Ask each farm:

---Farm Optimization---

Solve the functions of $\frac{\partial \mathrm{U}}{\partial \mathrm{LU}_i} = 0$, $\frac{\partial \mathrm{U}}{\partial \lambda} = 0, \lambda \geq 0$

Obtain expected land-use composition: solve-cropland, solve-pasture, solve-woodland

If solve-woodland >= last-year-woodland, Then expected-woodland = solve-woodland

Else rescale woodland < last-year-woodland

If tree age >= cut age, Then expected-woodland = solve-woodland

If tree age < cut age, Then expected-woodland = last-year-woodland

Rescale expected-cropland and expected-pasture to ensure three expected values sum to 1

---Field location allocation------------------------------------

Ask each field in each farm:

Calculate field utility for each land-use activity:

field-utility-cropland, field-utility-pasture, field-utility-woodland

If (landuse = "WOODLAND" and field-tree-age < tree-cut-age)

Then land use = woodland

Else

If all the land use proportion are available

Then land use = one of the three land use activities with the highest field utility

If one land-use proportion is used up, two land use proportions area available

Then and use = one of the two land use activities with the highest field utility

If two land-use proportion is used up, one land use proportion is available

Then land use = the remaining land use

---Update variables--

Ask farms to calculate total farm utility:

Calculate sum of field utility

Calculate social utility
Total-farm-utility = sum of field utility + social utility

Calculate-farm-composition: cropland-percent, pasture-percent, woodland-percent
Update tree age and biomass density
Update land use view
Apply field land use values to patches
Set patch colors

Plot coverage of land use activities
Plot average farm utility

Appendix 3

Table A- 2 Scores of criteria classes

Category	Criterion	Class	Score	Source
Soil	CLI Soil Capacity Class	1	10	Akinci, Özalp & Turgut (2013)
		2	9	
		3	8	
		4	4	
		5	2	
		6	1	
		7, O, W	0	
	Texture	Loam	10	Ceballos-Silva & López-Blanco (2003)
		Sandy Loam, Silt Loam	8	
		Sandy Clay Loam, Silty Clay Loam	6	
		Clay loam	4	
		Gravelly Loam	2	
		Other	1	
	Drainage	Moderately Well	10	Fecteau (1985)
		Well, Imperfectly	8	
		Rapidly, Poorly	2	
		Very Rapidly, Very Poorly	1	
		Water	0	
Topography	Slope (%)	0-3	10	Ceballos-Silva & López-Blanco (2003)
		3-7	8	
		7-12	6	
		12-15	4	
		>15	1	
	Elevation (m)	0-300	10	Akinci, Özalp & Turgut (2013); Kaspar et al., (2003)
		300-700	9	
		700-1000	8	
		1000-1300	7	
		1300-1700	6	
		1700-2100	4	
		>2100	2	
	Aspect	S, Flat	10	Akinci, Özalp & Turgut (2013)
		SW, SE	8	
		W, E	7	
		NW, NE	5	
		N	2	
Climate (during	Mean Minimum Daily Temperature (℃)	>6.5	10	Ceballos-Silva & López-Blanco (2003)
		5.0-6.5	8	
		3.5-5.0	6	

growing season)		2.0-3.5	4	
		<2.0	2	
	Mean Maximum Daily Temperature (°C)	22-27	10	Ceballos-Silva & López-Blanco (2003)
		20-22	8	
		18-20	6	
		16-18	4	
		<16 or >27	2	
	Mean Total Precipitation (mm)	500-600	10	Fecteau (1985)
		400-500	8	
		300-400	6	
		150-300	4	
		<150, >600	2	
	Total Frost-free days	>120	10	Fecteau (1985)
		100-120	8	
		70-100	6	
		60-70	1	
		<60	0	

Appendix 4

University of Waterloo
December 16, 2015

Dear Resident,

I would like to invite you to participate in a University of Waterloo student research project titled "*Multi-criteria suitability analysis for corn growth in Southern Ontario, Canada*". The project involves identifying areas suitable for growing corn in Southern Ontario. **The project is being led by a Master's student (Li Zhang) in the Department of Geography and Environmental Management at the University of Waterloo under the supervision of Dr. Derek Robinson**. One of the goals of this work is to learn about what factors are important to farmers who grow or have grown corn versus what is reported in scientific articles. Because you are a farm operator in Southern Ontario, your opinions are important to this study and I would appreciate the opportunity to hear from you about this.

If you decide to volunteer, you will be asked to complete a 10-minute survey. The questions are quite straightforward where you only need rank factors affecting corn growth based on your knowledge and experience. Your participation in this study is voluntary. You may decline to answer any questions that you do not wish to answer and you can withdraw your participation at any time by not submitting your responses. There are no known or anticipated risks from participating in this study. All information you provide will be considered confidential and grouped with responses from other participants. Further, you will not be identified by name in my thesis or in any report or publication resulting from this study. Your confidentiality (email, address, and phone number, if provided) will be protected. The data collected through this study will be kept for a minimum of one year after completion of my thesis in my supervisor's lab at the University of Waterloo and then erased or shredded.

If you wish to participate, please fill in the attached survey document and mail it back to us with the self-addressed envelope provided.

Should you have any questions about the study, please contact either Li Zhang at l262zhan@uwaterloo.ca or Dr. Derek T. Robinson at dtrobinson@uwaterloo.ca (Tel: 519-888-4566 Ext.31789). Further, if you would like to receive a copy of the results of this study, please contact either investigator.

I would like to assure you that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about participation is yours. If you have any comments or concerns resulting from your participation in this study, please feel free to contact Dr. Maureen Nummelin in the Office of Research Ethics at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.
Thank you for considering participation in this study.

Consent to Participate:

With full knowledge of all foregoing, I agree, of my own free will, to participate in this study. By signing this consent form, you are not waving your legal rights or releasing the investigators or involved institution from their legal and professional responsibilities.

"I agree to participate." Signature:____

"I do not wish to participate." Signature:______________________________________

Survey Questions

1) Please *rank* the criteria in their order of importance (*1 being most important and 10 being the least important*) in affecting a location's suitability for corn growth. Criteria cannot be ranked equally.

Criteria	**Rank**
Canada Land Inventory (CLI) Soil Capacity Class	
Soil Texture	
Surface Slope (degree)	
Surface Elevation	
Surface Aspect	
Soil Drainage	
Minimum Average Daily Temperature (℃) during growing season	
Maximum Average Daily Temperature (℃) during growing season	
Average Monthly Precipitation during growing season	
Frost-free days	

2) If you would like to be informed about the study results, please leave your email (optional):

____

3) Any comments you would like us to be aware of.

____

____

____

Criteria Definitions

Please refer to these definitions of the criteria and their relevance to suitability for corn growth.

Canada Land Inventory (CLI) Soil Capacity Class: The classes indicate the soil potential and degree of limitation for field crops based on soil characteristics.

Soil Texture: A qualitative classification of soil based on soil physical texture, such as sand, silt, clay. Soil with different portion of sand, silt, and clay tends to have different suitability for crops.

Surface slope: The angle of inclination between the surface normal and a horizontal plane.

Surface Elevation: A location's height above or below the Earth's sea level.

Surface Aspect: The compass direction that a slope faces.

Soil Drainage: The natural or artificial removal of surface and sub-surface water from an area. Many agricultural soils need drainage to improve production or to manage water supplies.

Growing season: May to September for corn.

Frost-free days: The total number of days between the last frost date in the spring and the first frost date in the fall. The length determines the most suitable annuals and vegetables to grow given their days to maturity.