Integrating Soft Computing, Complex Systems methods, and GIS for modeling urban land-use change

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Abstract

The Logic Scoring of Preference (LSP) method is a part of general multicriteria decision making approach that has origins in the soft computing. The method can model simultaneity, replaceability, and a wide range of other aggregators to suit various evaluation objectives. As soft computing method, LSP is based on fuzzy reasoning and can aggregate an unlimited amount of inputs without loss of significance. The main objective of this research is to develop and test integrated methods that use LSP, complex systems theory and geographic information systems (GIS) to model urban land-use change. In this research study LSP is integrated into a GIS to determine land-use suitability and is integrated into both cellular automata (CA) and agent-based models (ABMs) to simulate urban growth at both regional and local spatial scales. LSP approaches were implemented with geospatial datasets for Metro Vancouver, Canada and several scenarios of land-use change have been created.

Keywords: Cellular Automata; Agent Based Modeling; Logic Scoring of Preference; Soft Computing; Geographic Information System; Land-Use Change;

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Chapter 1.

Introduction

1.1. Introduction

Urban land-use change is a dynamic spatio-temporal phenomenon that can be represented as a complex system (Batty, 2008). Complex systems operate using a bottom-up approach, involving the interaction of systems or individuals, to give rise to sophisticated patterns or rather more “complex” structures of components. Complex systems continuously modify their internal structure and through nonlinear processes and interactions, self-organize into several aggregated components, which undergo emergence, and cooperate with one another, allowing for the transition from the disaggregate, individual scale to the aggregate scale (Kwapien and Drozdz, 2012). Complex systems are flexible to perturbations in the system, even if coming from external factors (Morales-Matamoros et al., 2010).

Cities are interconnected to form a complex system of transportation, land use, demographics, and topography that require a sophisticated model framework. Common features shared between cities and complex systems are: adaptation to change, meaning that cities can easily modify their structure in reaction to changes and have adapted themselves to different social and technological innovations, selection, meaning that the trajectories of cities are parallel; cities tend to change in similar ways over time as they adapt to changes, and cooperation: growing globalization has led to connections between foreign cities, and caused cities to act cooperatively with one another (Bretagnolle et al., 2003).

The networking capabilities exhibited within cities illustrate the collective behavior and self-organization properties associated with complex systems. Moreover, similar to complex systems, cities are bottom up, characterized by local complex interactions that through spatial interactions bring about more global, city scale patterns (Albeverio et al., 2010).

Cellular automata (CA) and agent-based models (ABMs) are two types of computational models that are capable of representing complex systems. When linked to a geographic information system (GIS), CA models and ABMs are demonstrated to be useful methods to capture the interactions that occur in cities, and are able to simulate urban growth processes (Batty et al., 1999; Brown et al., 2005).

Beginning in the early 90s, the connection between chaos theory and fractal geometry became well established (White and Engelen, 1993). Geographers began to see this connection in the dynamics of city change and growth (Batty, 2008), due to growth and dynamics having the ability to be characterized as complex systems (Wolfram, 1998). For this reason, cellular automata models quickly transformed into the most widely used urban growth model (Santé et al., 2010). Cellular automata models take initial parameters at a very small, local, and create complex growth patterns at larger scale (Chopard and Droz, 1998).

Cellular automata models consist of a grid of cells with a finite number of states. Cell states in a CA model change due to local neighborhood interactions based upon user defined transition rules (Batty and Xie, 1994). In the literature there exist many developed methods of integrating GIS and CA to simulate different urban growth patterns (White and Engelen, 1993; Clarke et al., 1997; Wu and Webster, 1998; Maithani, 2010, Wagner 1997; Batty et al., 1999). These methods aim to realistically simulate the dynamic growth of urban systems by taking their complexity into consideration.

Linking GIS with CA allows for the development of spatial models over larger scales, such as the San Francisco Bay area (Clarke et al., 1997), at various spatial resolutions from coarse 400m to fine 20m (Dietzel and Clarke, 2004). GIS-CA models often operate on a grid of equal area cells (Itami, 1994). GIS-CA models can look at localized factors (White and Engelen, 1997), as well as broad scale factors such as socio-economic and bio-physical factors (Ward et al., 2000). GIS-CA models can capture the fractal form of urban systems (White and Engelen, 1993). Transition rules in

GIS-CA model can either be static, or dynamic (Deadman et al., 1993). Advanced mathematical operations associated with other modeling methods do not have to be used, and instead the analysis of a much simpler system represented by CA can be performed (Portugali et al., 1994). Another benefit of using CA for simulating urban growth is that CA models can simulate micro and macro phenomena together (De Kok et al., 2001). Moreover, CA models can take local interactions and develop patterns on a more global scale, similar to the type of interactions occurring in cities at an individual, neighborhood level creating city scale patterns. GIS-CA models of urban land use change can also be extended using additional mathematical frameworks, such as geo-algebra (Takeyama and Couclelis, 1997), neutral networks (Li and Yeh, 2002b; Pijanowski et al., 2002), fuzzy logic (Liu and Phinn, 2013; Wu, 1996; Dragicevic, 2004), principal component analysis (Li and Yeh, 2002a), Bayesian Networks (Kocabas and Dragicevic, 2006), multi-criteria evaluation (MCE) techniques with analytical hierarchy processes (Wu and Webster, 1998; Yu et al., 2010) or Markov Chain analysis (Myint and Wang, 2006; Jokar et al., 2013).

A GIS-CA model integrated with MCE methods is capable of developing land suitability maps critical in developing the initial parameters and transition rules for cellular automata models (Wu and Webster, 1998). The goal of MCE methods is to obtain an optimal solution under a set of predefined factors and constraints (Wu and Webster, 1998). MCEs provide tools for analyzing the complex trade-offs between choice alternatives with different environmental and socio-economic impacts (Jankowski, 1995). MCEs do this by combining the information from several input parameters into a single suitability index.

Several research studies have developed approaches that integrate MCE, cellular automata, and GIS in order to provide a more realistic urban growth simulation: one that can be validated with independent datasets with greater quantitative and qualitative success. Applying MCE in a CA model facilitates an alternative approach to capturing behavior when designing CA transition rules (Wu and Webster, 1998). Wu and Webster (1998) integrated MCE and CA to model land-use change in Guangzhou, China. Several factors are combined, such as: distance to major transportation networks, distance to residential housing, among others. Maithani (2010) integrated MCE with CA to reveal the relationships between future urban growth potential and site attributes within the City of Changsha, China. Chen et al. (2010) use multi-criteria suitability evaluation to simulate urban growth in Waterloo, Canada over an extended time period. Yu et al. (2010) use an analytical hierarchy process MCE to assess land-suitability for potential irrigated agriculture in Queensland, Australia.

In the same way that CA modeling dominated the focus in the field of land use modeling in the nineties, agent-based modeling has received attention in the land use and urban growth modeling community in the past decade (Matthews et al., 2007). Agent based models consist of a collection of autonomous decision-making entities, known as agents (Bonabeau 2002). While there is no precise definition of an agent, from a modeling standpoint there are three main features shared by most agents (Castle and Crooks 2006): *autonomy*, wherein agents can exchange information among one another and make independent decisions, *heterogeneity*, and *activity*, meaning that agents can apply independent control in a situation. Other features of agents are that: they are *pro-active* and *goal directed* they are *reactive* and *perceptive*; they are characterized by *bounded rationality*, meaning that agents can have only local access to information and be restricted from accessing global information, and furthermore they are *interactive*, *mobile*, and *adaptive*. The ABM framework focuses on agent behaviors and dynamics. Agents are given a set of rules that guide their actions both within the environment that they are coded and among one another. Similar to CA models, ABMs are often used to simulate how a system evolves over time.

ABMs simulate land-use change through the representation of stakeholders such as residents, city planners, and developers as agents (Li and Liu, 2007; Xiao et al., 2010). The stakeholder agents have their decision-making algorithms based on a multi-criteria evaluation (MCE) approach (Rui and Ban, 2010; Xiao et al., 2010; Li and Liu, 2007), or with fuzzy logic and reasoning often used to evaluate and standardize the variables that agents consider in their decision making (Graniero and Robinson, 2006). ABMs can be linked to real geospatial data to provide simulation outcomes (Jjumba and Dragicevic, 2011).

Several examples in the literature exist of integrating ABMs in a GIS environment while this link and use of real GIS datasets is still challenging. Crooks (2010) used vector GIS to represent not only geographic detail, but also geometric detail (points, lines, shapes). His model involved a geographic region divided into irregular polygons, and several classes of agents representing people of different ethnicities. He had the agents interact with one another and with the urban polygon-based environment in order to simulate residential segregation. Jjumba and Dragicevic (2011) used data at the cadastral level in vector GIS model to simulate land-use change at a high resolution within an ABM framework. The Agent-iCity model incorporated urban planner, housing developer, household, and retail agents to simulate land use change at the cadastral level in neighborhoods of Chilliwack, Canada. It is further characterised by automatic parcel subdivision that enhance modeling process and represent urban planner activities. Robinson et al (2012) simulated the impacts of residential land management on carbon storage through the implementation of four different land-management strategies in an ABM. Each of their four strategies involved different levels of management of residential land parcels. They observed the impact that these four scenarios had on the carbon storage per land parcel.

Several approaches exist that model urban growth using MCEs integrated in both CAs and ABMs. MCEs are based on soft computing principles, wherein the solution to a given problem is characterized by an inexact solution. Soft computing methods (such as MCEs) allow for imprecision, uncertainty, and approximation in their solutions. There are limitations in existing MCEs used in CAs and ABMs, especially pertaining to the representation of human decision-making logic. Alternative MCEs can be used to better represent human decision-making in CAs and ABMs. Experimenting with other methods in realm of soft computing and multi-objective optimization, such as Logic Scoring of Preference (LSP) method, is one way how MCE approach can be enhanced and consequently add value to the complex system modeling.

1.2. Research Problem

Rapid urban growth in cities around the world is transforming both urban and rural environments. Urban growth has detrimental effects on the natural landscape, it takes over current agricultural and farm lands, threatens environmentally sensitive habitats, and socially, economically, and physically affects the humans that cause it (Tong et al., 2012). Urban growth and associated urban sprawl “has been and will continue to be one of the biggest human impacts on the terrestrial environment" (Kaufmann et al., 2007). Continued rise in city populations leads to increasing housing prices that force residents to locate further away from urban centers (Glaeser et al., 2006) causing residents to be pushed further from pre-existing transportation networks resulting in increased commuting times and greater reliance on transportation. As population is growing and people continue to move to urban areas, it is important to gain an insight into the impacts of urban development in order to better manage the land-use change process. Spatio-temporal modeling approaches can be used to forecast the dynamics of urban growth, change in transportation networks, and household mobility. Furthermore, they can be used as decision-making and policy-orientated planning tools to determine what would happen if defined policy choices are made according to assumptions and parameterizations established within spatial models.

CAs and ABMs are two types of spatial models that are capable of simulating the dynamics of urban systems. When linked to a GIS, CAs and ABMs are able to capture the interactions and processes that occur in cities, and are able to simulate urban growth (Batty et al., 1999; Brown et al., 2005). CAs (Wu and Webster, 1998) and ABMs (Li and Liu, 2007) can be integrated with MCE methods to improve analysis and simulation results. However, existing MCE methods that have been used within GIS frameworks have some limitations.

Several fundamental properties of MCE have been identified, including: the ability to combine any number of inputs, the ability to combine objective and subjective inputs, the ability to combine absolute and relative criteria, flexibility of attributes, among others (Dujmovic and De Tre, 2011). All major existing MCE methods such as simple additive scoring, the multiattribute value technique, the multiattribute utility technique, analytic hierarchy process, and ordered weighted averaging are unable to satisfy all the fundamental properties required in multicriteria decision models, including: the ability to combine any number of attributes, the ability to combine objective and subjective inputs, the ability to combine absolute and relative criteria, flexible adjustment of relative importance of attributes, modeling of simultaneity requirements (the ability to express variable degrees of simultaneity when combining inputs), modeling of replaceability requirements (the ability to express variable degrees of replaceability when combining inputs), modeling of balanced simultaneity/replaceability, modeling of mandatory, desired, and optional requirements, modeling of sufficient, desired, and optional requirements, and the ability to express suitability as an aggregate of usefulness and inexpensiveness (Dujmovic and De Tre, 2011). The logic scoring of preference method (LSP) however can satisfy all these properties.

The Logic Scoring of Preference (LSP) is a soft computing based method used for analyzing complex trade-offs between choice alternatives that characterizes a wide range of human decision-making logic. Logical human decision-making follows a series of steps: an objective is defined, a set of variables or factors relevant to the objective are determined, these factors/variable are classified based on their importance, and a decision is made based on the objective and set of factors relevant to that objective. LSP best expresses human reasoning through the use of variable *ANDness* (also known as simultaneity) and *ORness* (also known as replaceability) among inputs, used when combining factors relevant to an objective (Dujmovic et al., 2009). The use of variable ANDness and ORness is similar to approaches used in the ordered weighted averaging (OWA) method. The OWA method allows a decision maker to identify criteria and define the relative importance of criteria by assigning weights. Weighted criteria are then combined using an OWA aggregator, allowing representation of several aggregation operators such as: maximum, arithmetic mean, median, and minimum, and degrees of ANDness and ORness. OWA however, is unable to model mandatory, desired, and optional requirements (Dujmovic and De Tre, 2011), a key fundamental property of any multicriteria decision-making (MCDM) approach. When combining inputs together in the LSP based MCE approach, each input has some degree of suitability. Additionally, the output of the combination of a set of inputs also has some degree of suitability, reflecting the suitability of each of the individual inputs under combination. Unique to the LSP-MCE, a continuous degree of *simultaneity* or *replaceability* is applied when combining inputs: reflecting whether or not the inputs under combination must all be satisfied to have a high output suitability (*simultaneity*), or whether or not the satisfaction of one or more inputs cat negate the necessity for other inputs to be satisfied (*replaceability*). LSP also allows for the inclusion of a large number of inputs without loss of significance on any one input; a feature missing in currently used MCE approaches.

LSP provides an alternative to existing MCE approaches for combining relevant factors pertaining to a particular objective, such as combining factors pertinent to land-use change to evaluate residential land-use suitability, as is performed in this thesis. Implementing LSP allows users to produce models that generate reliable results in relation to the inputs, logic aggregators, and weights of relative importance chosen. The step-wise logic aggregation structure of LSP also allows for extreme flexibility through its use of continuous logic, represented in terms of simultaneity and replaceability (Dujmovic et al., 2010). Its use of continuous logic also allows the LSP to better represent human decision-making logic when compared to other MCE approaches.

Due to its ability to overcome two main shortcomings of other MCEs: the inclusion of a large number of inputs without loss of significance, and the inclusion of continuous decision making logic, this research study explores the use of the LSP approach within three settings. The first involves using real geospatial data within a GIS in determining land-use suitability, the second uses LSP within a CA model to simulate land-use change, and the third implements LSP as a method for determining agent decision-making logic within an ABM. The following questions are the main drivers of this thesis:

1. Can LSP method be integrated into GIS and with the use of rea geospatial dataset?
2. What are the possible results when implementing LSP into a GIS-based CA model?
3. Can the logic framework be set out so that the LSP method can useable in the framework of an ABM and for agent's decision-making reasoning?

1.3. Research Objectives

In order to address the research questions, the main goal of this thesis research is to develop and implement an urban residential land-use change model that integrates the LSP method into both a CA model and an ABM. As a soft computing method, LSP has significant observable advantages over other spatial optimization methods (Dujmovic and De Tre, 2011). For this reason, it will be used within the existing model types (CA and ABM), each linked to real geospatial data through the use of a GIS. The main objectives of this research are as follows:

1. To integrate LSP method into a GIS with the use of real geospatial datasets to evaluate residential land-use suitability across a regional urban environment;
2. Development of the LSP-CA model integrated with GIS to simulate land-use change using geospatial datasets for a regional urban environment;
3. Development of a LSP-ABM to simulate residential land-use change at a cadastral level of a local urban neighbourhood where agents' behaviour and decision-making is modeled with LSP-based reasoning and with the use of GIS and geospatial datasets.

Existing research studies have implemented the LSP approach to determine land-use suitability and to simulate land-use change within a CA model (Minardi, 2012) or used LSP method within hypothetical data (Dujmovic et al., 2008) to prove the theoretical concepts of integration of soft computing. This thesis extends these research efforts by considering much larger urban environments, using real geospatial datasets, integrating far more factors into multiple LSP approaches, and rigorously calibrating and performing sensitivity analysis on the LSP approach. Additionally, the use of the LSP approach in an ABM improves on existing research efforts by improving the representation of human-decision making in the algorithms used for the decision-making of stakeholder agents.

1.4. Study Sites

Geospatial data for the region of Metro Vancouver, British Columbia, Canada was used (Figure 1-1). For Chapters two and three, raster-based GIS data sets covering the entire extent of Metro Vancouver were used for developing LSP aggregation structures and suitability maps. Metro Vancouver was used due to its size: one of the goals of the thesis is to use LSP to evaluate land-use suitability in a regional urban environment. Additionally, Metro Vancouver has demonstrated recent dynamics of urban and residential housing expansion at the rural-urban fringe.

Chapter four uses vector-based data over a smaller spatial extent for implementing an LSP-ABM model. The LSP-ABM model is the implemented on the datasets for Clayton-Cloverdale neighborhood of Surrey, BC, Canada, a municipality within Metro Vancouver. Clayton-Cloverdale was used for three reasons. The first reason is due to the availability of large and detailed geospatial datasets provided by the City of Surrey, BC. Additionally, the City of Surrey, BC, is one of the fastest growing cities in Canada (Statistics Canada, 2011) and more particularly the dynamics of development of Clayton-Cloverdale, characterized by rapid, planned expansion made it an adequate study site for this research. Finally, Clayton-Cloverdale has a strong vision for community design, with an extensive neighbourhood concept plan (Condon and Johnstone, 2003), allowing model verification and comparison to the existing neighbourhood plans.

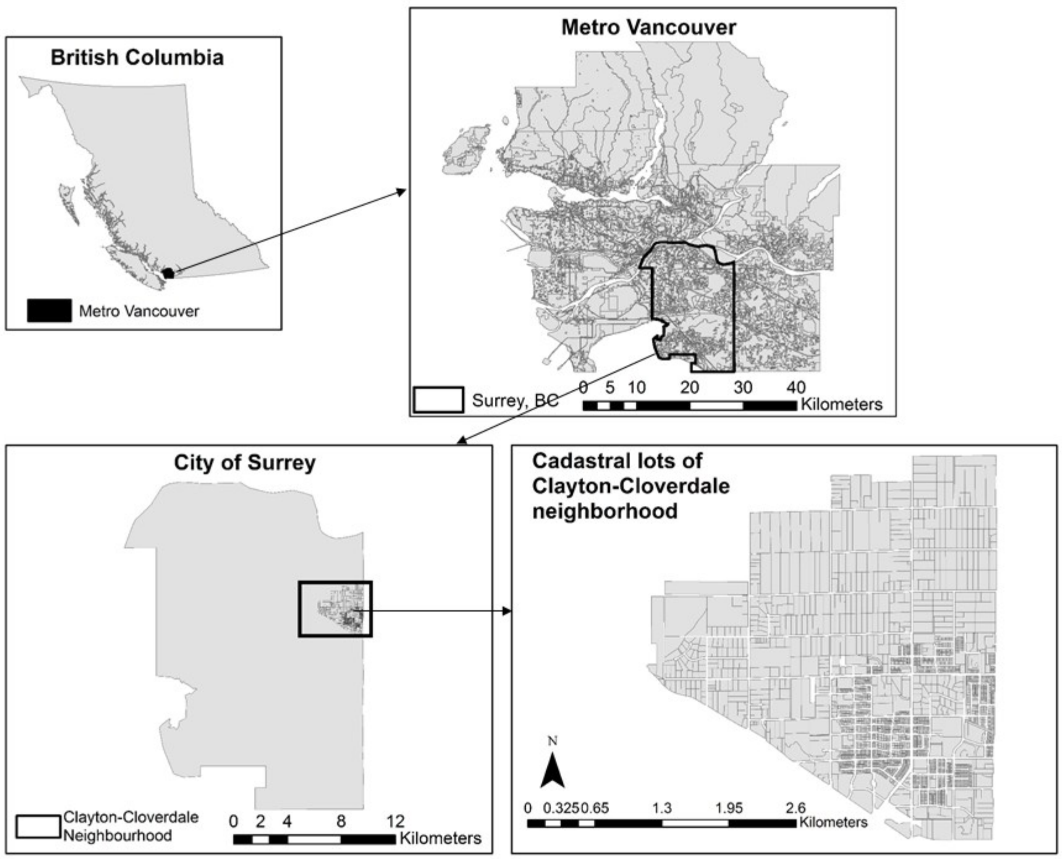

Figure 1-1. Study areas: Metro Vancouver, and the Clayton-Cloverdale neighborhood in the City of Surrey, British Columbia, Canada

1.5. Thesis Overview

This thesis contains five chapters. Following the Introduction, Chapter two explains the development of the LSP method for determining suitable locations for urban residential land-use change. LSP is integrated into a GIS and applied to real geospatial data covering the area of Metro Vancouver, Canada. Three scenarios were developed and tested on Metro Vancouver. The study site was divided into 20 metre spatial resolution, with a suitability assigned to each cell within the study site. Suitability for residential land-use change was evaluated based upon logic conditions and input aggregations established in each of the LSP aggregation structures for the three scenarios. Elementary criteria were established, standardized, assigned logic parameters of mandatory or optional, and categorized based on input type. Criteria were then combined within LSP attribute trees, and LSP aggregators for the combination of inputs were chosen in order to develop LSP aggregation structures. Outputs were represented as raster suitability maps, with values between zero: representing completely unsuitable locations for residential land-use change, and one: representing completely suitable locations for residential land-use change. Output maps for each of the scenarios were compared. The purpose of this section is to test and develop LSP aggregation structures, and also provide potential sites for residential land-use change based upon spatially referenced suitability values.

In Chapter three, the LSP method has been integrated into a GIS-based CA model of regional urban growth. LSP was used alongside neighborhood and transition rules established in a CA model, with output LSP suitability maps integrated with land-use change maps in a CA model to determine new areas of residential growth. CA models were calibrated by adjusting various internal aspects to produce simulations that best replicate the actual dynamics of residential land-use change in the chosen study site, performed by comparing simulation results with existing land-use datasets. Several output land-use maps were produced that provide simulation scenarios for residential land-use change in Metro Vancouver, Canada. Chapters two and three use the IDRISI GIS software (Eastman, 2012) to operationalize the LSP land-use suitability maps and create CA model outcomes.

Chapter four presents the development of an agent based model integrated with the LSP method used to simulate residential land-use change dynamics at the very local neighbourhood scale. The model was developed using geospatial data from the Clayton-Cloverdale neighbourhood in the City of Surrey, BC, Canada. Individual agents representing residents and developers are the main components of the model. These agents interact amongst one another based on a defined set of rules to simulate the residential landscape of the study area on a cadastral scale. Resident agents' decision making approach is based on the LSP method, with each individual agent having their own unique way of aggregating inputs. Four scenarios were developed, with output simulations displayed through the use of vector GIS. For the implementation of the LSP-ABM approach the REPAST (North et al., 2013), a Java-based integrated development environment (IDE) software were linked with GIS using ArcGIS 10 (ESRI, 2011) to provide the model simulation outputs. This thesis concludes with Chapter five that presents the overall conclusion of the thesis research, summarizing the obtained results, as well as limitations and possible future directions of the research.

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Chapter 2.

Logic Scoring of Preference and Spatial MultiCriteria Evaluation for Urban Residential Land Use Analysis

2.1. Abstract

The Logic Scoring of Preference (LSP) method is a general multicriteria decision-making approach with origins in the soft computing discipline. The method can model simultaneity, replaceability and a range of other aggregators to match various evaluation objectives. It allows the aggregation of a large number of data inputs without loss of significance as for some other commonly used GIS-based MCE methods. Moreover the LSP method uses fuzzy reasoning for the decision making process. The objective of this study is to design and test an integrated method that incorporates the LSP with GIS for the multicriteria evaluation (MCE) of land suitability applied to new urban residential development in the Metro Vancouver region, British Columbia, Canada. Several factors influencing land use change were selected to construct the aggregation structure for the LSP-GIS model and implemented for decision-making purposes. The results indicate the LSP method provides more fine scale choices for multicriteria evaluation of urban land suitability. Consequently, planners and decision-makers can encode a wider variety of planning perspectives and obtain a larger variety of feasible output parcels for use in the planning process.

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2.2. Introduction

Urban growth and associated urban sprawl has been and will continue to be one of the largest sources of human impact on the terrestrial environment (Kaufmann et al., 2007). Continued rise in city populations leads to elevated housing prices that force residents to locate further away from urban centers (Glaeser et al., 2006) and further from pre-existing urban transportation network, which in turn leads to increased commuting times and greater reliance on automobiles making humans an ever increasing environmental threat (Glaeser and Kahn, 2004). As a result of the harmful consequences associated with urban growth and subsequent sprawl, policies must be formulated to understand and provide improved urban growth forecasting in order to better manage urban sprawl. Spatial decision-making and land-use suitability analysis is one way to identify the most appropriate spatial patterns for future land uses based on a set of preferences and requirements (Malczewski, 2004). Multicriteria evaluation (MCE) methods, a specific type of spatial decision support systems (SDSSs), provide complex trade-off analysis between choice alternatives with different environmental and socio-economic factors (Carver, 1991). In terms of land-use change, MCE has been used to investigate various applications related to land suitability (Voogd, 1983). MCE methods are often used for spatial optimization, and can be linked with GIS and used within a spatial decision support system (SDSS). They are tools designed for decision makers to explore, structure, and solve complex spatial problems (Densham, 1991). The goal of optimization is to obtain an optimal solution under a set of predefined factors and constraints for analyzing the complex trade-offs between choice alternatives with different environmental and socio-economic impacts (Carver, 1991). This is accomplished by combining the information from several input parameters into a single suitability index. Spatial optimization models benefit greatly from the addition of MCE analysis due to site-specific evaluation inquiries that need to be undertaken.

Spatial MCE methods are structured using approaches such as the analytic hierarchy process (AHP), simple additive scoring (SAS), multiattribute value technique (MAVT), multiattribute utility technique (MAUT), ordered weighted averaging (OWA), and outranking methods. All MCE methods model human decision-making logic to analyze the complex trade-offs between choice alternatives. However, they have been criticized for producing an oversimplification of reality that is complex (Dujmovic et al., 2009; Malczewski, 2006). These claims are based on the fact that existing ordinary ranking methods commonly used in GIS-based MCE do not adequately represent human decision making logic or observing properties of human reasoning (Dujmovic et al., 2009). The Logic Scoring of Preference (LSP) is a method of analyzing complex trade-offs between choice alternatives that characterizes a wide range of human decision-making logic. In addition to weights of preference, LSP works with aggregators representing a spectrum of conditions ranging from conjunction to disjunction (simultaneity to replaceability) (Dujmovic et al., 2009).

The specific objective of this study is to integrate the LSP into a GIS-based urban spatial multicriteria evaluation method in order to evaluate locations for residential growth given a large set of choice alternatives. The LSP method was used in three scenarios developed in a raster GIS environment. This LSP-GIS integrated model will determine transition potentials for spatial locations for residential land use based upon the combination of factors pertinent to land-use change.

2.3. Theoretical Background

The Logic Scoring of Preference method (LSP) follows an aggregation structure where data inputs are represented on a standardized scale and organized into relevant attributes (Dujmovic et al., 2008). Inputs are grouped categorically, and arranged on a LSP attribute tree. They are then combined through the use of several LSP aggregators, which represent a spectrum of conditions ranging from simultaneity (*ANDness*) to replaceability (*ORness*). The LSP aggregators form the LSP aggregation structure (Dujmovic et al., 2009). LSP generates reliable results in relation to the inputs and parameters for chosen aggregation. Two features that make the LSP method unique and more effective than other MCE methods are: (i) the use of the step-wise logic aggregation structure which allows for flexibility through its use of continuous logic represented in terms of simultaneity and replaceability (Dujmovic et al., 2010), and (ii) the ability to include a large number of inputs into an LSP aggregation structure without loss of significance for any individual input due to the type of logic expressions used in the LSP method.

The LSP was first theorized and developed for applications in computer science, such as windowed environment software evaluation (Dujmovic and Bayucan, 1997), evaluation of Java integrated development environments (IDE's) (Dujmovic and Nagashima, 2006), comparison of search engines (Dujmovic and Bai, 2006), as well as other multi-criteria evaluation approaches. Recently, the LSP has been linked with spatial data and GIS, and the multicriteria evaluation method has been used for solving problems in the field of spatial science. Dujmovic et al. (2010) proposed the concept of LSP aggregated geographic suitability maps which represent a continuous degree of suitability with respect to a particular purpose or objective. The main goal of these suitability maps, or S-maps, is to provide a suitability degree for a geographic region for purposes such as: suitability for industrial development, agriculture, housing, education, and recreation (Dujmovic et al., 2008). In particular, the LSP approach was used to determine suitability for residential land use change (Dujmovic and De Tre, 2011) where various criteria for residents to move into homes were analyzed, with the LSP method used to aggregate the criteria and determine spatially optimal house locations. The LSP method is implemented in three stages as follows: (1) Input Criteria, (2) LSP attribute tree, and (3) LSP aggregation structure.

2.3.1. Input Criteria

The use of the LSP as a general multicriteria evaluation method necessitates the choices of criteria relevant to the desired purpose or objective, and with the elected input criteria grouped into relevant categories. Since the combination of inputs is based on a comparison of their simultaneity or replaceability, similar attributes are grouped so that they are combined together first in the LSP aggregation structure. Once input criteria are chosen, they must be expressed as either *mandatory*, meaning the input must be satisfied, or *optional*, meaning it does not have to be satisfied.

2.3.2. LSP Attribute Tree

Once relevant input criteria are chosen, grouped categorically, and expressed as either mandatory or optional, the construction of the LSP attribute tree can begin. The LSP attribute tree organizes the decision problem and contains all relevant attributes and parameters. Inputs are on the leaves of the tree, and combined together using the

LSP aggregators until one overall output is obtained. Prior to inputs being combined, they are transformed from their existing units onto a standardized unitless scale. This is achieved using fuzzy transformation functions. Numeric values in the outputs of these functions represent logic conditions that reflect the objective of the study.

2.3.3. LSP aggregation structure

Within the LSP attribute tree are individual LSP aggregators, used to describe the parameterization and step-wise combination of inputs based on logical requirements and weighting parameters (Dujmovic and Scheer, 2010). LSP aggregators express the combination of mandatory, (+), and optional, (-) input criteria. Each LSP aggregator expresses the combination of input parameters on a spectrum of *ANDness* and *ORness*, conditions ranging from full conjunction, C, to full disjunction, D. Table 2-1 depicts different levels of *ANDness* and *ORness*, also known as *simultaneity* and *replaceability* respectively. Each LSP aggregator has an associated *r* value, used in mathematical functions expressing the combination of inputs through the use of a single LSP aggregator.

Table 2-1. LSP aggregators representing simultaneity and replaceability

Simultaneity

Symbol	C	C++	C+	C+-	CA	C-+	C-	C–	A
r	$-\infty$	-9.06	-3.51	-1.655	-0.72	-0.148	0.261	0.619	1.0

Replaceability

Symbol	D	D++	D+	D+-	DA	D-+	D-	D–	A
r	∞	20.63	9.521	5.802	3.929	2.792	2.018	1.449	1.0

Each LSP aggregator used reflects the degree of simultaneity, neutrality, or replacability desired to be expressed between the inputs considered. The further along the spectrum from neutral (A) to full conjunction (C) (Table 2-1) the aggregator used is, the stronger and more restrictive the degree of simultaneity is. The further in the other direction, from neutral (A) to full disjunction (D), the stronger is the replaceability among inputs. Neutral (A) is used to express neither simultaneity nor replaceability. LSP aggregators can be grouped into one of seven aggregator types (Dujmovic and De Tre, 2011). These include: Full Conjunction (LSP aggregator C in Table 2-1), Hard Partial Conjunction (using aggregators such as C++, C+, C+-), Soft Partial Conjunction(C-, C–), Neutrality (A), Soft Partial Disjunction (D–, D-, D-+, DA), Hard Partial Disjunction (DA, D+-, D+, D++) and Full Disjunction (D). Choosing the LSP aggregator is determined by the desired level of simultaneity or replaceability between inputs that the decision maker wants to express. A Hard Partial Conjunction (HPC) operator is used to express the combination of mandatory inputs, whereas a Soft Partial Conjunction operator is less restrictive, and is appropriate for the combination of optional inputs. The analogue is true for Hard Partial Disjunction and Soft Partial Disjunction operators.

When combining two or more mandatory inputs, or two or more optional inputs, each of the LSP aggregators combines the inputs using a *generalized conjunction disjunction* (GCD) function described in (Dujmovic et al., 2009), and shown in (1). However, the combination of mandatory with optional inputs requires using the conjunction partial absorption (CPA) function, which uses a different mathematical function described in (Dujmovic, 1979), and shown in (2). Given a set of input parameters $X_1,\ldots,X_n$, the generalized conjunction disjunction is computed using the weighted power mean:

$$GCD(X_1,\ldots,X_n) = [W_1 X_1^r + \ldots + W_n X_n^r]^{1/r} \qquad (1)$$

where $GCD(X_1,...,X_n)$ is the output suitability from the combination of input parameters, $X_1,...,X_n$. $W_1,...,W_n$ are used to express the relative weights of preference (where inputs deemed more significant to the overall output are assigned higher weights of preference) on inputs $X_1,...,X_n$, and r is used to express the degree of simultaneity and replaceability among the inputs $X_1,...,X_n$.

Given a mandatory input x, and an optional input y, there are two different variants for the CPA function:

$$CPA(X,Y) = \{(1-a)[bx^{r_1} + (1-b)y^{r_1}]^{r_2/r_1} + ax^{r_2}\}^{1/r_2} \qquad (2)$$

$$\begin{aligned}&\text{Where either } r_1 < 1, r2 \geq 1, \text{or } r1 \geq 1, r2 < 1, \text{ and}\\ &\quad a = W_1, b = W_2 \text{for } r_1 < 1, r2 \geq 1, \text{ (CD-variant)},\\ &\quad a = W_2, b = W_1 \text{for } r_1 \geq 1, r2 < 1, \text{ (DC-variant)}.\end{aligned}$$

The CPA aggregation scheme operates so that the optional input(s) penalize the overall output value from the combination of mandatory and optional inputs. In other words, given a non-zero mandatory input(s) value(s) (as a zero value will lead to a zero value after the combination of mandatory and optional inputs), the lower the value(s) of the optional input(s), the greater the penalty applied to the output value after the combination of the mandatory and optional inputs. However if the optional input(s) value(s) are a maximum (such as Y=1 in the case of this model), then a reward is applied. Full information on penalty and rewards with respect to the CPA aggregator can be seen in (Dujmovic, 1979).

2.3.4. Linking LSP and GIS

Spatially referenced raster data is one source of inputs in the LSP method. Fuzzy suitability functions can be generated in the GIS database to standardize the inputs. These fuzzy functions take inputs in their original units and transform them onto the same standardized scale such as the unit interval. Often this standardized scale is representative of a suitability index, where spatial locations with higher values on the standardized scale have greater suitability with respect to the desired objective. Inputs, intermediate results, and outputs can be represented as spatial maps depicting a continuous surface of values across an entire study site under question. The LSP-GIS approach can be linked with a spatial decision support system, and can therefore assist in providing more effective solutions to planning and decision-making problems.

2.4. LSP-GIS Method for Urban Residential Land Suitability

In this study the LSP-GIS method was used to determine spatially optimal locations for urban residential growth across the regional district of Metro Vancouver Canada (Figure 2-1). Input criteria consisted of selected factors and data that influence residential growth, with three types of LSP aggregators used for the analysis: neutrality

(A), weak partial conjunction (C– and C+), strong partial conjunction (CA and C+). Three realistic and practical scenarios were developed, each of which represent models of strong simultaneity, meaning that when combining inputs, all the inputs must have high degrees of satisfaction (indicating high values in their suitability maps) in order to have a high output value.

2.4.1. Study Area and Data

The LSP-GIS method was implemented using the following datasets for year 2006: (i) 20 meter resolution digital elevation model (DEM), (ii) transportation networks (bus, light rail, and roads), (iii) land-use data (Figure 2-1), and (iv) Canada Census data. Both the ESRI ArcGIS and the IDRISI Selva GIS software were used to implement the LSP-GIS method.

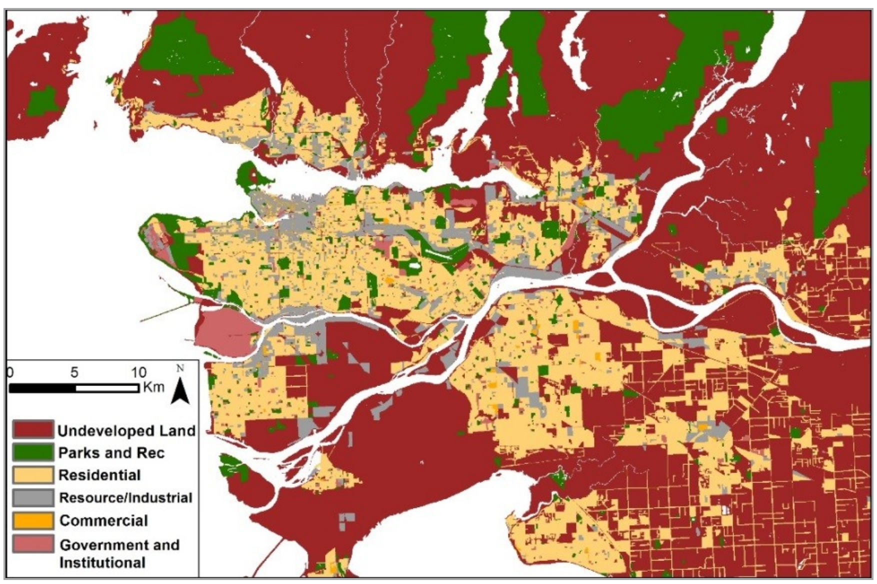

Figure. 2-1. Land-use map for Metro Vancouver Metropolitan Area for 2001.

Three scenarios were designed to best represent the various situations for possible urban residential growth. Scenario 1 is designed with the intended goal of determining suitable locations for suburban development. Density near downtown Vancouver is high. Additionally, housing prices in downtown Vancouver and closer to it are very high and unaffordable, making it important to develop the rural-urban fringe which is the furthest suburbs from downtown Vancouver. Scenario 2 has its focus on family-oriented growth while Scenario 3 was taking in consideration the importance of the transportation network. The geography is a limiting factor in the Metro Vancouver region with the many rivers, bridges and elevation differences making travel time to work and back long. Many residents do not live in close proximity to their workplace especially those living in the suburban areas, far from the central business district and far from efficient public transportation. For these reasons the three scenarios were designed to place greater emphasis on certain categories of importance for residential urban development.

2.4.2. Elementary Criteria Definition

For the purpose of illustrating the elementary criteria definition, Scenario 1 is used as an example. The input data contained 19 datasets standardized using the functions as presented in Figure 2-2, evaluated using the logic requirement of mandatory (+) or optional (-), and grouped into four categories (Table 2-2). Inputs were transformed from their original units into a standard continuous scale representing suitability using fuzzy suitability functions. Fuzzy suitability function shape was determined based on the value of suitability desired to be expressed at particular values for an individual input. For example, any location less than 200 meters from a park is deemed perfectly suitable for this study site and assigned a value of 1 in the fuzzy suitability function for the "distance to parks" input. Additionally, function shapes are based on techniques used in previous studies (Dujmovic et al., 2009). Suitability values range from 0 to 1 where 0 represent a completely unsuitable area and 1 represent a completely suitable area, and the intermediate values are dependent on the shape of the fuzzy functions. Figure 2-2 represents the complete list of fuzzy suitability functions used to transform the input datasets for all three scenarios based on the following categories:

Terrain and Environment: Slopes from 0 to 30 degrees are considered suitabile. From 30 to 40 degrees there is decreasing suitability, and a slope beyond 40 degrees is considered completely unsuitable. South facing homes, with aspect values between 135 and 225 degrees are most suitable, due to sunlight exposure. Elevation decreases in suitability from sea level (less than 50 metres) to 1000 metres, beyond which the elevation is completely unsuitable.

Amenities: For each of the amenities, locations in closer proximity are considered more suitable: suitabilities decrease as distance increases, based on driving or walking times. Some amenities penalize (have a lower suitability) if the distance is too small.

Accessibility: Similar to amenities, closer proximity to transportation (roads, bus, light rail, airport) is most suitable, unless the proximity is too close in which case is it considered unsuitable due to noise.

Population: The three distance criteria all favor close proximity locations. Growing communities (larger population growth) are more suitable, and communites with lower median incomes (hence more affordable homes) are more suitable.

The Scenario 2 uses the same set of elementary criteria and transformation functions as Scenario 1, but with the logic requirements different for some of the input criteria. Scenario 3 uses a subset of 10 of the 19 inputs used for Scenario 1, with the same transformation functions but different logic requirements. Criteria were chosen based on previous MCE/LSP studies (Dujmovic et al., 2009), as well as based on the desired objective of a scenario. After criteria were determined, then four natural groups for the criteria were developed (terrain and environment, amenities, accessibility, population). Only four criteria groups were developed to make the LSP attribute trees and aggregation structures more computationally simplistic and easier to follow for the user/decision-maker.

Table 2-2. Elementary criteria for Scenario 1

Terrain and Environment	Amenities	Accessibility	Population
(+) Slope	(-) Distance to beach	(+) Distance to major roads	(+) Distance to residential housing
(+) Aspect	(-) Distance to coast	(-) Distance to bus lines	(+) Distance to low density areas
(-) Elevation	(-) Distance to parks	(-) Distance to light rail	(+) Distance to family areas
	(-) Distance to shopping	(-) Distance to airport	(-) Population growth
	(-) Distance to care facilities	(-) Amount of sustainable transport	(-) Median income
	(+) Distance to schools		

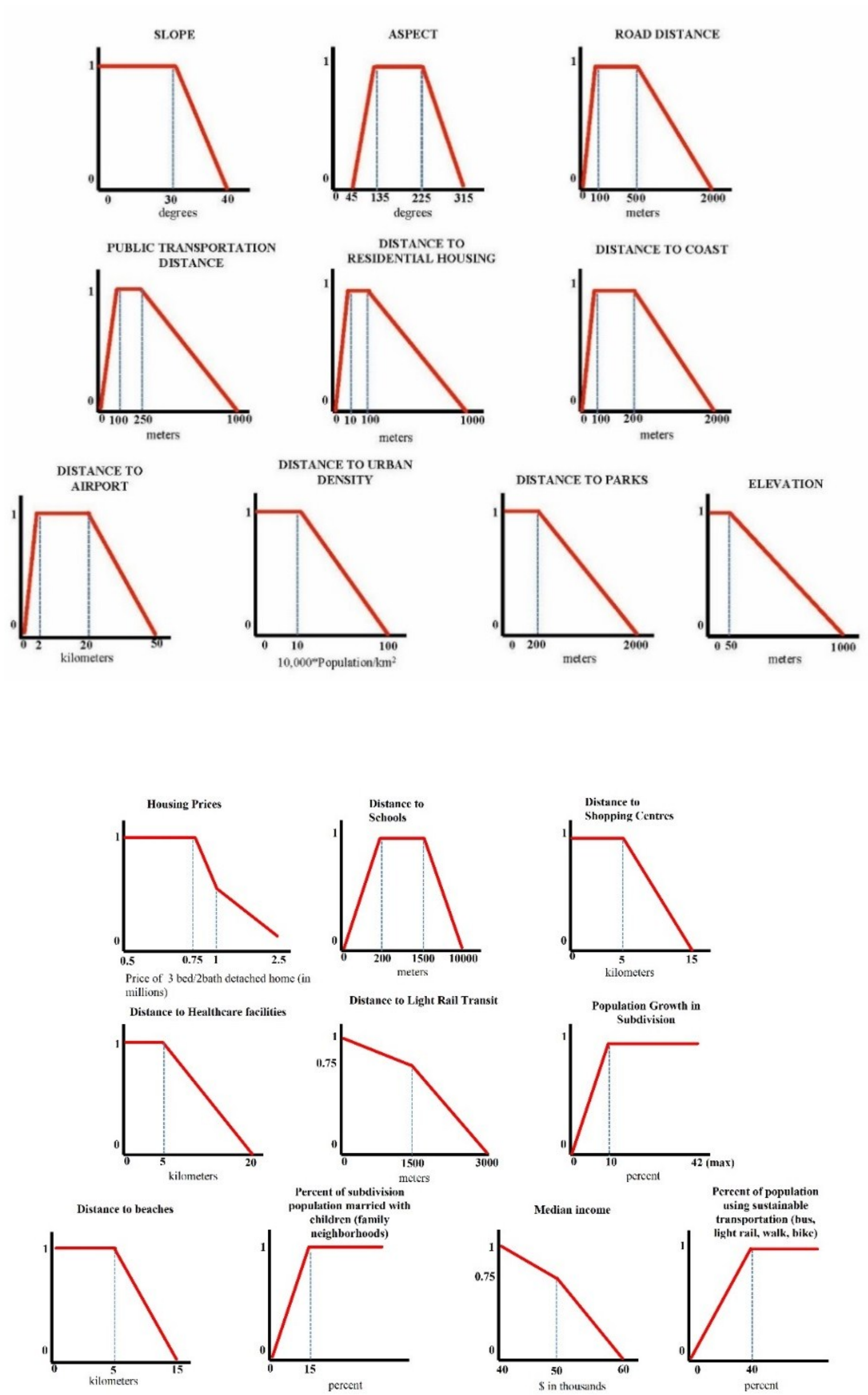

Figure. 2-2. Elementary criteria transformation functions for all three scenarios.

2.4.3. LSP Aggregation Structure

In this study, three types of LSP aggregators were used to combine the inputs: neutrality (A), weak partial conjunction (C- and C-+), and strong partial conjunction (CA and C+). The weighted power mean (WPM) (Dujmovic et al., 2010) was used when combining mandatory inputs together or optional inputs together:

$$S(X,Y) = [(W_u(X))^r + (W_p(Y))^r]^{1/r} \qquad (3)$$

where *S(X,Y)* is the output suitability map, and *Wu* and *Wp* are the relative weights of preference on inputs *X* and *Y* respectively. For combining both mandatory and optional inputs together, the conjunction partial absorption (CPA) formula is used:

$$S(X,Y) = [(1-W_1)[W_1X^{r_1} + (1-W_1)Y^{r_1}]^{r_2/r_1} + W_2X^{r_2}]^{1/r_2} \qquad (4)$$

where *X* is the mandatory input with weight W_1, and *Y* is the optional input with weight W_2.

The suitability maps created from fuzzy linear functions applied to the input datasets form the input criteria for the LSP aggregation structure enabled in the GIS software. The weighted power mean and CPA functions were used to manipulate the suitability maps and create the aggregation for each scenario. Map algebra tools enabled n the implementation of WPM and CPA functions in the GIS software.

A framework for the choice of aggregators for combining inputs was determined. The combination of optional and mandatory inputs together necessitates the choice of two aggregators (Figure 2-3). The first aggregator, r_1 is always the neutrality aggregator, A, such that the CD-variant of the CPA formula (2) can be used. As required by the CD-variant, the second aggregator r_2 is always strictly a weak or strong partial conjunction aggregator. The satisfaction of a mandatory input is required, meaning that in its fuzzy suitability map it must have a value greater than 0. While an optional input does not need to be satisfied, a higher the value in the fuzzy suitability map (closer to 1) gives a reward to the overall output (higher suitability values in the output map).

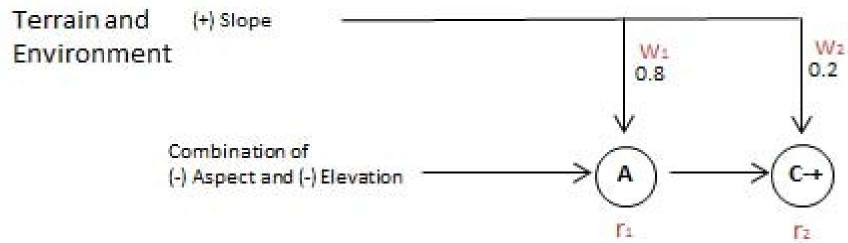

Figure 2-3. Example from LSP aggregation structure of Scenario 1: the combination of a mandatory (Slope) with optional (Aspect and Elevation) inputs.

Both scenarios 1 and 2 operate on two similar aggregation structures (Figure 2-4 and 2-5), with greater influence placed on inputs in the amenities and accessibility categories. The inclusion of many inputs in Scenarios 1 and 2 demonstrate one of the main benefits of the LSP method to be implemented: the inclusion of many inputs without loss of importance. Scenario 3 (Figure 2-6) is focused on the proximity of the transportation network. Within any of the aggregation structures for scenarios 1, 2, or 3 (Figures 2-4, 2-5, 2-6), inputs are combined in a single aggregator (moving left to right in the aggregation structure), the level of *simultaneity* increases, and aggregators with stronger partial conjunction (CA, C+-, etc.) are used. This type of aggregation structure is known as a *conjunctive canonical aggregation structure with increasing ANDness* (Dujmovic and De Tre, 2011), and is most appropriate for logic aggregation of suitability maps. Therefore, as can be seen in Figures 2-4, 2-5, and 2-6, within any individual category (ex. amenities), the LSP aggregators used are either *neutrality* (A), or a weak partial conjunction (C–, C-, C-+), and as inputs from multiple categories are combined (moving further to the right in the aggregation structure), the LSP aggregators used have stronger partial conjunction (CA, C+-, C+). Weights used when combining inputs were determined based on weighting schemes used in previous MCE/LSP studies (Dujmovic et al., 2009), as well as based on the user's desired level of influence for each input on the global suitability for each scenario, and local suitability: when an input is combined with other inputs within the aggregation structure.

Figure 2-4. LSP Aggregation Structure for Scenario 1

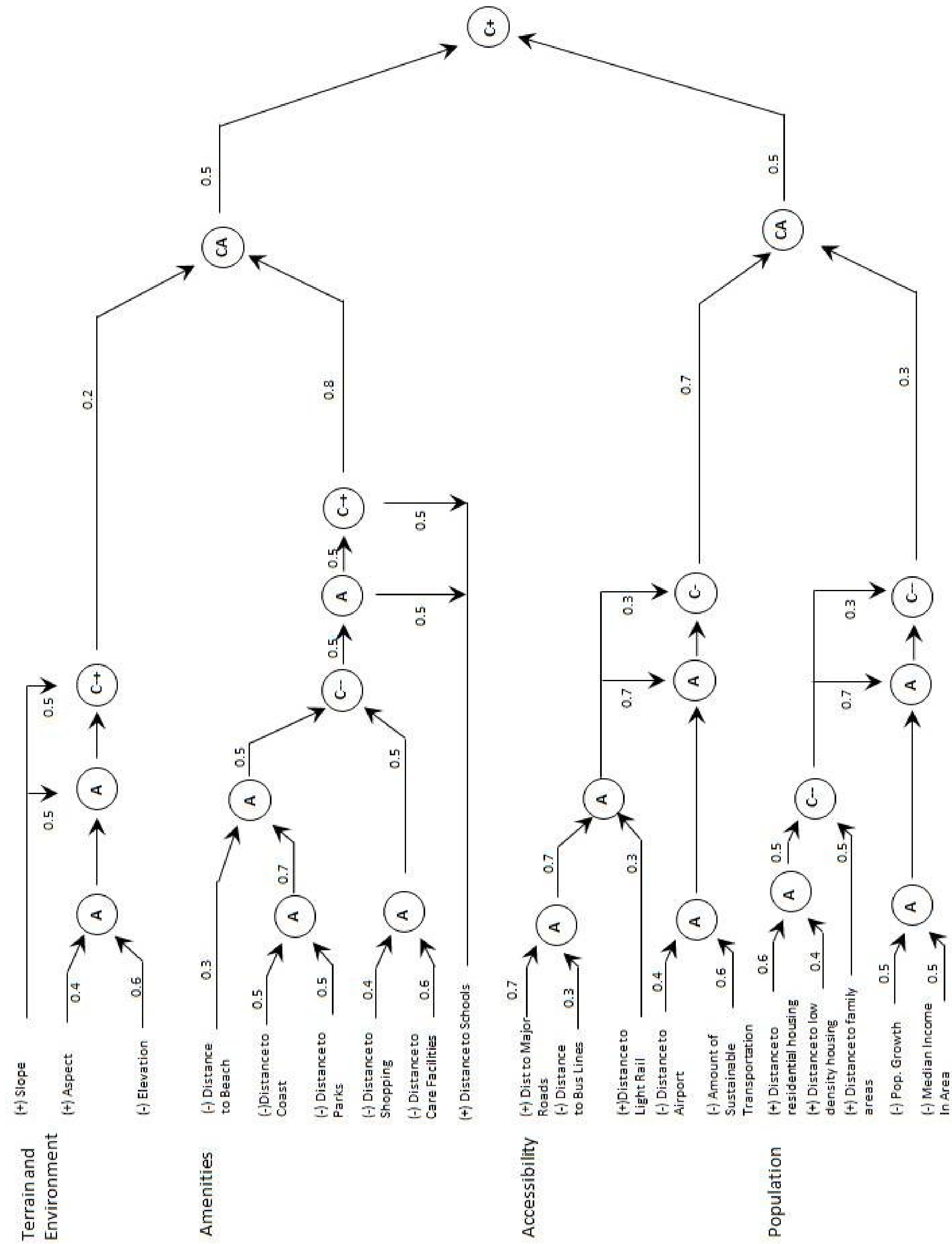

Figure 2-5. LSP Aggregation Structure for Scenario 2

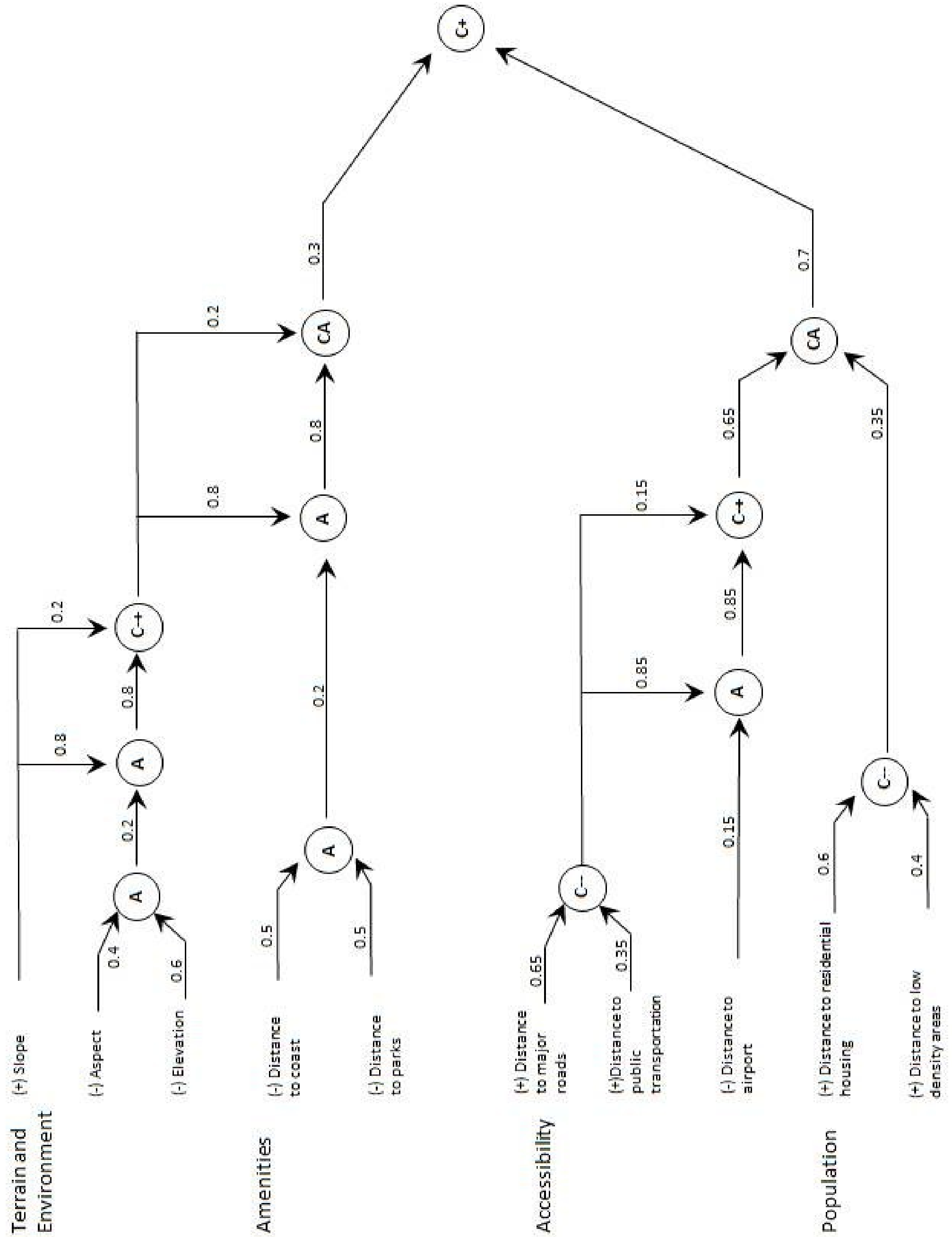

Figure 2-6. LSP Aggregation Structure for Scenario 3

2.4.4. Results

The residential urban suitability output maps for each scenario are shown in Figure 2-7. The open land use class has been considered and the LSP output values for the suitability are grouped into five categories with each covering a particular range. Classification of categories was based on natural breaks (Jenks) of the data. The five categories are: high suitability (LSP suitability output between 0.788 and 1.000), medium-high suitability (0.592-0.788), medium suitability (0.404-0.592), medium-low suitability (0.161-0.404), and low suitability (0.000-0.161). High suitability is an indicator of a compounding satisfaction of several input parameters that follow the logic parameters set out in the attribute tree and aggregation structure.

All three scenarios have high suitability values in the undeveloped areas near the rural-urban fringe. Scenario 1 shows significant growth in the southeast section of Metro Vancouver, a much less densely populated section of the region with much more rural and affordable land for new residential development. Scenario 2 has high suitability values in a significant number of areas across the study site as criteria chosen such as proximity to schools, shopping centers and parks among others are providing suitable site for residential developments that may target new families. The Scenario 3 on transportation is clearly evident: with higher suitability values nearer to freeways, transportation lines, and major roads. Figure 2-8 represent municipality of Cloverdale, part of City of Surrey, indicating subsections of output maps depicting the three scenarios. This area is particularly known for a fast residential suburban development and the obtained maps could be informative for municipal planners. The LSP map outputs collectively confirm the expected spatial patterns of the scenarios and therefore add significant confidence to the utility of the LSP approach for potential decision making.

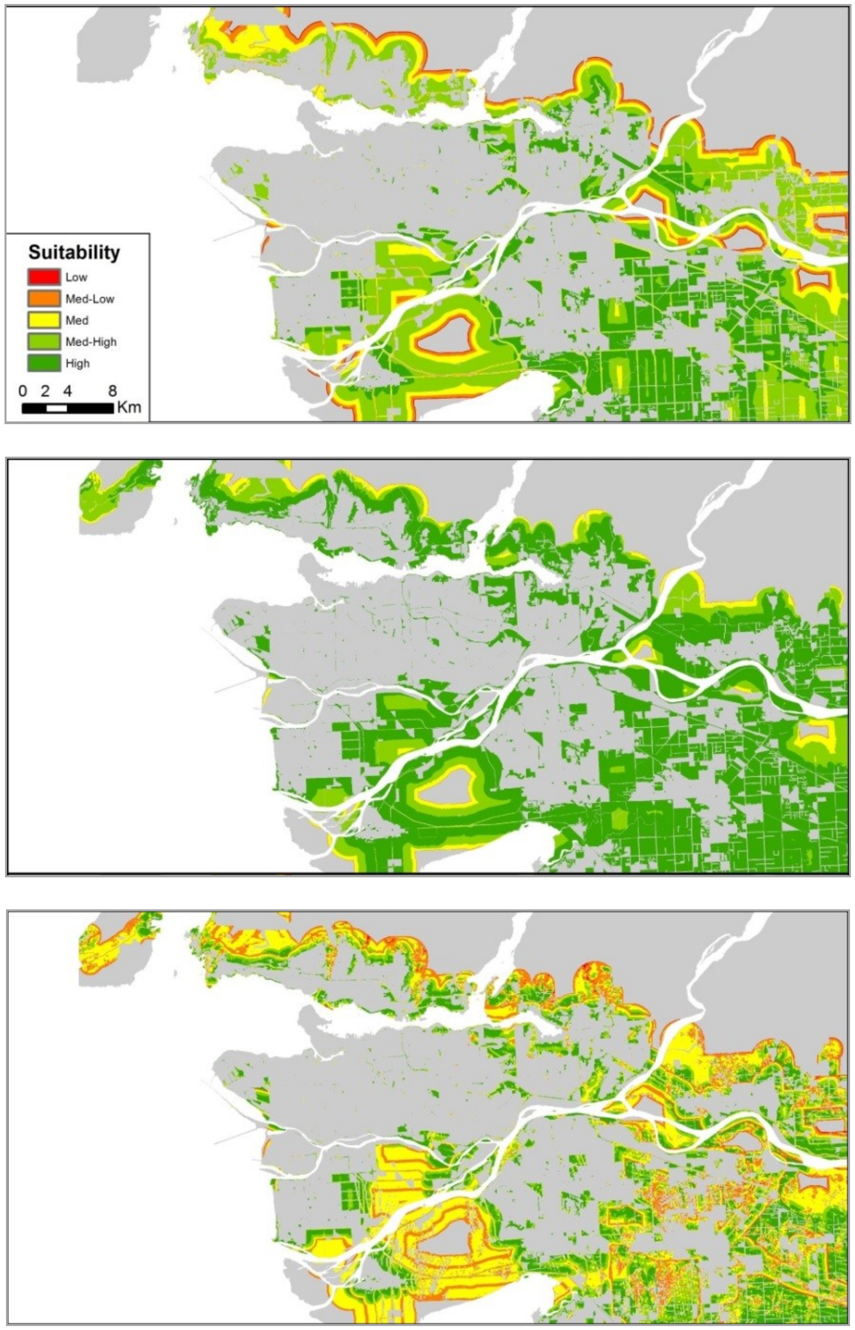

Figure 2-7. LSP-based MCE urban residential land suitability outputs for Scenarios 1 (top), 2 (middle), and 3 (bottom). Green is the class with highest, red is with lowest suitability score suitability for housing development

2.5. Conclusion

The LSP method was applied in this study to evaluate the suitability for residential development across the regional district of Metro Vancouver. Three scenarios were designed with each using a different LSP aggregation structure. Input criteria in the aggregation structures consisted of factors relevant to residential land-use change. Inputs were standardized using fuzzy suitability functions. Standardized input criteria were then combined sequentially by a series of LSP aggregators until an overall suitability output map was obtained. The final LSP suitability output maps of the three scenarios depicted high suitability in suburban areas as well as high suitability along major transportation lines such as highways and bus routes. The entire implementation was done within the GIS software with outputs displayed as static maps.

LSP is a reliable procedure to model the combination of several inputs to obtain an output suitability score without losing importance in the individual inputs themselves, and at the same time allowing the expression of continuous logic. The results can be used within geosimulation models of urban growth. The robustness of the model depends heavily on the number of input parameters considered, choices for these parameters, and sophistication of the LSP aggregation structure. Furthermore, the success of the analysis depends highly on parameter choices made at each stage of the model, determined based on what logic conditions are desired to be expressed based on the objective of the model, as well as based on approaches used in previous studies (Dujmovic et al., 2009). In this study, the output spatial patterns derived from the LSP maps confirmed the expectations from the scenarios and hence add to the confidence of the LSP approach integrated within GIS-based MCE and applied to real geospatial datasets.

2.6. Acknowledgments

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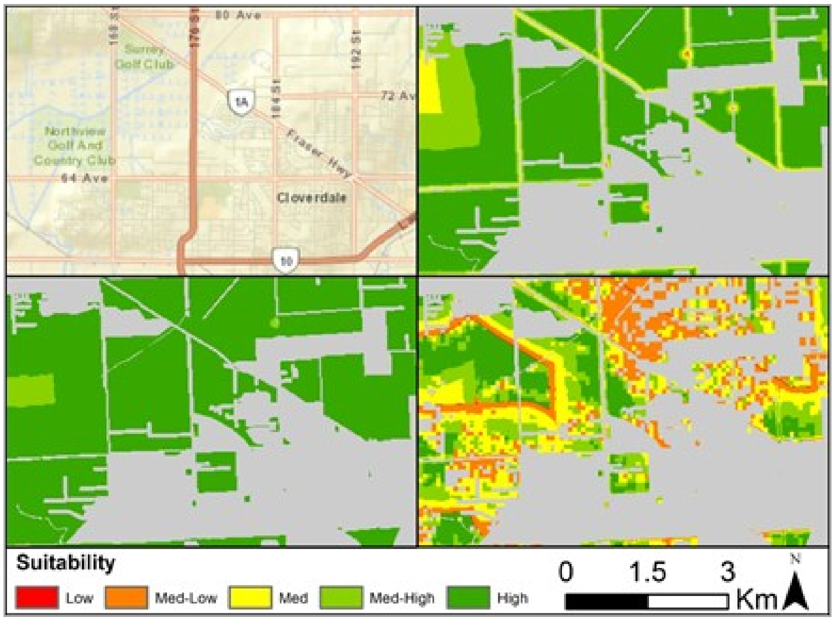

Figure 2-8. Municipality of Cloverdale (Google Map top left) and the urban residential land suitability outputs for Scenario 1 (top right), 2 (bottom left), and 3 (bottom right).

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Chapter 3.

Soft Computing and Cellular Automata model for urban land-use change: Application of the Logic Scoring of Preference Method

3.1. Abstract

The integration of geographic information systems (GIS) with cellular automata (CA) allows for the development of spatial models capable of simulating a diverse range of geographical phenomena. GIS-CA models can benefit from the integration with a multi-criteria evaluation (MCE) method. Some MCE methods however, have been criticized for their inability to fully express human decision making logic, due to their inability to satisfy all fundamental properties of multicriteria decision making (MCDM). The Logic Scoring of Preference (LSP) method is a MCDM approach that can model simultaneity, replaceability, and a wide range of other aggregators to suit various evaluation objectives. In particular, one of its main goals is to replicate human decision making logic. The main objective of this study is to develop and test an integrated method that incorporates LSP into a GIS-CA model to simulate residential land-use change. Geospatial data for Metro Vancouver Area, Canada, has been used to test the proposed method. Several criteria pertinent to land use change were used to build the aggregation structure for the model, with raster based GIS used to implement the decision-making approach. The obtained results indicate that LSP GIS-CA method provides improved accuracy for simulations of residential land-use change.

The version of this chapter will be submitted to the *Journal of GeoInformation*, coauthored with S. Dragicevic

3.2. Introduction

To provide more realistic land-use change models, the paradigm in the field of spatial modeling has shifted towards describing cities (and urban land-use change) as complex systems (Batty, 2008). Complex systems are composed of individual elements (or simple systems) that dynamically interact, and continuously modify their internal structure to self-organize into several aggregated components. These aggregated components undergo emergence, and create patterns arising out of the interactions between individual constituents of the complex system and their environment (Kwapien and Drozdz, 2012). This cooperative behavior from the disaggregate, individual scale to the aggregate scale allows components of complex systems to become flexible to internal or external system perturbations (Manson, 2001; Morales-Matamoros et al., 2010; Kwapien and Drozdz, 2012).

Cities are interconnected to form a complex system of transportation, land use, demographics, and topography that require a sophisticated model framework in order to represent them (Maithani, 2010). They share common features and behaviors consistent with those of complex systems. Among these are: adaptation to change, selection, and cooperation (Bretagnolle et al., 2003). The biggest link between cities and complex systems lies within their dynamics. Cities at a bottom up local spatial level are characterized by complex interactions occurring on a small spatial scale that through spatial interactions give rise to patterns occurring at larger city or regional scales (Albeverio et al., 2010). Additionally, the networking capabilities exhibited within cities illustrates the collective behavior and self-organization properties associated with complex systems.

Cellular automata (CA) is a type of computational model that is capable of simulating complex systems. When linked to a geographic information system (GIS), CA models are able to capture the interactions and processes that occur in cities, and are capable of simulating residential land-use change (Batty et al., 1999; Brown et al., 2005). For this reason, CA models quickly transformed into the most widely used urban land-use change model. CA models are capable of taking initial parameters at a very small, disaggregate scale, and creating extremely complex growth patterns, as seen in populations acting at their most individual level creating complex city dynamics.

CA models consist of a grid of cells with a finite number of states (Batty, 2008). Cell states in a CA model change due to local neighborhood interactions based upon user defined transition rules. Many methods of integrating GIS and CA to simulate different urban growth patterns have been developed (White and Engelen, 1993; Clarke et al., 1997; Wu and Webster, 1998; Maithani, 2010). These methods aim to accurately simulate the growth of urban systems by taking into consideration their complexity.

Linking together a GIS and CA model allows for the development of spatial models over large scales, such as the San Francisco Bay area (Clarke et al., 1997), and at very fine resolutions (Dietzel and Clarke, 2004). These GIS-CA models can simulate a diverse range of geographical phenomena. Portugali et al. (1994) conceives the city as a self-organizing system and were among the first to use CA as a method to provide urban simulations. CA was used because of its simplicity: CA allows for abstention from the advanced mathematical operations associated with other modeling methods and instead turn to the analysis of a much simpler system represented by cellular automata. Furthermore as CA are based on cells they can be easily linked to raster based geospatial data (Portugali et al., 1994). CA models are built out of discrete spatial units, with the properties of spatial units determined in relation to their neighbors. Another benefit of using CA for simulating urban growth is that they can model micro and macro phenomena together in order to create urban simulations.

There are several enhanced CA models of urban and regional growth the incorporate additional techniques that improve on modeling results in various ways. Deadman et al. (1993) developed a stochastic CA, wherein some cell states change based on stochastic influences. White et al. (1997) developed an asynchronous growth CA model, with land-use classes transitioning on different temporal intervals. De Kok et al. (2001) developed an urban land-use change model that differentiates between macro and micro scales, with the macro-scale model based on land-use changes, and the micro-scale model based on system dynamics. Stevens and Dragicevic (2007) combined irregular polygons and Euclidean distances to develop a CA model that was able to function at the cadastral level, rather than on a field of gridcells. While the aforementioned studies all modify particular components of a CA model (temporal interval, scale, grid cells, or stochasticity), another way of enhancing a CA model is by integrating an additional approach into the model. For example, Takeyama and Couclelis

(1997) developed a CA model implementing Geo-algebra, a generalization of map algebra that performs spatial data manipulations for spatial models within a common framework. De Almeida and Glenrani (2005) employed neural networks in the parameterization of their CA model to simulate urban land use change in the city of Piraccaba, Brasil. Kocabas and Dragicevic (2006) integrated Bayesian Networks and CA models to model land use change. These studies all add some additional approach into CA models, rather, or in addition to modifying components of the CA model itself. One method of providing geospatial simulations while incorporating land suitability is to employ GIS-based multi-criteria evaluation into CA.

Determining land-use suitability is an important step towards building an accurate spatial model of urban land-use change. Spatial models can be integrated with multi-criteria evaluation (MCE) methods that are capable of developing land suitability maps critical in developing the initial parameters and transition rules for cellular automata models (Barredo and Sendra, 1998). MCE can be used within a spatial decision support system (SDSS): to allow decision makers to explore, structure, and solve complex spatial problems (Densham, 1991). MCEs combine input criteria and generate a single suitability index for spatial locations, given a particular objective and study area.

Many research studies have developed approaches that integrate GIS based MCE and CA in order to provide a more realistic urban growth simulation: one that can be validated with independent datasets with greater quantitative and qualitative success. Applying MCE in a CA model facilitates an alternative approach to capturing behavior when designing CA transition rules (Wu and Webster, 1998). Wu and Webster (1998) integrated MCE and CA to model Guangzhou, China. Several criteria with associated weights relative to their importance on urban growth are inputted, such as distance to major transportation networks and distance to residential housing. Maithani (2010) integrated MCE with CA to reveal the relationships between future urban growth potential and site attributes within the city of Changsha, China. Clarke et al. (1997) use a form of MCE in their SLEUTH model of urban land-use change, combining together urban growth characteristics to assign probabilities to locations for urban land-use change. Li and Yeh (2002) developed a NN based CA model for simulating land-use changes using GIS. NN was used to determine potentials for transition between different land-use classes. Yu et al. (2010) used analytic hierarchy process (AHP) as a procedure for weighting relevant criteria to simulate evaluation of irrigated cropland suitability in Australia. Myint and Wang (2006) integrated markov chain analysis and CA to predict land use land cover change in Norman, Oklahoma using fuzzy logic and MCDM approaches.

Spatial models that incorporate MCE have been criticized by researchers for their inability to represent human decision making logic (Dujmovic et al., 2009). Existing MCE methods such as analytic hierarchy process (AHP), simple additive scoring (SAS), multiattribute value technique (MAVT), multiattribute utility technique (MAUT), ordered weighted averaging (OWA), and outranking methods do not have the specific goal of observing human decision making logic within their MCE structures. The ways in which these methods combine inputs are often derived from weighted linear combination. The ability to express inputs as either mandatory or optional in LSP provides improved simulation of human decision making logic over existing MCEs. Human decision making logic is also better replicated by soft computing logic aggregators, used when combining two or more inputs in the LSP method, a feature unavailable in any existing MCE method. Any time two or more inputs are combined in the LSP method, the combination must be represented on a scale of *simultaneity* and *replaceability*. These two terms refer to whether both inputs must have high values for the combination to have a high output value (simultaneity), or whether only one, or a select few inputs must have high values for the output (of the combination of inputs) to have a high value (replaceability). This type of thinking involved when combining inputs is more in line with the actual human decision-making process. The observation of human decision making logic within MCDM methods reduces uncertainty, and allows for more realistic results in spatial simulations. Another shortcoming of existing GIS-MCE methods is that they are limited in the number of criteria that they can take into consideration. The LSP method however is able to combine any number of attributes (Dujmovic et al., 2009), due to its inclusion of soft computing logic aggregators.

The main objective of this study is to implement the Logic Scoring of Preference method into a CA model simulating land-use change. LSP will be used as an approach for combining various land-use datasets to provide suitability maps useful for determining optimal areas for new residential development. Outputs of the LSP approaches used will then be integrated into a CA model to provide residential land-use change simulations in Metro Vancouver over the next twenty years. The LSP method will be used in three scenarios integrated into a GIS-CA model. Each of the three scenarios implements LSP in a different way; using different forms of LSP aggregation structures to develop land-use suitability maps.

3.3. Theoretical Background

3.3.1. Soft Computing and GIS

Soft computing (SC) is a term that can be applied to many computing practices such as: fuzzy logic (FL), probabilistic reasoning (PR), neural networks (NNs), and genetic algorithms (GAs) (Bonissone, 1997). Soft computing is the antithesis of hard computing, which deals with precision and certainty. The theory behind soft computing is that attempting to attain precision and certainty may require too much computational cost and effort, and that imprecision and uncertainty should be used wherever possible (Zadeh, 1994). Soft computing can solve problems not previously possible to be solved by hard computing methods, at a low computational cost (Dote and Ovaska, 2001). Applications of soft computing exist across a wide spectrum of fields. Calise (1996) used NN for flight control of an aircraft. Chakraborty et al. (1999) used GAs to deal with channel assignment problems for radio networks. Nitta (1993) used NN to improve air conditioner design by improving air temperature regulation, capacity, and air stream direction. Niittymaki (1999) used FL to create more efficient traffic signal control algorithms.

In addition to more traditional computing fields, practices of soft computing have made their way to the field of GIS. Zhu et al. (2001) used FL to infer soil composition across a landscape. Metternicht (2001) used FL, remote sensing, and GIS to map landscape features related to salinity in the Punata-Cliza Valley of Bolivia. Pijanowski et al. (2002) used NN and GIS to forecast land-use changes in Michigan’s Grand Traverse Bay Watershed. NN was used to combine together 10 criteria pertinent to urban land-use change, such as distance from lakes and distance from roads to determine areas predicted to change to an urban land-use classification. Mas et al. (2004) used GIS and NN to combine selected environmental variables relevant to land-cover change to determine deforestation risk in a tropic forest region in southeast Mexico. Bone et al. (2006) used FL to develop a fuzzy-constrained CA model of forest insect infestations. Fuzzy sets were used for representing tree susceptibility to mountain pine beetle attack. Pradhan (2011) used GIS based FL to produce landslide susceptibility maps in locations across Malaysia.

LSP is a MCDM approach with origins in soft computing, first applied in the field of computer science. LSP has been used for topics such as windowed environment software evaluation (Dujmovic and Bayucan, 1997), evaluation of Java IDEs (Dujmovic and Nagashima, 2006), and comparison of search engines (Dujmovic and Bai, 2006). LSP has also been integrated with GIS: to develop land-use suitability maps, or s-maps (Dujmovic et al., 2008). The LSP method is used to assign suitability scores reflective of suitability for land-use change, to locations over a continuous landscape.

3.3.2. The Logic Scoring of Preference Method

The LSP is used as a method for criteria evaluation and comparison that uses observable human decision-making logic and fuzzy conditional requirements (Dujmovic, 2007). LSP operates by combining together a set of inputs, or requirements, on a scale of continuous (fuzzy) preference logic (Dujmovic, 2007). When combining two or more inputs, a degree of simultaneity, or replaceability is evaluated. These degrees allow the decision-maker to determine whether both or all of the inputs under combination must be highly satisfied for there to be a high satisfaction in the output (indicating a high degree of simultaneity), or whether only one or a select few of the inputs under combination have to be highly satisfied for the output to have a high satisfaction. In existing MCEs, inputs are often assigned some type of weight of preference when they are being combined. Consequently the overall output is generally only going to be highly satisfied if each individual input itself has high satisfaction, or at the very least if the inputs with high weights of preference applied to them have high satisfaction. The assigning of aggregators with degrees of simultaneity and replaceability associated with them offers a way around this problem. Within LSP, depending on the aggregators used, the satisfaction of any or all of the inputs under combination has the potential to lead to a high satisfaction in the output. The continuous preference logic used for combining inputs sets the LSP method apart from existing MCE approaches by providing enhanced observable human decision-making logic, and allowing for an unlimited number of inputs to be combined (Dujmovic, 2011). Within the LSP method, parameterizations are made defining the aggregation of all inputs together to evaluate an overall suitability score. Suitability scores are represented on a continuous scale, such as 0 to 1, where 0 is completely unsuitable, and 1 is completely suitable for the given objective (similar to scales used in other soft computing methods, such as FL). The continuous scale of suitability allows for the inclusion of imprecision and uncertainty in the decision making process. Assigning degrees of fuzzy continuous logic however only consists of one part of the overall LSP method; several more steps are required to be taken for implementation of the LSP method. The step by step procedure for implementing the LSP method to create land-use suitability maps is detailed in the methods section of this paper.

To evaluate the combination of two or more inputs on a continuous scale of *simultaneity* and *replaceability*, LSP aggregators are applied. LSP aggregators represent a spectrum of conditions ranging from *full conjunction* to *full* disjunction with respect to the combined inputs. Prior to inputs being combined and LSP aggregators being assigned, each individual input must be assessed as either *mandatory* or *optional*. *Mandatory* inputs are those which must be satisfied, meaning that there must be some degree of satisfaction of the input in order to for there to be any degree of satisfaction in any output using the mandatory input in its combination. *Optional* inputs do not require a degree of satisfaction in the same way *mandatory* inputs do, however any degree of satisfaction present for an *optional* input provides either a penalty or reward to any output using the optional input in its combination (Dujmovic, 1979).

With inputs assessed as either mandatory or optional, LSP aggregators may be assigned to the combination of inputs. Table 1 depicts a full list of LSP aggregators, separated into two categories: *simultaneity*, and *replaceability*. The further along the spectrum from neutral (A) to full conjunction (C) (table 1) the aggregator used is, the stronger and more restrictive the degree of simultaneity is. The further in the other direction, from neutral (A) to full disjunction (D), the stronger the replaceability among inputs is. Neutral (A) is used to express neither simultaneity nor replaceability. LSP aggregators can be grouped into one of seven aggregator types (Dujmovic, 2007). These include: Full Conjunction (LSP aggregator C in Table 1), Hard Partial Conjunction (using aggregators such as C++, C+, C+-), Soft Partial Conjunction (C-, C–), Neutrality (A), Soft Partial Disjunction (D–, D-, D-+, DA), Hard Partial Disjunction (DA, D+-, D+, D++) and Full Disjunction (D). The choice of LSP aggregator used is determined by the desired level of simultaneity or replaceability between inputs that the decision maker wants to express. A Hard Partial Conjunction (HPC) operator is often used to express the combination of mandatory inputs, whereas a Soft Partial Conjunction operator is less restrictive, and is appropriate for the combination of optional inputs. The analogue is true for Hard Partial Disjunction and Soft Partial Disjunction operators.

Table 3-1. LSP aggregators and associated exponents

Simultaneity

Symbol	**C**	**C++**	**C+**	**C+-**	**CA**	**C-+**	**C-**	**C--**	**A**
r	**-∞**	-9.06	-3.51	-1.655	-0.72	-0.148	0.261	0.619	1.0

Replaceability

Symbol	**D**	**D++**	**D+**	**D+-**	**DA**	**D-+**	**D-**	**D--**	**A**
r	**∞**	20.63	9.521	5.802	3.929	2.792	2.018	1.449	1.0

When inputs of the same type (either all mandatory or all optional) are combined together, a Generalized Conjunction Disjunction (GCD) function is used to mathematically evaluate the combination of inputs in the LSP method (Dujmovic et al., 2009). Given a set of input parameters $X_1,\ldots,X_n$, the generalized conjunction disjunction is computed using the weighted power mean as follows:

$$GCD(X_1,\ldots,X_n)=[W_1X_1^r+\ldots+W_nX_n^r]^{1/r} \quad (1)$$

where $GCD(X_1,\ldots,X_n)$ is the suitability for input parameters $X_1,\ldots,X_n$, $W_1,\ldots,W_n$ are used to express the relative importance of usefulness and inexpensiveness of inputs $X_1,\ldots,X_n$, *and* r is a value associated with an individual LSP aggregator (Table 3-1), used to express the desired degree of simultaneity and replaceability among the inputs $X_1,\ldots,X_n$.

When inputs of different types are combined (i.e optional inputs with mandatory inputs), the conjunction partial absorption (CPA) function is used (Dujmovic, 1979). Given a mandatory input X and an optional input Y, there are two variants for the CPA function:

$$CPA(X,Y)=\{(1-a)[bx^{r1}+(1-b)y^{r1}]^{r2/r1}+ax^{r2}\}^{1/r2} \quad (2)$$

where either r1<1, r2>=1, or r1>=1, r2<1 and:

$a=W_1$, $b=W_2$ for r1<1, r2>=1, (CD-variant),

$a=W_{2,}$ $b=W_1$ for r1>=1, r2<1, (DC-variant)

Choice of aggregators for combining mandatory with optional inputs is different from choice of aggregators for combining inputs of the same type. The penalty and reward provided by optional inputs is less than the penalty and reward provided by mandatory inputs (Dujmovic, 2007). The simplest way to choose an appropriate CPA aggregator is to consider the desired values for penalty and reward. The desired weights of preference and LSP aggregator can be determined from looking at penalty reward tables, shown in Dujmovic (1979).

Implementing LSP allows users to produce models that generate reliable results in relation to the inputs, logic aggregators, and weights of relative importance chosen. The step-wise logic aggregation structure of LSP also allows for extreme flexibility through its use of continuous logic, represented in terms of simultaneity and replaceability of suitability inputs in relation to one another (Dujmovic et al., 2010). LSP also allows for the inclusion of large numbers of inputs in its structure, without loss of significance due to its logic expressions.

3.4. Methods

3.4.1. GIS based LSP-CA model structure

Given that LSP is a type of MCE approach, combining a GIS-LSP method into a CA model is similar to other GIS-MCE approaches (Figure 3-1). Analogous to other

MCE approaches, LSP consists of a set of input criteria combined together to obtain an output map depicting land-use suitability. However, significant differences exist between the structure of an LSP method and other MCE approaches. A number of steps must be taken to developing a GIS-LSP CA model. Implementation of the LSP method in GIS requires first that some set of input datasets are obtained from GIS databases or remote sensing. Next, these inputs must be categorized, and standardized so that they are represented on the same scale representing suitability (Dujmovic et al., 2008). Next, the attribute tree must be developed, defining the step-wise combination of inputs. Following that, LSP aggregators must be assigned each time two or more inputs are combined in the attribute tree, creating an aggregation structure. From there, an output map representing suitability for the desired objective can be obtained, wherein particular spatial locations on the map are assigned suitability values (related to the given objective, determined by the use of LSP).

The output suitability map obtained by implementing the LSP method can be integrated into a CA model. Each iteration, a CA model determines some set of potential transition sites, i.e. locations on a map that may change state (for example from one land-use class to another) based on the neighborhood configurations and transition rules applied. These locations determined to transition (change state) also have an associated LSP suitability value, determined from implementation of the LSP method. As a result, the locations determined to transition can be ranked based on their LSP suitability value, and a subset of the total set of locations determined to transition can be deemed suitable enough, and actually transition from one state to another (for example from one land-use class to another). The type of structure used for combining LSP and CA is similar to how previous studies have combined MCE and CA. Wu and Webster (1998) used AHP to develop a suitability metric for land conversion integrated into a CA model. Similar to integrating LSP and CA, in their model the suitability metric developed was integrated after both the neighborhood configuration and transition rules had been established, to aid in determining a set of cells to transition. There exist alternative methods for integrating MCE with CA, exhibited by Li and Yeh (2002), who developed a NN-based CA model to evaluate conversion probability for multiple land-uses. In their model, instead of implementing NN after CA transition rules and neighborhood configuration had been established, NN was used as the basis for transition rules in the model: cells would transition from one land-use type to another that is associated with the highest conversion probability.

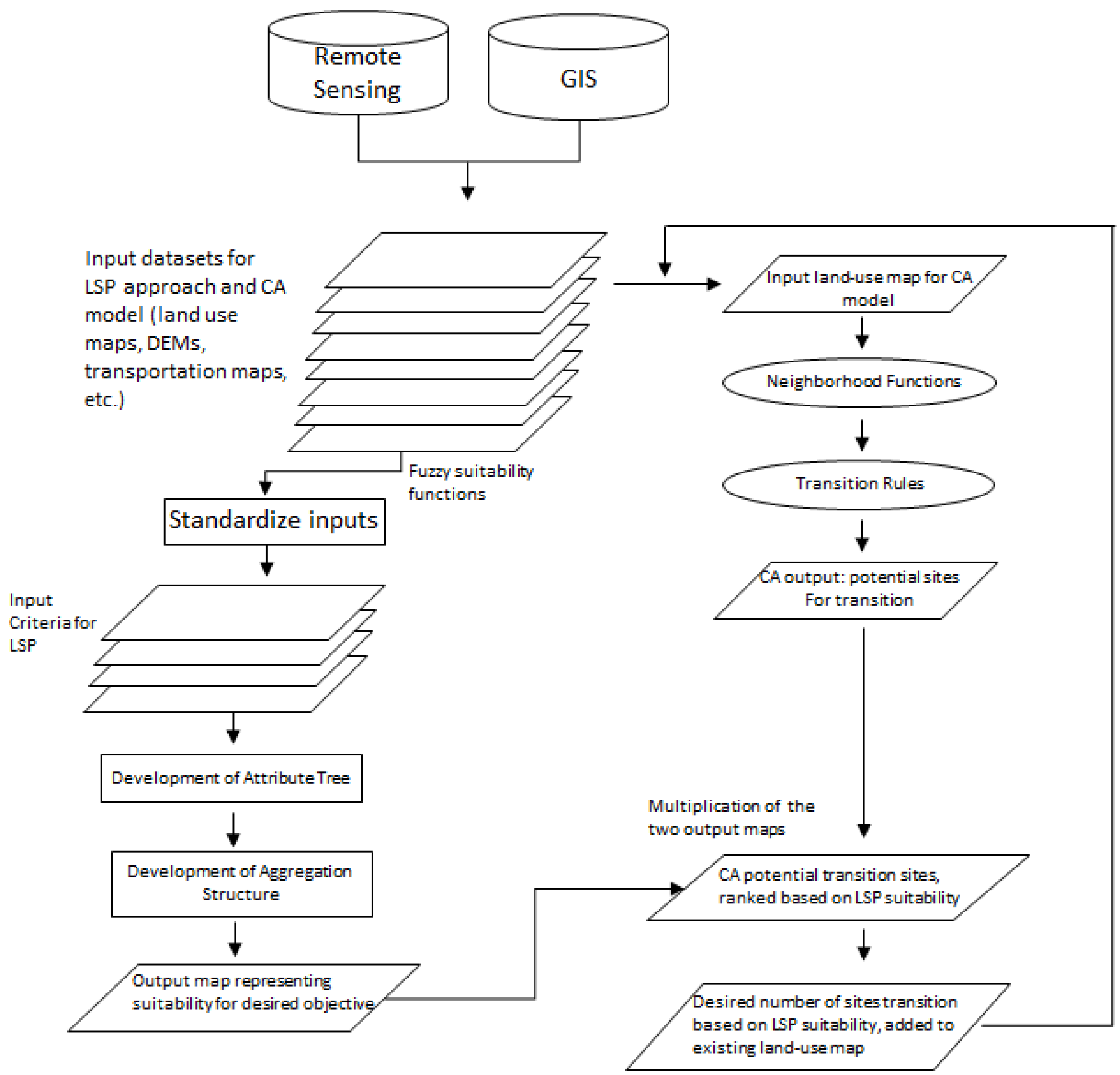

Figure 3-1. Flowchart for a basic LSP-CA integrated model

Integrating a GIS-based MCE method into a CA model is performed through a number of steps. First, MCE suitability analysis is performed: input parameters are chosen, and combined together to obtain an overall land-use suitability score for each spatial location. Next, the framework elements of the CA model are established:

neighborhood properties are chosen (size and shape), transition rules are selected, and a temporal interval is established. From implementing the neighborhood and transition rules, potential sites for transition are determined. The suitability output from the MCE approach is then multiplied together with the transition potential output from the CA model. The multiplication of these two creates a new output: one which ranks all potential transition sites (from the CA model) based upon their suitability, from highest to lowest (with suitability provided by the MCE output). From here, a set of criteria is established determining how many of the potential sites would transition. Usually this involves selecting the *n* most suitable transition potential sites based on their suitability value obtained from the MCE approach. These transition sites are overlaid with the existing data, allowing for further iterations to occur.

3.4.2. Input Criteria and Attribute Tree for LSP Aggregation Structures

Inputs consist of datasets evaluated as mandatory (+) or optional (-), grouped together into a set of categories based on similarity among criteria. Prior to the development of an LSP attribute tree, inputs must be transformed from their original units onto standard continuous scale representing suitability, with respect to the desired purpose or objective of the given study. For urban land-use change, input criteria often consist of raster-based maps (a region divided up into equal area grid cells), such as land-use maps, transportation maps, and digital elevation models (DEMs). These maps are standardized through the use of fuzzy suitability functions to create fuzzy suitability maps. Fuzzy suitability maps assign suitability values to each raster cell, with values often ranging from 0 to 1: 0 representing a completely unsuitable spatial location, and 1 representing a completely suitable spatial location with respect to a given input. The (standardized) fuzzy suitability maps represent the input criteria for the LSP method. The input criteria are grouped categorically and combined together in the LSP attribute tree.

To aid in the conceptualization of the LSP method, an example set of input criteria have been developed, along with a LSP attribute tree and aggregation structure, with the objective being to determine suitability of spatial locations for urban land-use change. The standardized, elementary criteria consist of 21 inputs in four categories:

Terrain and Environment: Slope, Aspect, Elevation, Distance to beaches, Distance to Coast, Distance to Parks.

Amenities: Distance to Care Facilities, Distance to Shopping, Distance to Entertainment Zones, Distance to Schools.

Accessibility: Distance to Major Roads, Distance to Bus Lines, Distance to Light Rail Transit, Distance to Airport, and the Amount of Sustainable Transport used in area.

Population: Distance to Residential housing, % Families living in the area, Distance to low density housing, Distance to Urban Core, Population growth of area, Median Income of area.

These inputs represent criteria relevant to urban land-use change. Each elementary criteria is a suitability map, divided into raster grid cells, with each cell having a value from 0 to 1 inclusive representing suitability. Representing inputs in this way facilitates the use of map algebra to combine inputs together, with the combination of inputs occurring in the LSP attribute tree. Figure 3-2 depicts the LSP attribute tree, which organizes the decision problem, and combines input criteria together stepwise, until one overall output is obtained. Inputs are at their most individual level on the left of the figure, grouped into each of the four categories. Additional inputs are further combined together until one overall output is obtained (on the right-hand side of the figure), representing the combination of all input criteria. Inputs are represented as either mandatory (+) or optional (-) in the attribute tree. Within any individual category (such as terrain and environment, amenities, etc.), it is common for mandatory inputs to be combined with other mandatory inputs first, and optional inputs to be combined with optional inputs first, proceeded by the combination of inputs of different type (mandatory with optional). This reasoning has to do with computational efficiency: each time mandatory and optional inputs are combined together, additional, and more sophisticated nonlinear equations are used in the calculation of their output. However, it should be noted that changing the order in which inputs are combined has the potential to lead to different values in the output. An attribute tree can be thought of as a directed graph, where the input criteria make up the leaves (vertices with only one edge attached to them) of the tree, the individual LSP aggregators, representing the combination of inputs, make up the internal vertices of the tree (vertices with two or more edges attached to them). Then, there exists a single vertex representing the combination of all leaves (inputs) of the tree with an associated value representing overall suitability with respect to all input criteria.

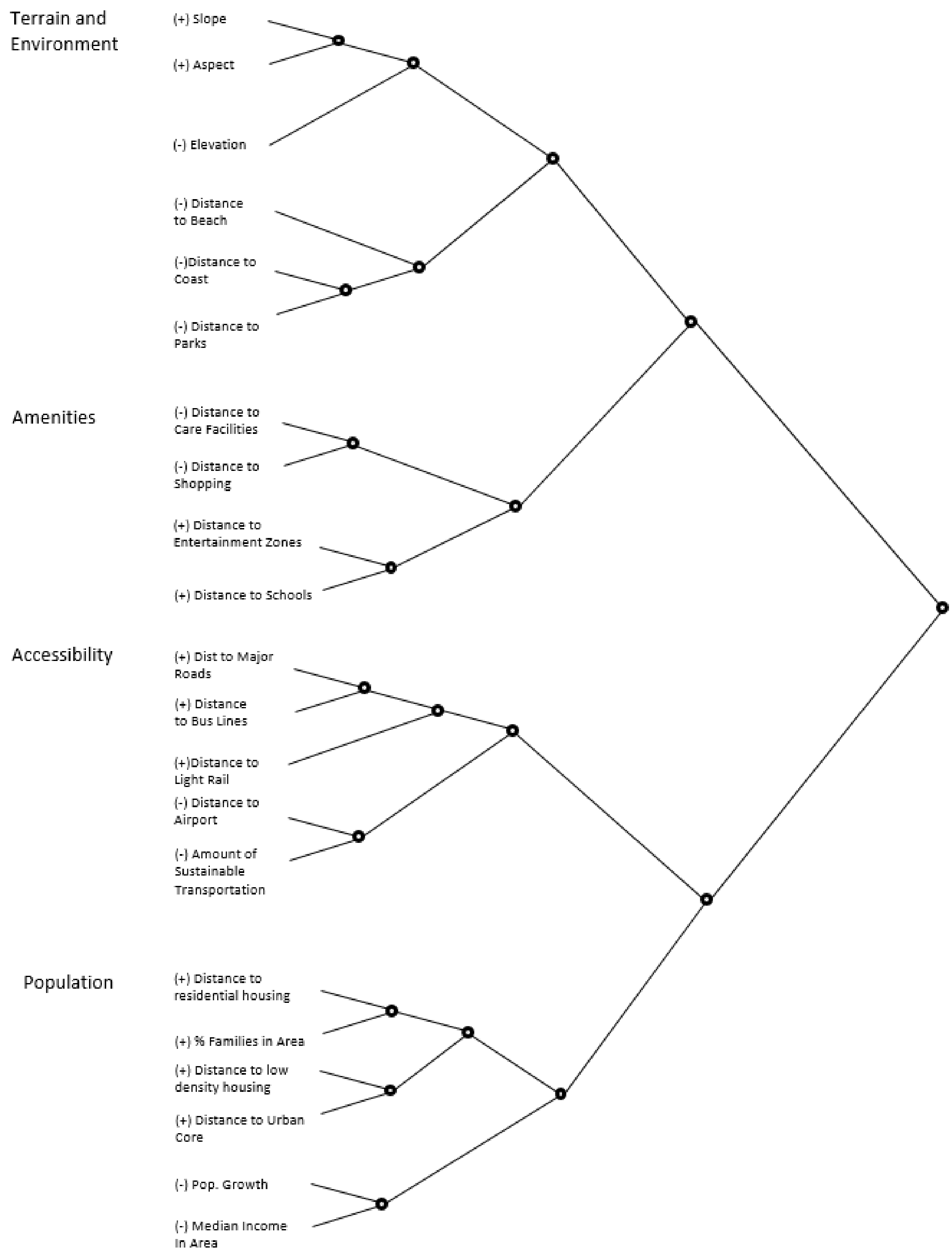

Figure 3-2. Example of a LSP attribute tree

3.4.3. LSP Aggregation Structures

The addition of aggregators into attribute trees form LSP aggregation structures. For LSP aggregation structures, each node representing the combination of inputs in Fig. 3-2 is represented by a single LSP aggregator corresponding to a degree of simultaneity or replaceability among inputs.

Several LSP aggregators were implemented in the attribute tree for the provided example. Figure 3-3 depicts the LSP attribute tree with the inclusion of LSP aggregators. Letters (A, C-+, C+, etc.) appear at each of the nodes of the attribute tree. These letters have a corresponding degree of simultaneity or replaceability (Table 1).

Within the LSP aggregation structures, the degree of simultaneity increases as the degree of each node increases (when an increasing number of inputs are combined into an individual LSP aggregator). This implies that the *r* values of LSP aggregators decreases (Table 1) as the number of inputs combined into an individual aggregator increases. This type of structure is most appropriate for logic aggregation of suitability maps, and is known as a *canonical aggregation structure* (Dujmovic and De Tre, 2011).

Both the GCD and CPA functions are used for combining inputs. In the context of suitability maps, the GCD is given by:

$$S(X,Y) = [(W_u(X))^r + (W_p(Y))^r]^{1/r}$$

where X and Y are two suitability maps: either from an individual input in the aggregation structure, or from combination of inputs. S(X,Y) is the output suitability map, and W_u and W_p are used to express the relative importance of usefulness and inexpensiveness of inputs X and Y. For combining both mandatory and optional inputs together, the conjunction partial absorption (CPA) formula is used:

$$S(X,Y) = [(1-W_1)[W_1X^{r_1} + (1-W_1)Y^{r_1}]^{r_2/r_1} + W_2X^{r_2}]^{1/r_2}$$

where X is the mandatory input (or combination of inputs) with weight W_1, and Y is the optional input (or combination of inputs) with weight W_2.

Within the WPM and CPA functions, map algebra operates on a cell-by-cell basis for each cell in the raster suitability maps. For mandatory inputs, *M*, any cell with a value of zero (indicating a completely unsuitable location) will also have a value of zero in any output map having *M* as an input. Optional inputs provide a penalty or reward to the output, depending on the value in each cell (Dujmovic, 1979).

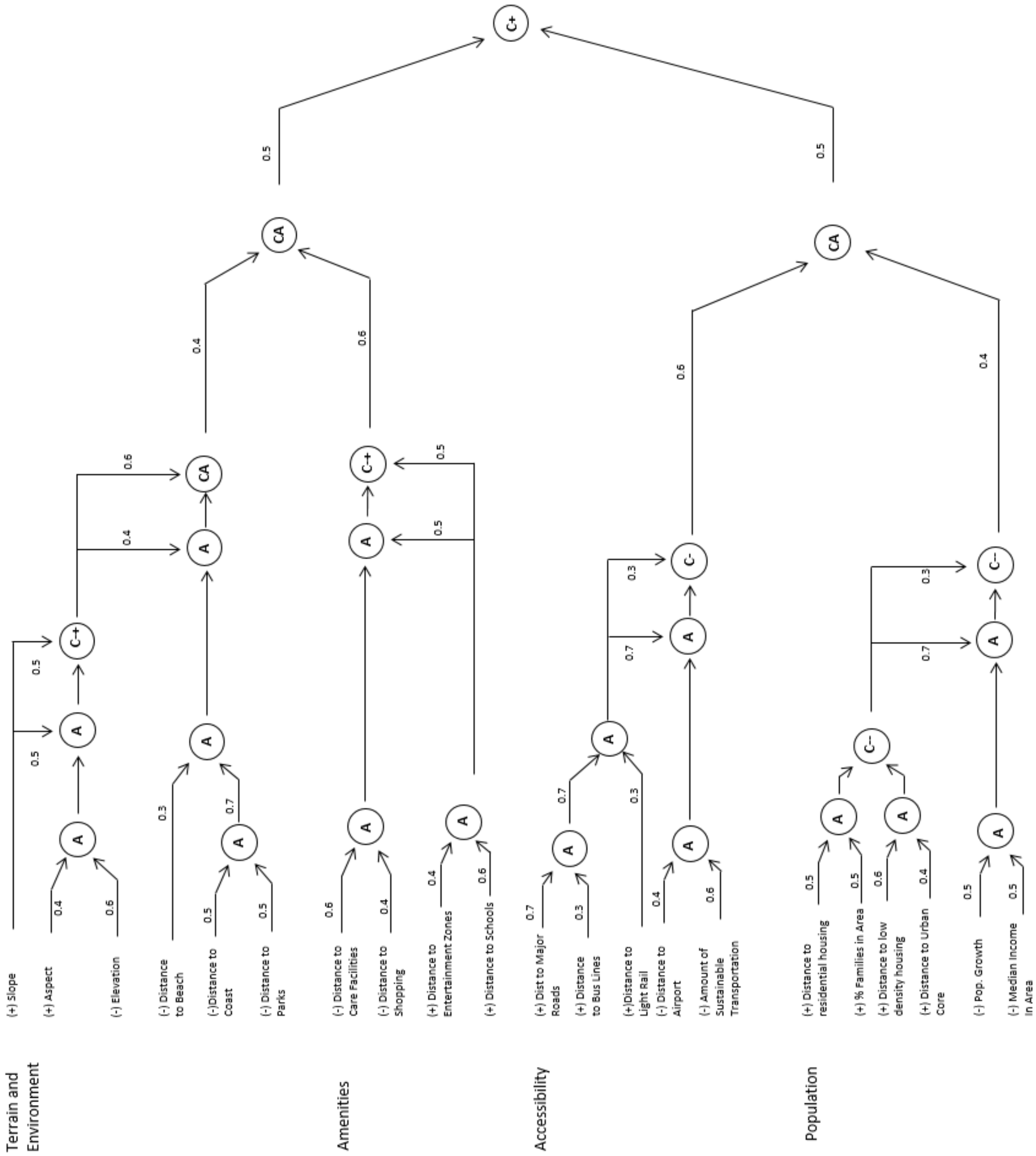

Figure 3-3. Example of a LSP aggregation structure

3.4.4. LSP-CA Integration

After the LSP aggregation structure is developed, an overall degree of suitability is obtained with respect to the desired objective (Figure 3-1). This degree of suitability is assigned to a set of spatial locations across a given study site. Given that CA is operating on a tessellation of grid cells, the degree of suitability obtained from implementing the LSP method is also assigned to a set grid cells streaming from the raster GIS data. A site is divided up into discrete grid cells, and LSP suitability values are assigned to each individual discrete grid cell for the given study site.

The CA model evaluates a set of grid cells in the site eligible to transition from one state to another. In order for LSP and CA to be integrated, they must both have the same objective, meaning that if the objective of the CA model is to transition cells from state A to state B, then the objective of the LSP method must be to determine the suitability for new cells of state B. This is so that after the CA model evaluates a set of cells with the potential to transition from state A to state B, the LSP model can be used to evaluate whether or not those potential transition cells have high enough suitability to change to state B. By integrating LSP and CA in this method, LSP acts as an additional barrier for transitioning cells. Of the cells determined to transition in the CA model, the LSP method will determine which of those determined cells are actually suitable enough to transition. From there, a subset of the entire set of cells CA deemed had the potential to transition will actually transition, which can be then added into existing datasets.

3.5. LSP-CA Model Implementation

3.5.1. Datasets and Software

The regional district of Metro Vancouver is used to create simulations for the LSP-CA model. Input data consists of several datasets: a 20 meter resolution digital elevation model (DEM), transportation data (bus route, skytrain, and road networks), land-use datasets, and Canada Census data. The ESRI ArcGIS software (ESRI, 2011) and IDRISI Selva GIS (Eastman, 2012) software were used to create the LSP-CA model. Python scripting, and the IDRISI Python application programming interface was used to develop LSP aggregation structures, and for use in sensitivity analysis.

3.5.2. Scenarios

Three scenarios are created for implementing the LSP-CA method, each of which is oriented towards a particular objective for simulating residential land-use change. Scenario 1 is designed to be transportation oriented, Scenario 2 is family oriented, and Scenario 3 is suburban oriented. Scenarios simulate residential land-use change through the transition of land-use classified raster cells from non-residential land-use classes such as open area and resource and industrial to a residential land use class. Each of the three scenarios is initialized using data from 2001. Data for 2006 is used to provide calibration for each of the scenarios. Input criteria for scenario 1 are shown in Table 3-2. Input criteria for scenario 2 and scenario 3 are shown in Table 3-3. Fuzzy transformation functions used to standardize inputs prior to their inclusion in LSP aggregation structures are shown in Table 3-4.

Table 3-2. Inputs for Scenario 1

Scenario 1			
Terrain and Environment	Amenities	Accessibility	Population
(+) Slope	(-) Distance to coast	(+) Distance to major roads	(+) Distance to residential housing
(-) Aspect	(-) Distance to parks	(+) Distance to public transportation	(+) Distance to low density areas
(-) Elevation		(-) Distance to airport	

Table 3-3. Inputs for Scenarios 2 and 3. Symbols such as (+,-) indicate the input is mandatory in Scenario 2 and optional in Scenario 3

Scenarios 2 and 3			
Terrain and Environment	Amenities	Accessibility	Population
(+,+) Slope	(-,-) Distance to beach	(+,+) Distance to major roads	(+,+) Distance to residential housing
(-,+) Aspect	(-,-) Distance to coast	(-,-) Distance to bus lines	(+,+) Distance to low density areas
(-,-) Elevation	(-,-) Distance to parks	(+,-) Distance to light rail	(+,+) Distance to family areas
	(-,-) Distance to shopping	(-,-) Distance to airport	(-,-) Population growth
	(-,-) Distance to care facilities	(-,-) Amount of sustainable transport	(-,-) Median income
	(+,+) Distance to schools		

Table 3-4. Fuzzy linear transformation functions for elements of the LSP attribute tree

Category	Input	Units	Function Breakpoints				
			a	b	c	d	e
Terrain and Environment	Slope	Degrees	(0,1)	(30,1)	(40,0)	n/a	n/a
	Aspect	Degrees	(0,0)	(45,0)	(135,1)	(225,1)	(315,0)
	Elevation	Metres	(0,1)	(50,1)	(1000,0)	n/a	n/a
Amenities	Distance to Beach	Kilometers	(0,1)	(5,1)	(15,1)	n/a	n/a
	Distance to Coast	Metres	(0,0)	(100,1)	(200,1)	(2000,1)	
	Distance to Parks	Metres	(0,1)	(200,1)	(2000,0)	n/a	n/a
	Distance to Shopping	Kilometers	(0,1)	(5,1)	(15,1)	n/a	n/a
	Distance to Care Facilities	Kilometers	(0,1)	(5,1)	(20,1)	n/a	n/a
	Distance to Schools	Metres	(0,0)	(200,1)	(1500,1)	(10000,1)	n/a
Accessibility	Distance to Major Roads	Metres	(0,0)	(100,1)	(500,1)	(2000,1)	n/a
	Distance to Bus Lines	Metres	(0,0)	(100,1)	(250,1)	(1000,0)	n/a
	Distance to Light Rail	Metres	(0,1)	(1500,0.75)	(3000,0)	n/a	n/a
	Distance to Airport	Kilometers	(0,0)	(2,1)	(20,1)	(50,0)	
	Amount of Sustainable Transportation	Percent	(0,0)	(40,1)	n/a	n/a	n/a
Population	Distance to residential housing	Metres	(0,0)	(10,1)	(100,1)	(1000,0)	n/a
	Distance to low density housing	10,0000*Population/(km^2)	(0,1)	(10,1)	(100,0)	n/a	n/a
	Amount of Families in Census Subdivision	Percent	(0,0)	(15,1)	n/a	n/a	n/a
	Population growth in municipality (5yr)	Percent	(0,0)	(10,1)	n/a	n/a	n/a
	Median Income in Area	Percent	(40,1)	(50,0.75)	(60,0)	n/a	n/a

Metro Vancouver has many spatial restrictions regarding new residential development. The presence of large water bodies such as the Pacific Ocean and Fraser River, as well as the North Shore Mountains geographically restrict growth in Metro Vancouver. Furthermore, growth in Metro Vancouver is also limited by the presence of the Canada-US border, defining the region's southernmost edge. Given the existing settlement of the region along with these natural geographic limitations, a significant amount of new residential development is forced to occur in the southwestern portion of the region, known as the Fraser Valley (the basin of the Fraser River). Zoning regulations also limit the location of growth in Metro Vancouver. Municipalities within the region restrict large geographic parcels solely for the use of agriculture, known as agricultural land reserve (ALR) parcels. As a result, clustering is seen in municipalities with significant ALR zoning, with residential developments built around ALR boundaries. Despite these many restrictions, there are several rural-urban fringes within Metro Vancouver with the potential to accommodate new residential development.

Transportation-Oriented Scenario

Scenario 1 (Fig. 3-4) incorporates a LSP aggregation structure that is heavily transportation-oriented. Metro Vancouver is a region highly dependent on its transportation network. Due to geographical limitations, many citizens do not live in close proximity to their workplace, especially those living in the suburban areas, far from the central business district. For these reasons, it is important to have a scenario that places greater importance on proximity to existing transportation networks. In the accessibility category of the LSP aggregation structure for Scenario 1 (Fig. 3-4), the input criteria of distance to major roads and distance to public transportation are both assigned as mandatory inputs, meaning that for a spatial location to be evaluated as suitable, it must have a non-zero value in the fuzzy suitability maps for both distance to major roads and distance to public transportation inputs. Suitable spatial locations must be within an adequate proximity to existing transportation networks. Furthermore, high weights of preference are placed on both inputs, as well as the accessibility category of inputs as a whole, further necessitating the need for spatial locations to be in close proximity to transportation networks to receive high LSP output suitability scores.

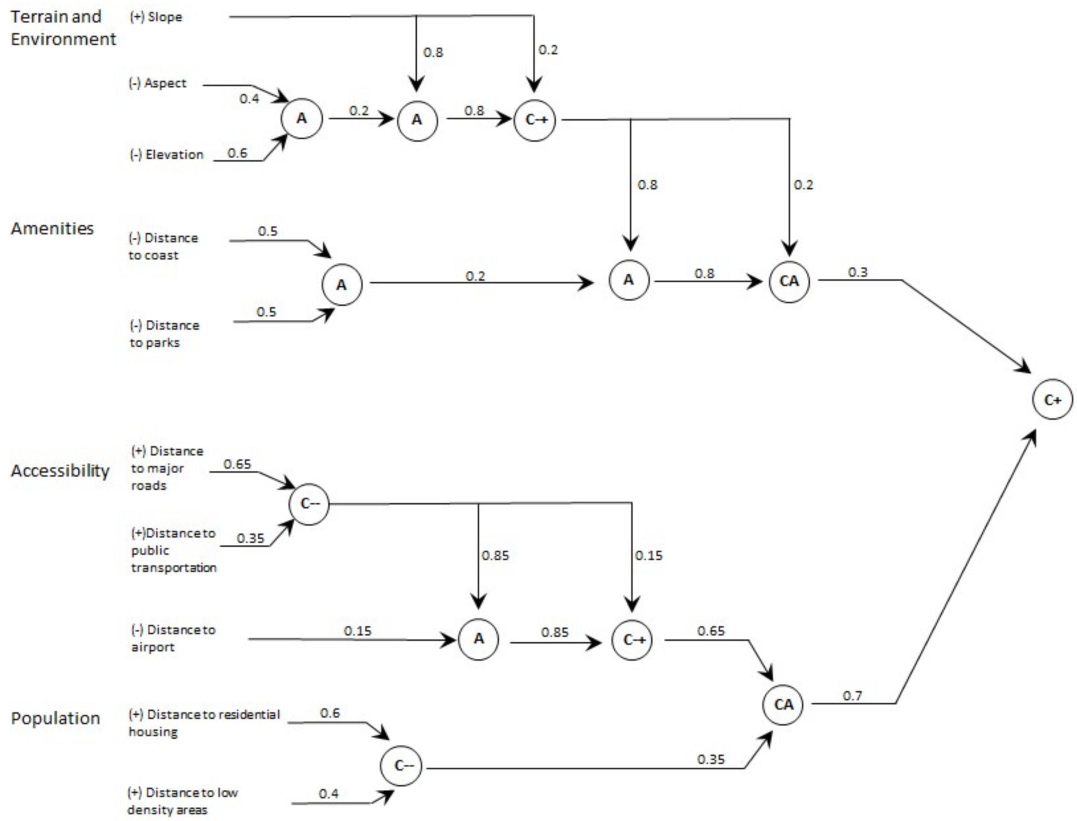

Figure 3-4. LSP aggregation structure for Scenario 1: transportation oriented growth

Family and Suburban-Oriented Scenarios

Scenario 2 focuses on family oriented growth, and scenario 3 focuses on suburban development. Both scenarios follow similar LSP aggregation structures (Figs. 3-5 and 3-6). The purpose of these two scenarios was twofold. One purpose was to observe differences in output results when several inputs are included in LSP aggregation structures compared to only a select few inputs (19 inputs for Scenarios 2 and 3 compared to 10 for Scenario 1). The other purpose was to observe changes in LSP output maps when changes are made to weights of preference, LSP aggregators, and logic conditions (mandatory or optional) for input criteria.

In year 2011, the number of census families in Vancouver grew by 9.2% from 2006 (Census Canada, 2012). Compared to a growth rate for Canada of 5.5% over the same period, it is clear that Vancouver is a fast growing region for families with young children. Scenario 2 addresses the need for new family housing through its focus on family oriented growth. Family oriented growth is represented in the LSP aggregation structure for Scenario 2 (Fig. 3-5) by means of placing greater importance on family-related amenities, such as distance to schools, as well as greater importance on accessibility, relative to other inputs in the LSP aggregation structure, as well as other scenarios, such that family members can commute from work to home more easily.

Housing prices in Vancouver are the second highest of any city in the world (Bertaud, 2013). However, the cost of single family homes decreases with increasing distance from the central business district (downtown Vancouver). For these reasons, it is important to have a scenario whose main focus is on development at the rural-urban fringe, near the furthest suburbs from downtown Vancouver. Scenario 3 attempts to achieve the goal of creating increased growth at the rural-urban fringe within the furthest municipalities from downtown Vancouver. This is achieved through placing higher logic preference (mandatory vs. optional) on input criteria in the population category (Fig. 3-6), in particular distance to low density housing, and more affordable housing.

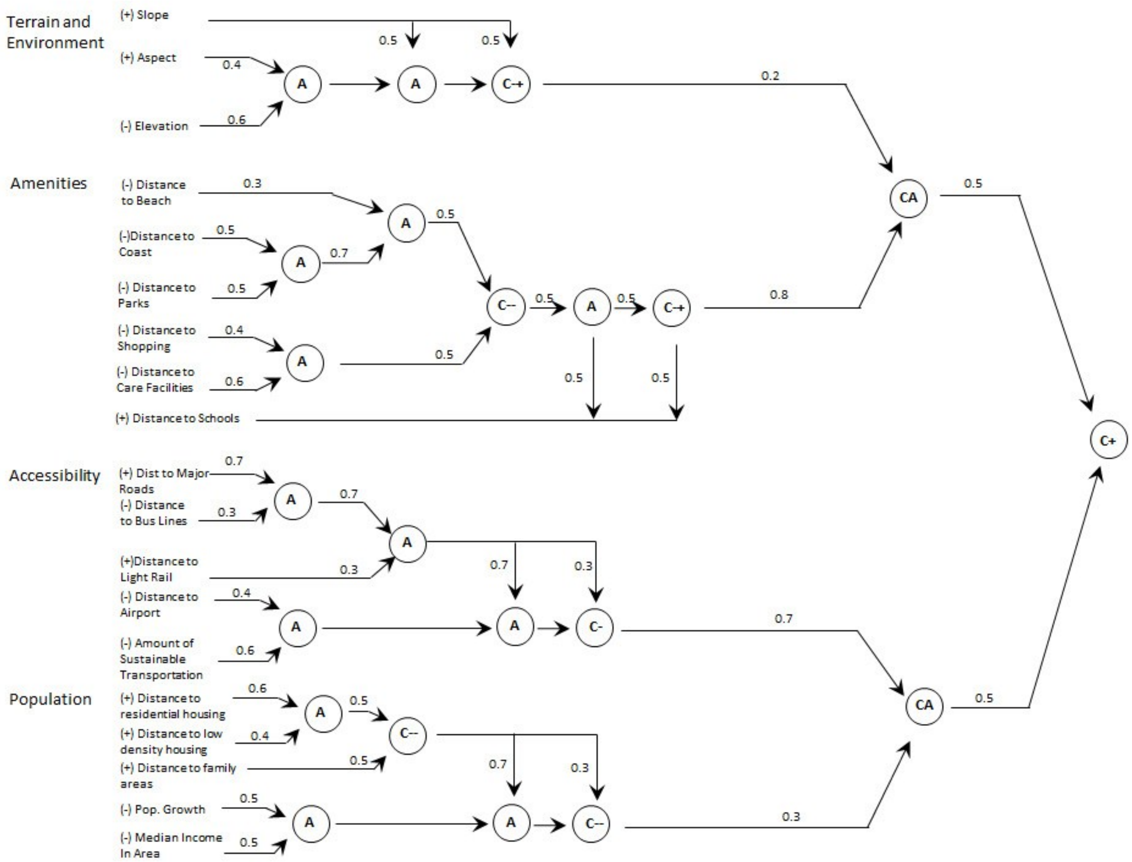

Figure 3-5. LSP aggregation structure for Scenario 2: family oriented growth

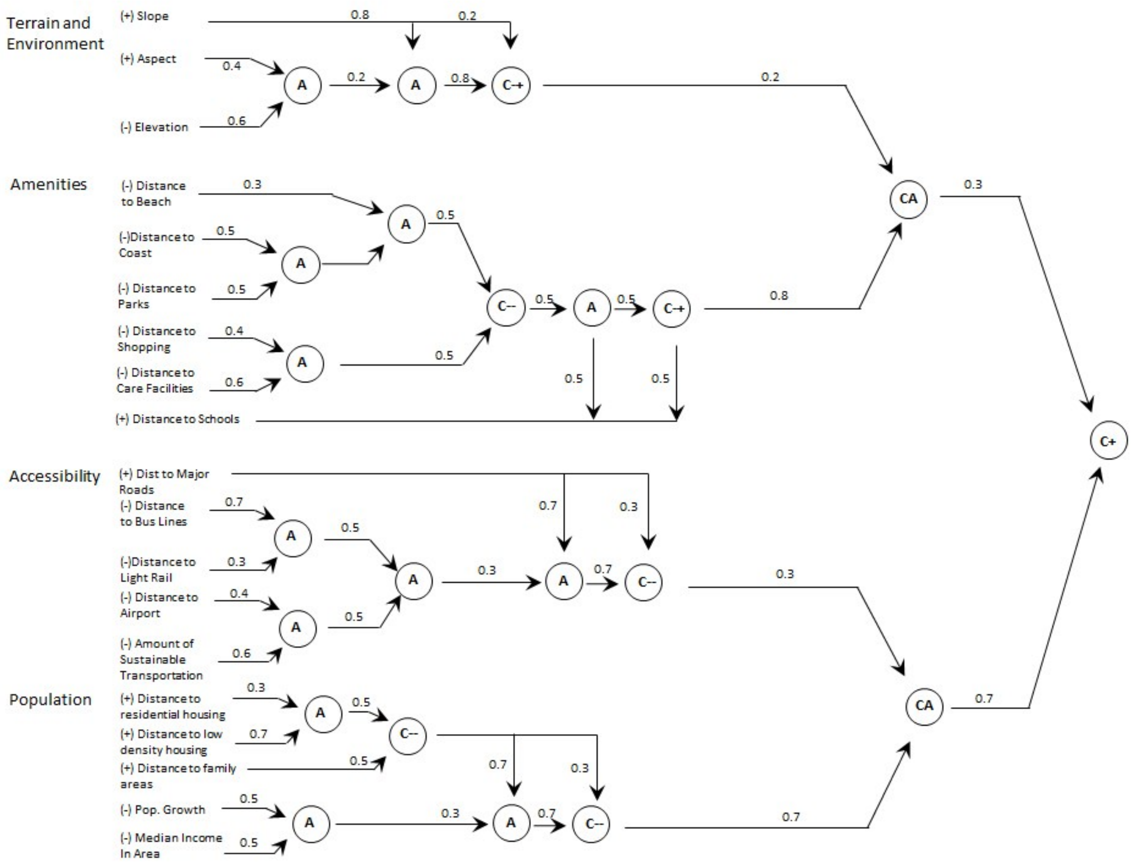

Figure 3-6. LSP aggregation structure for Scenario 3: suburban development

3.5.3. Model Calibration

The LSP-CA model was calibrated using actual land-use data. Initialized with datasets for the year 2001, simulations were projected to year 2006, with iterations occurring on a single year basis. Simulation results were compared to actual 2006 land use data on a cell by cell basis using kappa statistics (Monserud and Leemans, 1992). Kappa statistics are a mean to compare agreement with two datasets. The equation is given by:

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

Where Pr(*a*) is the relative observed agreement, Pr(*e*) is the probability of agreement by chance.

Several different elements of the LSP-CA models were altered for each scenario, including the neighborhood size and type, including/excluding zoning restrictions, and the suitability of each land-use class for residential development.

Three types of Moore neighborhoods were tested: a 3x3, 7x7, and 21x21 neighborhood. Moore neighborhoods consider a grid of *n* x *n* cells, where *n* is an odd natural number. The central cell of the grid is influenced by all other cells in the *n* x *n* grid. The 3x3 Moore neighborhood gives a kappa statistic value of 0.62, higher than when using a 7x7 neighborhood, which gave a kappa value of 0.54 or a 21x21 neighborhood, which gave a kappa value of 0.51. As a result the 3x3 neighborhood was used when implanting each of the three CA scenarios. When evaluating kappa statistic values, two sets of maps were compared: a map depicting cells that transitioned from non-residential land-use classes to the residential land use class in simulations, and a map depicting cells that actually transitioned from non-residential land-use classes to the residential land-use class between 2001 and 2006 in Metro Vancouver.

Among all land-use classes (government and institutional, commercial, resource and industrial, parks and recreation, and undeveloped land), 40% of the new residential areas for the year 2006 were classified as resource and industrial in the 2001 land-use map, and 60% were classified as undeveloped land. For this reason, it is assumed that giving a higher weight of preference for undeveloped land than resource and industrial (and weights of zero for all other land-use classes) will give the most accurate results. However, with the two equally weighted the kappa statistic value is higher than if weighted proportionately, with a value of 0.82 indicating high agreement with actual data. In Metro Vancouver, development is restricted by zoning of the existing agricultural land: certain spatial boundaries exist which can only be zoned for agricultural use. With these boundaries added in, there is a slight improvement in simulation agreement to actual data, with a kappa value of 0.83. By performing model calibration, it is determined that the following model properties should be used in each scenario: a 3x3 Moore neighborhood, weighting each land-use class equally for transition, and including agricultural zoning restrictions into the model.

3.5.4. Cellular Automata Simulations

Each of the three scenarios developed in section 3.4 are integrated into CA models that simulate residential land-use change in Metro Vancouver. Changes in residential land-use are depicted through the use of static land-use maps (Fig. 3-7) updated on a yearly basis throughout simulations. Over time, cells in the land-use maps transition from land-use classes other than residential (in particular open area cells, and resource and industrial cells) to a residential land-use class. The CA model operates by transitioning cells from non-residential to residential in a series of steps. First, Boolean maps are created, separating the land-use maps into one of two classes assigning the class a value of 1 if a cell's current land-use is residential, and assigning the class a value of 0 otherwise. Neighborhood and transition rules are applied to land-use data to simulate urban growth, performed by determining a set of non-residential cells that are eligible to transition to residential at each iteration. All three scenarios operate using a normalized Moore (3x3 cell) neighborhood around each cell. Cells transition from non-residential land use classes to the residential land-use class if there is any existing residential density in the neighborhood around the cell. In addition, eligible cells are assigned suitability for transition from 0 to 1 based on the existing land-use class of a cell. Higher values indicate a higher possibility to transition from non-residential to residential. Cells in the resource and industrial land-use class and open area land-use class have the highest possibility to transition.

Outputs from the three LSP scenarios are then integrated into the CA model. The final LSP suitability outputs from the LSP aggregation structures of each scenario (Figs. 3-4,3-5,3-6) provide cell-specific rankings representing suitability, from 0 (completely unsuitable) to 1 (completely suitable) inclusive. Of the cells deemed eligible for transition based on the neighborhood and transition rules applied in the CA model, the top *n* potential residential cells are chosen based on output suitability scores from the LSP aggregation structures. The value for *n* was determined by carefully calibrating the model output with 2006 land-use maps: after running the model for five iterations (from 2001 initialization to 2006), the value of *n* is set so that there is an equal number of residential cells in the simulated output as there are in the actual 2006 land-use maps. The top *n* eligible cells are then added to the residential Boolean map, and subsequently to the existing land-use map for the current iteration, representing the final output of the iteration. For each scenario the LSP-CA model was ran for 20 years, and verified after five years based on existing land-use datasets. A flowchart depicting the different elements incorporated into the CA model is shown in Fig. 3-8.

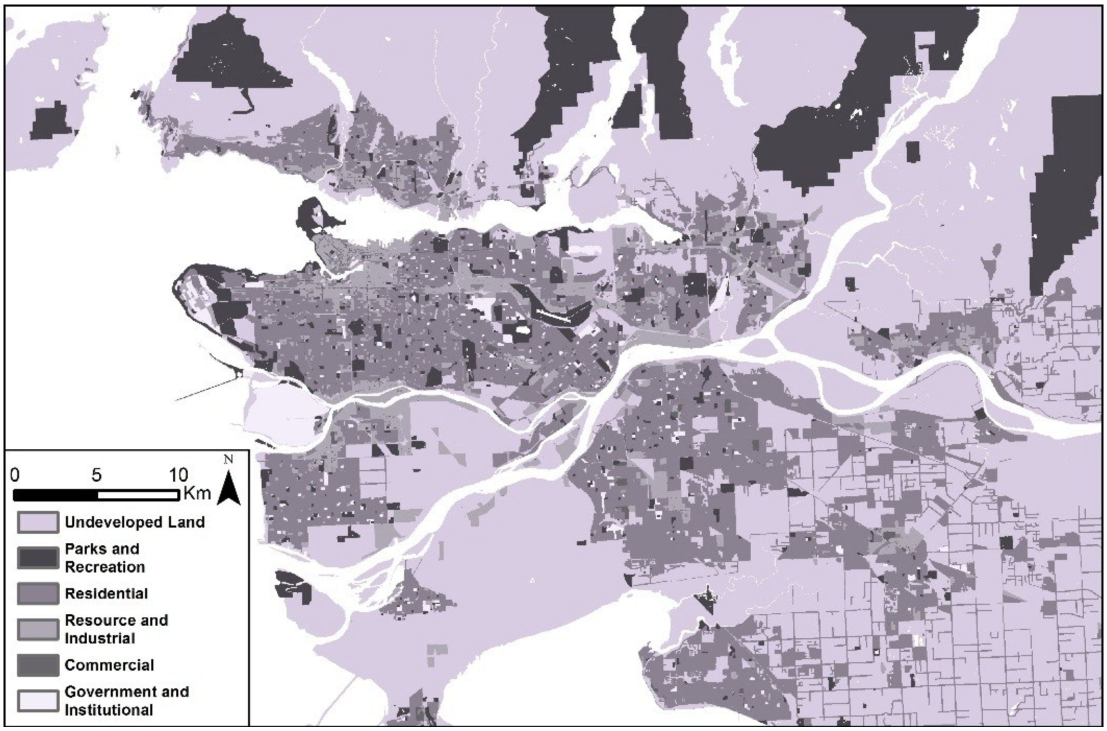

Figure 3-7. Land use map for Metro Vancouver for year 2001

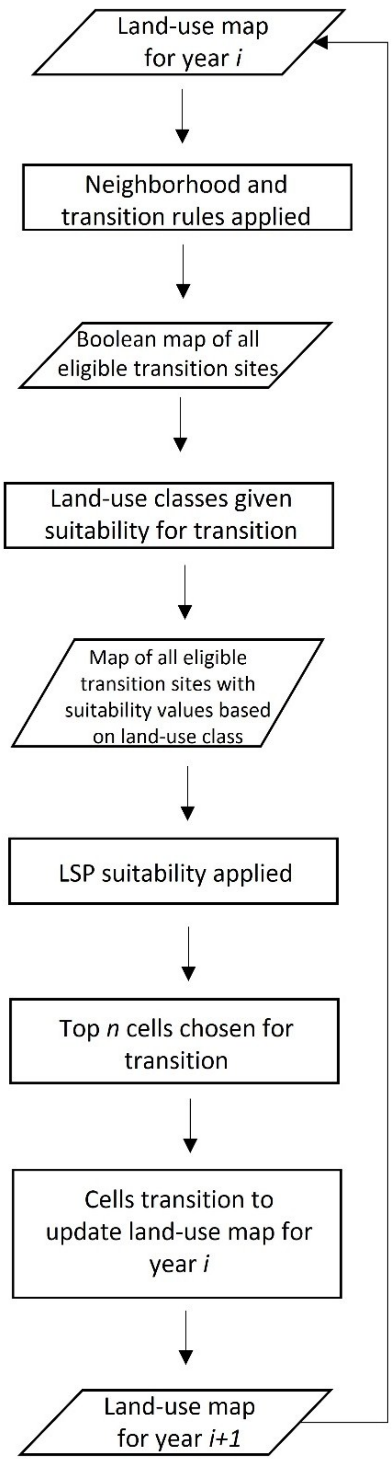

Figure 3-8. Flowchart of CA model

3.5.5. Simulation Results

Each LSP aggregation scenario is implemented into the LSP-CA model framework created. Simulation outputs for all three scenarios are shown in Fig. 3-9 which depicts output land-use maps after 5 years of simulation, and Fig. 3-10, which depicts output land-use maps after 20 years of simulation. Scenario 1's focus on transportation is clearly evident: with residential density increasing nearer to freeways, transportation lines, and major roads. Scenario 2 has increased density in urban, denser municipalities across the study site, whereas scenario 3 depicts significant growth in the southeast portion of the map, a much less densely populated region, with much more rural and affordable land.

Figure 3-11 depicts newly developed residential land-use cells after twenty years of simulation for each of the three scenarios. As expected, development in Scenario 1 follows existing transportation lines as closely as possible, with development occurring along existing bus lines, light-rail transportation lines, and major roads and freeways. None of the development in scenario 2 is in the further municipalities from downtown Vancouver. Although not the intention of the simulation, as it would be difficult for families to afford housing in the suburbs closer to downtown Vancouver, it is likely that these observed patterns are a result of heavy influence of input criteria in the accessibility category of the LSP aggregation structure for scenario 2. Scenario 3 shows much more growth in the further municipalities (southeast portion of study site) compared to any of the other scenarios. This is a result of scenario 3 being suburban-oriented, and heavy influence being placed onto input criteria within the population category of the LSP aggregation structure for scenario 3. Despite these differences observed after twenty years of simulation for each scenario, there are some commonalities observed between scenarios, in particular when comparing results in 2006, after five years of simulation. Each of the three scenarios depicts growth along the main transportation corridors of Metro Vancouver (along major highways and major transportation routes). Additionally, growth is observed to increase in the municipalities in the Southeast region of Metro Vancouver: areas where there is some existing density and infrastructure, however plenty of room for new residential development.

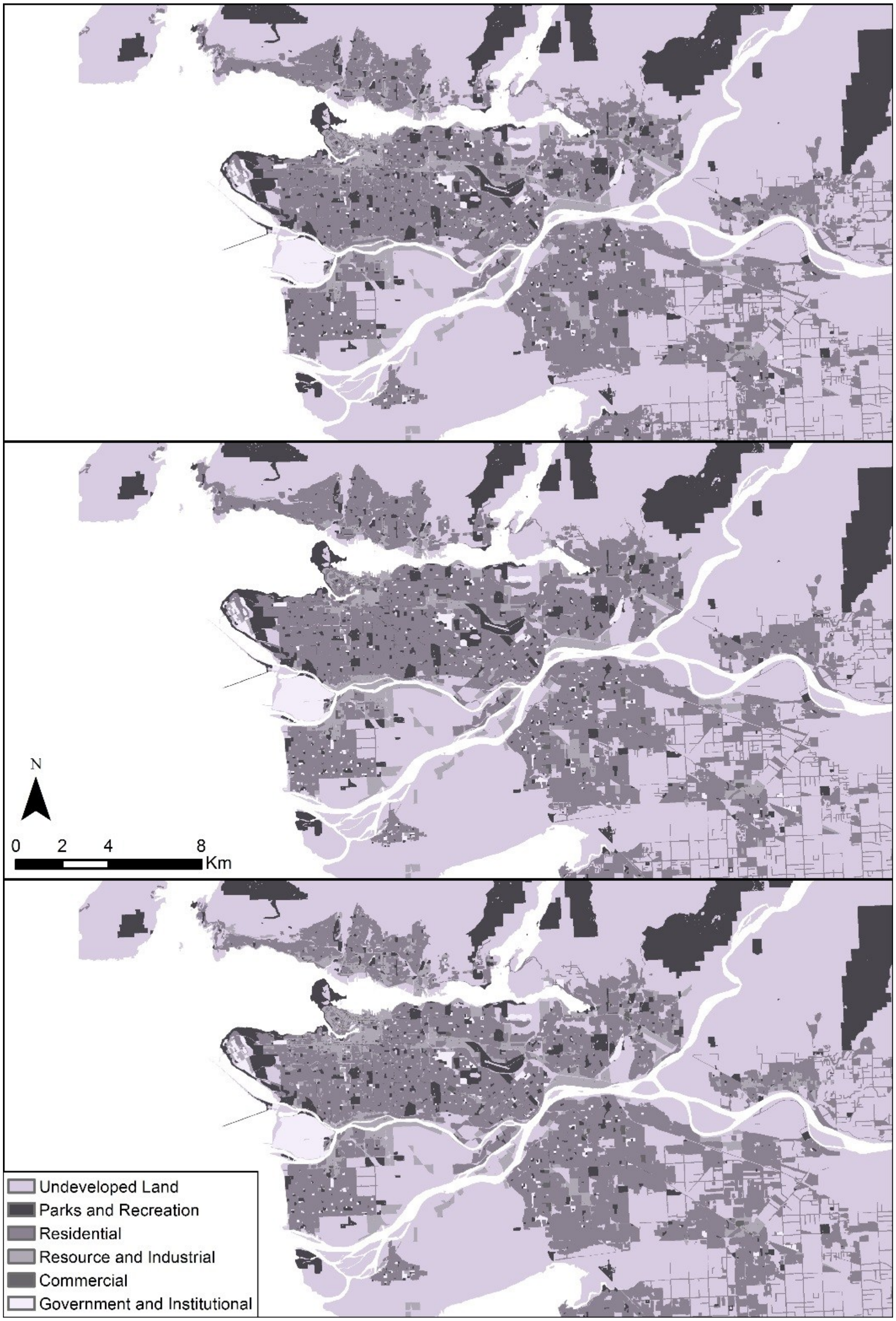

Figure 3-9. Scenario results for Scenario 1 (top), Scenario 2 (middle), and Scenario 3 (bottom) after five years, in the year 2006.

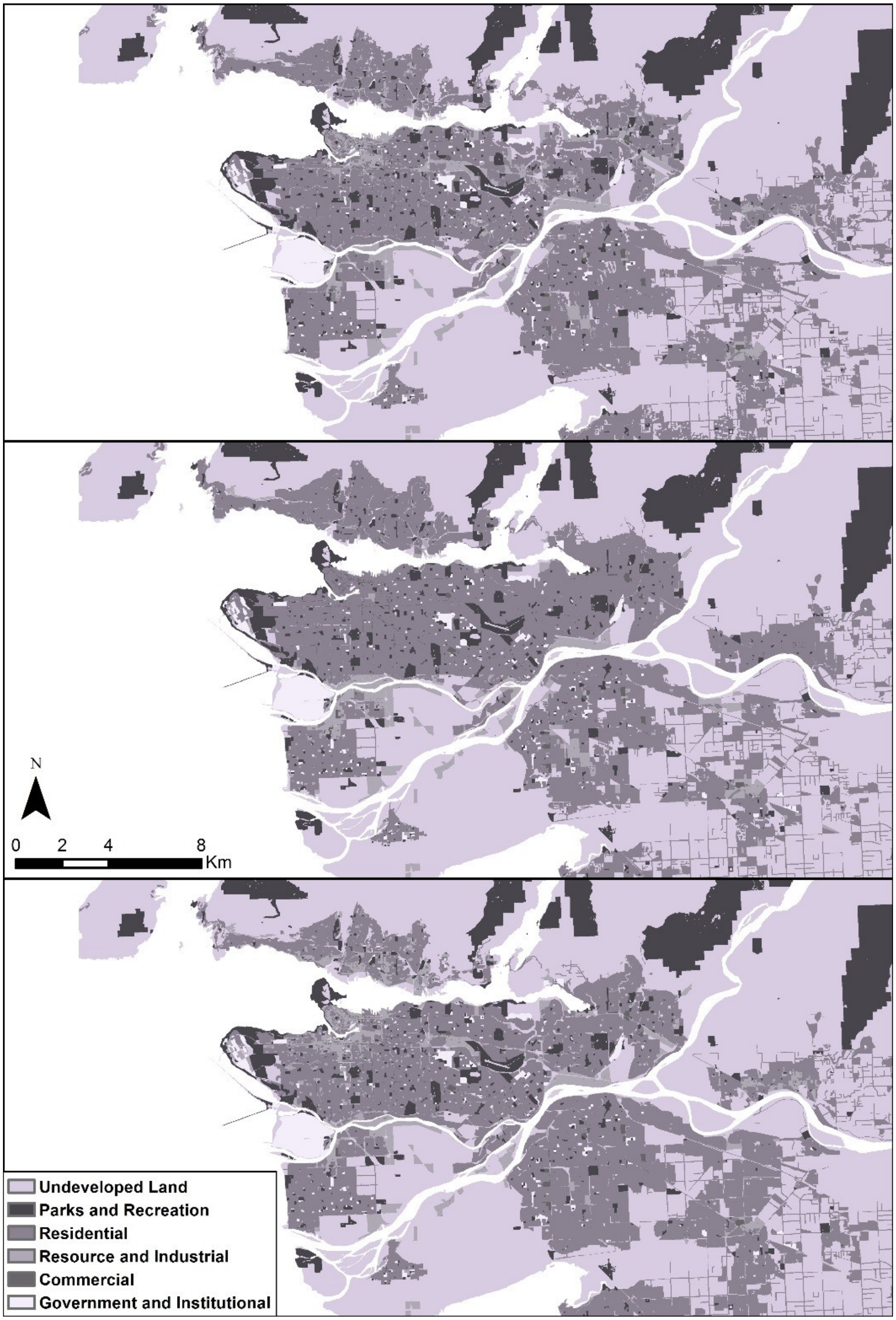

Figure 3-10. Scenario results for Scenario 1 (top), Scenario 2 (middle), and Scenario 3 (bottom) after 20 years, in the year 2021.

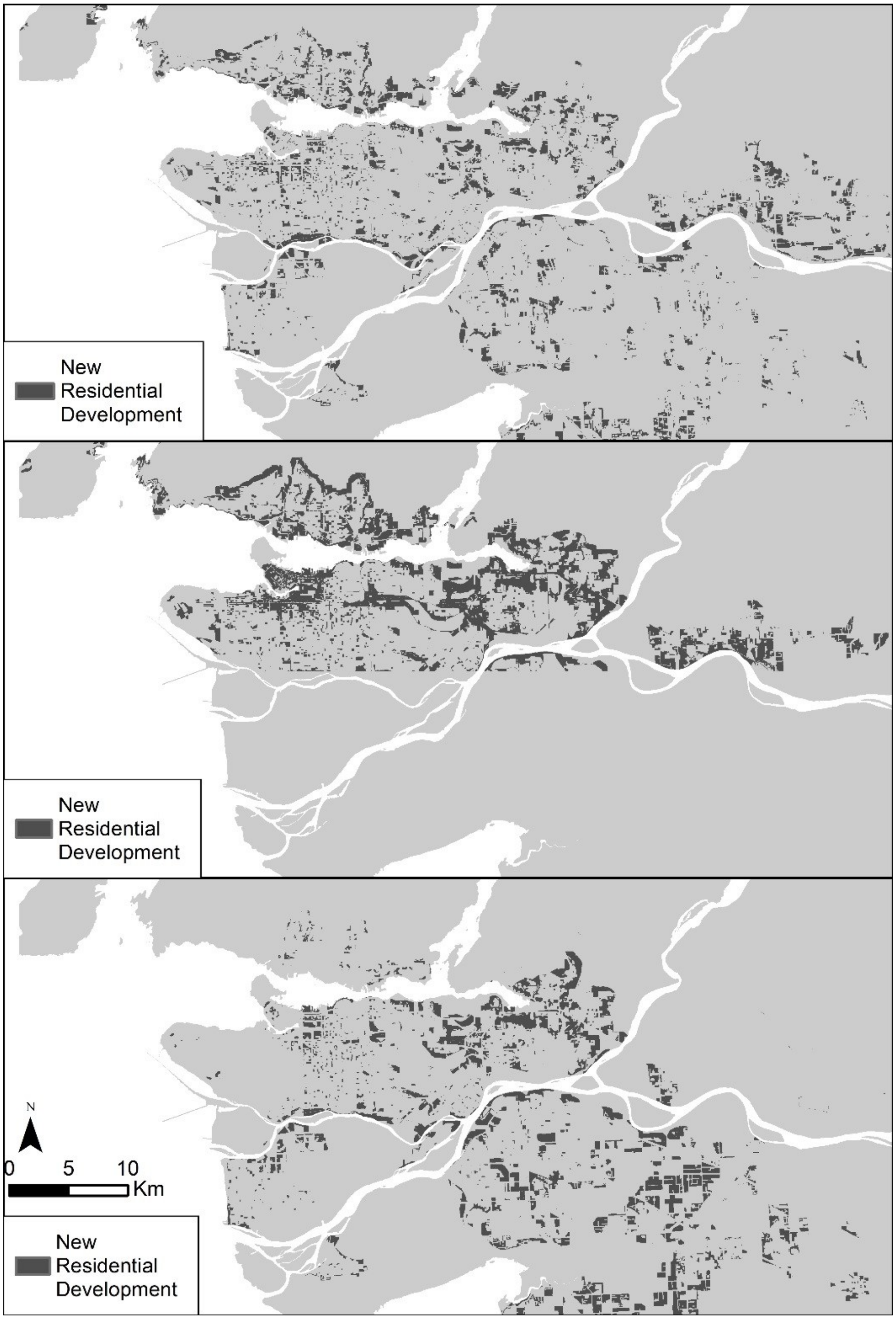

Figure 3-11. Boolean maps showing new residential development for Scenario 1 (top), Scenario 2 (middle), and scenario 3 (bottom)

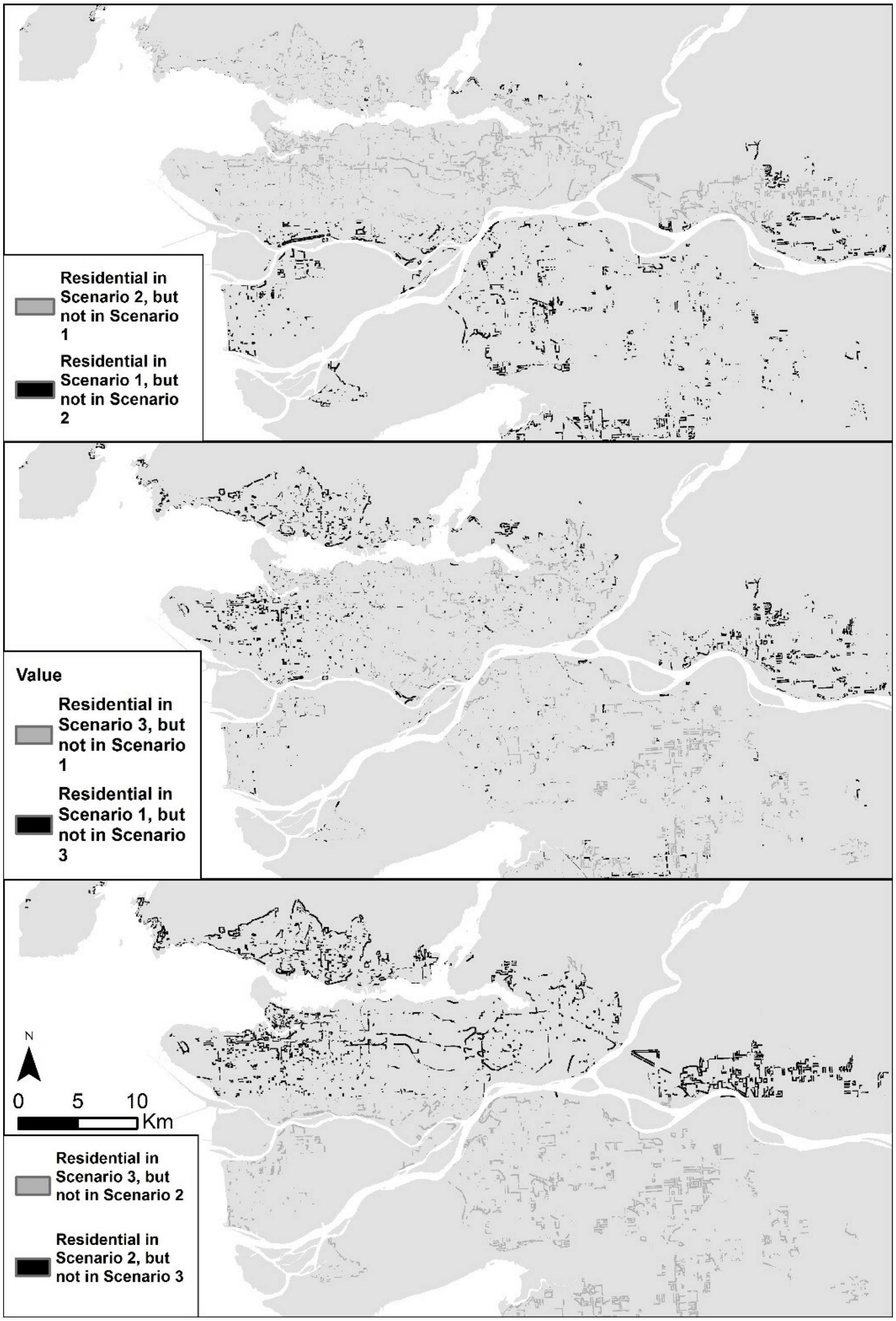

Figure 3-12. Maps depicting differences between residential land-use change after five years of simulation for each of the three scenarios. Each map depicts cells that become developed in one scenario, but not another

Each scenario simulates a significant amount of new residential development in Metro Vancouver (Fig. 3-13). There is an increase of 21.39%, 22.65%, and 21.84% in residential land-cover for scenarios 1, 2, and 3 respectively after twenty years of simulation. At the early iterations of simulations, there is an increased amount of residential development, which slows down in later iterations, depicted by the graph shape in Fig. 3-9. The slowing down of development over time is likely due to there being fewer suitable cells at later iterations of the simulations, due to the LSP method choosing the most suitable cells for residential development first, leaving the less suitable cells for future iterations.

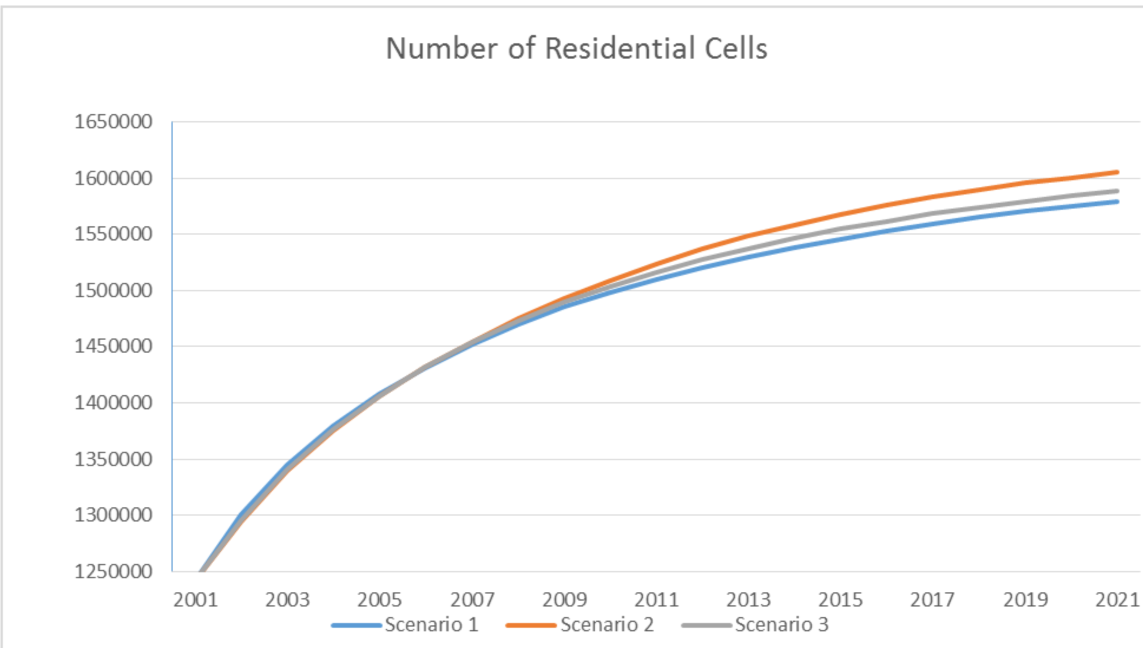

Figure 3-13. Number of total residential cells simulated in the study area for each of the three scenarios

3.5.6. Sensitivity Analysis

In order to test the LSP-GIS model's susceptibility to small perturbations made to values in an LSP aggregation structure, sensitivity analysis was performed. Scenario 1 was chosen as a basis for sensitivity analysis. Stochasticity was added into the aggregation structure for scenario 1 with respect to the weights of preference, as well as the individual LSP aggregators. Individual weights of preference were allowed to vary ±0.1 from their values in the LSP aggregation structure for scenario 1 (i.e. a weight of 0.5 could take a value from 0.4 to 0.6). LSP aggregators were allowed to vary between three values: one degree of replaceability more, the actual value, or one degree of simultaneity more. For example, if the LSP aggregator used in the aggregation structure is CA, then it can vary between C+-, CA, and C-+. With these two stochastic precedents established, several simulations were run to observe the changes made on the output map given changes in the aggregation structure. There is the potential for even small changes to either weights of preference or LSP aggregators to have large impacts on the output suitability maps. Figure 3-14 depicts four separate maps, where less than ten weights of preference and five LSP aggregators differ in the aggregation structure from one map to the next. As can be seen, the maps can vary by an extreme amount in certain spatial locations. For example, the top left map in figure 3-14 is drastically different than the bottom left and bottom right maps. Therefore, it is important to find values for the weights of preference and LSP aggregators that ensure that if small changes are made, there is as minimal as possible a change in the output suitability map. Several simulations can be run that make very small changes to weights and LSP aggregators (as small as a change to one individual weight or one aggregator). From there, the output maps can be averaged to give the output suitability map from a single LSP aggregator. Another lesson that can be learned from sensitivity analysis is that applying a *canonical aggregation structure*: one where the level of simultaneity increases as the number of inputs into any individual aggregator increases, leads to more consistent results. In simulations run where the level of simultaneity used was higher for aggregators in the initial stages of the structure (where fewer inputs are going into any one aggregator), the outputs tended to be much more variable, and prone to extreme change, such as those seen in the top left pane of figure 3-14. After performing sensitivity analysis, weights and aggregators chosen for each of the three scenarios were slightly modified, to see if there was the possibility for any large changes in output suitability maps. If large changes were noticed, either weights or aggregators were changed, or values for scenarios were obtained based on an average of several simulation runs.

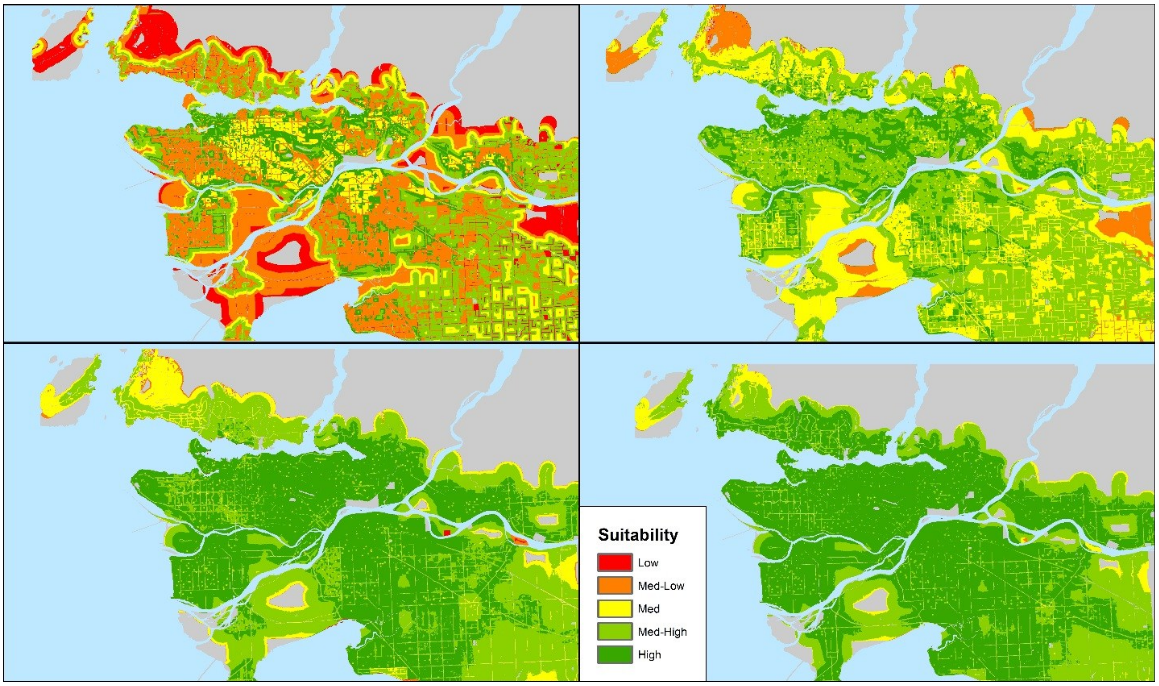

Figure 3-14. Four sample outputs developed from modifying weights of preference and aggregators in a single LSP aggregation structure

3.6. Conclusion

The LSP-CA model used in this project integrated suitability maps based on linear fuzzy functions through the use of an LSP aggregation structure, with the suitability maps combining together through different LSP aggregators. The final LSP suitability output was then run through a CA model to aid in cell state transitions. The entire process was performed in Macro Modeler within the GIS, *IDRISI*, with outputs displayed as static maps. LSP is a way of modeling the complex system interactions that occur in urban growth dynamics, as shown by our high kappa statistic values. The robustness of the model depends heavily on the choices for input parameters, sophistication of the LSP aggregation structure, and CA model. Furthermore, the success of the model also depends highly on parameter choices made at each stage of the model.

This CA model is very effective at simulating interactions on the regional scale, while looking at several physical factors within the region, however it is very limited in its ability to provide micro-scale simulations, at the individual and cadastral level. Most importantly, this CA model, and any CA model, is unable to simulate sophisticated dynamics within the system, between multiple stakeholders, such as at the resident-to-resident level, the developer to government level, or developer-to-developer level. In order to capture the interaction and communication between each of these stakeholders, and how urban dynamics are affected by these interactions, an agent-based model must be used.

3.7. Acknowledgements

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Chapter 4.

Integrating the Logic Scoring of Preference method for with Agent-Based Modeling: The case study of residential urban simulations

4.1. Abstract

The Logic Scoring of Preference (LSP) method is a part of general multicriteria decision making (MCDM) approach that has origins in the soft computing. The method can model simultaneity, replaceability, and a wide range of other aggregators to suit various evaluation objectives that are close to human reasoning. The LSP method is based on fuzzy reasoning and can aggregate an unlimited amount of inputs without loss of significance. The main objective of this study is to develop and test an integrated method that uses LSP to model the decision-making process of actors that influence urban residential development, as a part of an agent-based model (ABM) of urban land use change. Geospatial data for the Clayton-Cloverdale neighborhood of the City of Surrey, British Columbia, Canada, has been used to incorporate the proposed LSP agent-based model to simulate land-use change at a cadastral level. The model simulates the interactions of various stakeholders: residents, developers, and city planners together, each of which have separate and conflicting priorities. Obtained results indicate that LSP method is providing representations of agent decision making closer to actual human decision-making logic and allows for realistic modeling outcomes of urban residential land-use change.

A version of this chapter will be submitted to *the Environment and Planning B* journal coauthored with S. Dragicevic.

4.2. Introduction

Since the late twentieth century, the paradigm in land-use change research has been to describe cities as complex systems (Batty, 2008). Cities are self-organizing structures consisting individual interconnected components including transportation, land use, demographics, and topography, which through their interactions exhibit behaviors and properties associated with complex systems. They are characterized by local, complex interactions often seen as bottom-up that give rise to patters at larger spatial scales (Albeverio et al., 2010).

In the last two decades, cellular automata (CA) has been the predominant modeling approach used to simulate urban dynamics and residential land-use change (Ke and Fuling, 2010). They consist of a grid of cells with a finite number of states that change due to local neighborhood interactions based on transition rules. Despite their simple framework, CA models of urban systems can generate complex behaviors observed in urban systems (White and Engelen, 1993). However, the framework of CA models impose some limitations. CA models cannot represent complex interactions between individuals as transitions occur based on static cell states. Agent-based models (ABMs) are capable of solving issues raised by CA models by incorporating autonomous, heterogeneous agents into the model (Parker et al., 2003). Agents interact through cooperation and competition among one another and within their spatial environment. ABMs operate on a local scale, whose decisions and interactions with other agents create patterns at local and other spatial scales (Fontaine and Roundsevell, 2009).

Another limitation of CA models is their most common use of raster-based data to represent geographic features. At small-scales, spatial features such as houses, parks, commercial facilities, and schools are rarely adequately represented through assignment into cells on a square lattice. Instead, their shapes and sizes are often irregular, necessitating the use of vector-based GIS, which can represent spatial features as irregular spatial tesselations (Stevens and Dragicevic, 2007). ABMs, while still at the initial stages of full integration, are capable of using both raster and vector GIS datasets.

To simulate urban growth within ABMs agents are used to represent residents, city planners, developers, environmentalists, farmers or any other parties or stakeholders that can influence decisions or affect land-use change (Jjumba and Dragicevic, 2011; Ligtenberg et al., 2001; Evans and Kelley, 2004; Valbuena et al., 2010; Irwin and Bockstael, 2002; Lim et al., 2002). The decision-making algorithms for these agents are based on sets of criteria pertinent to each group of agents. For example, residents decide to occupy homes based on criteria such as a home`s value, its amenities, and its location. In order to combine criteria, and make agent decisions easier or optimal, a multi-criteria evaluation (MCE) approach may be used (Rui and Ban, 2010; Xiao et al., 2010; Li and Liu, 2007). Fuzzy logic and reasoning is also used to evaluate and standardize the variables that agents consider in their decision making (Graniero and Robinson, 2006).

MCE methods are part of MCDM and can assist in the creation of decision-making algorithms of agents' reasoning within ABMs. Model developed by Li and Liu (2007) use MCE to define a utility function for the decision-making algorithms of *resident agent*s. This utility function allows residential agents to assess the value of a potential residential site with regards to price, surrounding environment, accessibility, provision of general facilities, and educational benefits. However, MCE-based algorithms for agent decision-making in ABMs rely on weighted linear combination (WLC) based methods for MCE analysis (Rui and Ban, 2010; Xiao et al., 2010). WLC takes a set of input factors, and combines them together through the use of weights of preference: each factor is given some preference between 0 and 1 inclusive, and the sum of the weights on the factors being combined must add up to 1. WLC however has significant limitations arise when used in GIS-based MCE and as basis for decision-making of agents, especially pertaining to its ability to observe and simulate human decision-making logic.

Several fundamental properties of MCE methods have been identified for when MCE is used to combine factors to satisfy a given objective (Dujmovic et al., 2009). Some of these factors include: the ability to combine any number of inputs, the ability to combine objective and subjective inputs, the ability to combine absolute and relative criteria, flexibility of attributes, and the ability to retain and accurately represent human decision-making logic (Dujmovic and De Tre, 2011). MCE using WLC method is unable to satisfy all these properties. In particular, WLC cannot adequately represent human decision-making logic, nor incorporate a large number of factors in MCE analysis without loss of significance on any one individual factor. The Logic Scoring of Preference (LSP) method is capable of satisfying all fundamental MCE model properties. The use of variable ANDness (known as *simultaneity* in the LSP approach) and ORness (known as *replaceability*) among inputs in the LSP method allows LSP to better expresses human reasoning compared to existing MCEs (Dujmovic and De Tre, 2011). LSP also allows for the inclusion of an infinite number of inputs in MCE analysis, without loss of significance on any individual input. This is due to differences in the way LSP aggregates inputs together compared to other MCEs, in particular, the inclusion of *simultaneity* (ANDness) and *replaceability* (ORness) used when combining inputs. It is important to explore the use of LSP as an alternative method to WLC (and other existing MCEs), to model the decision-making processes of agents and their reasoning logic. Based on reasoning provided by Dujmovic et al. (2011), the use of LSP can improve the representation of human decision-making logic and provide more realistic algorithms for determining agent decision-making.

Therefore the main objective of this study is to implement the Logic Scoring of Preference (LSP) approach as a method for representing the decision-making process of agents in an ABM of land-use change. The proposed LSP-ABM method simulates residential land-use change on the cadastral scale. Various stakeholders including residents, developers, and city planners comprise the different agents within the model. Resident agents have their decision-making algorithms based on the LSP approach. This study also proposes four different scenarios that model urban growth the Clayton-Cloverdale neighbourhood of Surrey, British Columbia, Canada and based on real geospatial datasets at cadastral level.

4.3. Theoretical Background

4.3.1. Agent-based Models

Parallels between complex systems and city dynamics necessitate the use of computational complex system models such as ABMs to represent and analyse urban growth patterns. Applying agent-based models to simulate real urban systems and geospatial datasets is still in its early stages, but has gained a large amount of attention in the past decade (Matthews et al., 2007). Agent-based models were used for the simulation of micro-scale city dynamics (Benenson, 1998). Models such as UrbanSim (Waddell et al., 2003), and PUMA (Ettema et al., 2007) were some of the first agent-based simulations developed for supporting planning and analysis of urban development. The recent increase in the use of ABMs for modeling urban land-use change is largely due to a standardization of the modeling process through the ODD (overview, design concepts, and detailed) protocol (Grimm et al., 2010), as well due to the benefits associated with exploring policies related to urban planning (Ligmann-Zielinska and Jankowski, 2007).

Most ABMs consist of two components: the static, representing the environment within which agents act, and the agent layer representing autonomous, decision-making entities known as agents (Benenson, 1998; Bonabeau, 2002) that interact and generate changes within the model. A number of different types of agents compose the second layer. For example, in an ABM of land-use change, agents can include: *resident agent*s: those that want to move or relocate within the static environment, *government/planning agents*: those that zone or establish land suitable for development, and *developer agents*: those that build houses and subdivisions for the *resident agent*s These agents communicate, cooperate, and compete with one another to change the environment. It is difficult to precisely define an agent, however the main features shared by most agents are (Castle and Crooks, 2006): *autonomy*; agents can exchange information among one another and make independent decisions, *heterogeneity*, and *activity*; agents can apply independent control in a situation. Other features of agents are: *pro-activity*, agents are *goal directed,* they are *reactive* and *perceptive*, they are characterized by *bounded rationality*, meaning that they can be restricted to only partial access to the information, and they are *interactive*, *mobile*, and *adaptive*.

The ABM framework focuses on agent behaviors and dynamics. Agents are given a set of rules that define their interactions both with their surrounding environment and among one another. Similar to CA, ABMs are a bottom-up approach, capable of representing how system evolves over time based on the interactions of many individuals. They often are based on hypothetical datasets to provide simulations (Crooks, 2010; Ligtenberg et al., 2001; Shan and Zhu, 2007). Integrating real geospatial data increases the utility of models for decision-making purposes, and allows for more realistic simulations (Kocabas and Dragicevic, 2013; Evans and Kelley, 2004; Xiao et al., 2010; Irwin and Bockstael, 2002). Moreover, an agent based model capable of partitioning available land for urban development, and generating subdivisions with the use of geospatial datasets on a cadastral scale has been developed by Jjumba and Dragicevic (2011), however the agent reasoning was quite limited. As a result, incorporating MCE for agent-based modeling with GIS datasets has been advancing the agents' ability for decision-making (Zhang and Fontaine, 2010; Li and Liu, 2007; Xiao et al., 2010; Ligtenberg et al., 2001). Existing studies have incorporated simple GIS-based MCEs, based on weighted linear combination (WLC) as methods for evaluating agents' decision-making processes. The use of LSP can better represent human's decision-making reasoning integrated into agents' behaviour and decision-making.

4.3.2. The Logic Scoring of Preference Method in Spatial Applications

The LSP method was developed as an approach to combine criteria, with the aim to retain the logic of human decision-making. Human decision-making is represented through the inclusion of a continuous scale of *simultaneity* and *replaceability* used when combining criteria, features unavailable in other common GIS-based MCE. The LSP method has been used for applications in computer science such as: windowed environment software evaluation (Dujmovic and Bayucan, 1997), evaluation of Java IDEs (Dujmovic and Nagashima, 2006), and comparison of search engines (Dujmovic and Bai, 2006). More recently, LSP has been used for spatial applications, but mostly using hypothetical datasets. In particular, Dujmovic et al. (2008) developed the concept of LSP aggregated geographic suitability maps, or *s-maps*. S-maps assign a degree of suitability to a set of spatial locations on a continuous surface, for a specific purpose, such as: suitability for industrial development, agriculture, housing, education, or recreation. To implement the LSP method, the following steps must be taken:

1. **Establishment of set of input criteria:** Criteria are objective-specific and must be standardized and evaluated as mandatory or optional.

2. **Development of the LSP attribute tree:** The attribute tree provides an organized structure for the criteria established, defining the step-wise combination of criteria until one overall output representing the combination of all criteria is attained.

3. **Development of the LSP aggregation structure:** Any time two or more criteria are combined in the LSP attribute tree, an LSP aggregator must be applied, defining a degree of *simultaneity* or *replaceability* among the criteria. The set of LSP aggregators used comprise the entire LSP aggregation structure.

4. **Calculation of overall LSP suitability output:** The output obtained is a score representing suitability for a particular spatial location with respect to a particular objective.

Input Criteria

Inputs are a set of factors designated to be combined relevant to some objective or decision needed to be made. Inputs must be chosen and categorized based on similarity, such that similar inputs are combined first in the LSP aggregation structure. To combine inputs, they must first be standardized: each input must be transformed from their existing units onto a standardized scale representing suitability, where suitability is reflective of the objective under consideration. Inputs must also be expressed as either mandatory (denoted by a '+' sign) or optional (denoted by a '-' sign). If a mandatory input is completely unsuitable, having a suitability score of zero, then the overall LSP suitability score (the output of the entire LSP method) will also have a value of zero. Optional inputs do not have this requirement, however can provide a penalty or reward based on their input suitability values (Dujmovic, 1979). After input criteria have been chosen, standardized, and categorized, the LSP attribute tree can be developed.

LSP Attribute Tree

The LSP attribute tree organizes the decision problem and contains all relevant attributes and parameters. It takes all input criteria, and determines the order in which they will be combined together, up until and including the point at which all input criteria have been combined together. Figure 4-1 shows an example of a simple attribute tree with four inputs.

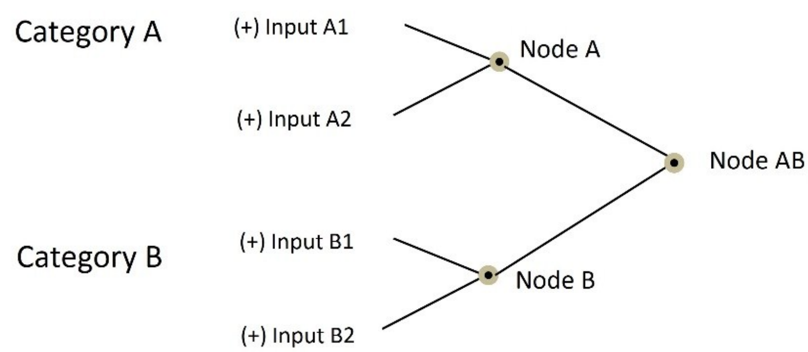

Figure 4-1. Example of a simple attribute tree for combining four inputs (A1, A2, B1, B2).

In this example, the input criteria are grouped into either category A, or category B. The assumption is that inputs A1, and A2 are more similar to each other than the inputs B1 or B2, and vice versa. Nodes A and B represent the combinations of inputs A1 and A2, and B1 and B2 respectively, and node AB represents the combination of all four inputs. In LSP aggregation structures, each node (A, B, and AB) have their own associated LSP aggregator.

LSP Aggregation Structure

The attribute tree allows for the design of an aggregation structure, which is composed of a series of LSP aggregators describing the parameterization and step-wise combination of inputs based on logical requirements and weighting parameters (Dujmovic and Scheer, 2010). The LSP aggregators express mandatory, (+), and optional, (-), requirements associated with input criteria. Each of the requirements is represented in a spectrum of conditions ranging from full disjunction, D, to full conjunction, C (Table 3-1).

Table 4-1. LSP aggregators and associated exponents

Simultaneity

Symbol	C	C++	C+	C+-	CA	C-+	C-	C--	A
r	$-\infty$	-9.06	-3.51	-1.655	-0.72	-0.148	0.261	0.619	1.0

Replaceability

Symbol	D	D++	D+	D+-	DA	D-+	D-	D--	A
r	∞	20.63	9.521	5.802	3.929	2.792	2.018	1.449	1.0

Each LSP aggregator used reflects the degree of simultaneity, neutrality, or replaceability desired to be expressed between the inputs considered. The further along the spectrum from neutral (A) to full conjunction (C) (Table 4-1) the aggregator used is, the stronger and more restrictive the degree of simultaneity is. The further in the other direction, from neutral (A) to full disjunction (D), the stronger the replaceability among inputs is. Neutral (A) is used to express neither simultaneity nor replaceability. For example, in Figure 4-1, if the satisfaction of input A1 negated the need for input A2 to be satisfied, and vice versa, then an LSP aggregator representing a high degree of replaceability (such as DA, D+-, etc.) would be assigned to node A. If inputs B1 and B2 both need to be satisfied to achieve a high satisfaction when combined, then an LSP aggregator with a high degree of simultaneity would be applied to node B, such as CA or C+-.

LSP aggregators can be grouped into one of seven aggregator types. These include: Full Conjunction (LSP aggregator C in Table 4-1), Hard Partial Conjunction (using aggregators such as C++, C+, C+-), Soft Partial Conjunction(C-, C–), Neutrality (A), Soft Partial Disjunction (D–, D-, D-+, DA), Hard Partial Disjunction (DA, D+-, D+, D++) and Full Disjunction (D). The choice of LSP aggregator used is determined by the desired level of simultaneity or replaceability between inputs that the decision maker wants to express. A Hard Partial Conjunction (HPC) operator is often used to express the combination of mandatory inputs, whereas a Soft Partial Conjunction operator is less restrictive, and is appropriate for the combination of optional inputs. The analogue is true for Hard Partial Disjunction and Soft Partial Disjunction operators.

LSP aggregators combine inputs of the same type (mandatory with mandatory, or optional with optional) using a generalized conjunction disjunction function described in Dujmovic et al. (2009). Given two input parameters $X_1,\ldots,X_n$, the generalized conjunction disjunction is computed using the weighted power mean:

$$GCD(X_{1,\ldots,}X_n)=[W_1X_1^r+\ldots+W_nX_n^r]^{1/r} \quad (1)$$

where $GCD(X_{1,\ldots,}X_n)$ is the suitability for input parameters $X_{1,\ldots,}X_n$. $W_1,\ldots,W_n$ are used to express the relative importance of usefulness and inexpensiveness of inputs $X_{1,\ldots,}X_n$, *and* r is used to express the degree of simultaneity and replaceability among the inputs $X_{1,\ldots,}X_n$.

When combining inputs of different type (mandatory inputs with optional inputs), the conjunction partial absorption (CPA) function is used (Dujmovic, 1979). Given a mandatory input (or set of inputs) X, and an optional input (or set of inputs) Y, there are two variants for CPA:

$$CPA(X,Y)=\{(1-a)[bx^{r_1}+(1-b)y^{r_1}]^{r_2/r_1}+ax^{r_2}\}^{1/r_2} \quad (2)$$

Where either $r_1<1, r2\geq 1$, or $r1\geq 1, r2<1$, and
$a=W_1, b=W_2$ for $r_1<1, r2\geq 1$, (CD-variant),
$a=W_2, b=W_1$ for $r_1\geq 1, r2<1$, (DC-variant).

CPA operates on a penalty reward scheme (Dujmovic, 1979). Lower suitability values for optional inputs apply penalty to the CPA output value, and higher values provide reward to the CPA output value.

LSP Suitability Output

Once all inputs have been combined in the LSP attribute tree, and LSP aggregators (as well as their weights of preference) have been assigned, the overall suitability output is obtained.

Implementing LSP allows users to produce models that generate reliable results in relation to the inputs, logic aggregators, and weights of relative importance chosen. The step-wise logic aggregation structure of LSP also allows for extreme flexibility through its use of continuous logic, represented in terms of simultaneity and replaceability (Dujmovic et al., 2010). LSP also allows for the inclusion of large numbers of inputs in its structure, without loss of significance due to its logic expressions.

4.4. Methodology: Integration of LSP into an Agent-Based Model

The ABM consists of various agents that represent stakeholders responsible for urban land-use change. The flowchart of the modeling structure is presented on Figure 4-2. Three groups of stakeholder agents are given consideration in the model: *city planner agent*s, *developer agent*s, and *resident agent*s. These three agents groups interact and cooperate amongst one another to shape urban land-use change across the study site over time. *City planner agent*s act to make sure that policies and planning guidelines are followed. Also, they decide on land subdivisions to lots to make them available for *developer* and *resident agent*s. *Developer agents* choose new parcels of land to purchase and develop based on the expected profit that can be obtained from developing housing on particular parcels, as well as the demand from *resident agent*s for parcels in certain locations, and of certain densities (i.e. high density, medium density, and low density). *Resident agent*s then examine through newly developed and existing vacant lots in the study site and choose to occupy lots that they deem most suitable. The LSP method is used to represent the reasoning behind the individual *resident agents*, and is used to assign suitability scores to individual lots in the study site. Three groups of *resident agent*s are considered in the model are: *senior, single,* and *family* agents each with their own set of preferences and decision-making logic, and each of whom assign their own individual suitability scores to vacant lots in the study site.

The Clayton-Cloverdale neighborhood of Surrey, British Columbia (BC), Canada (Figure 1-1) has been chosen for simulation of the model. Surrey is one of the fastest growing cities in Canada (Statistics Canada, 2011), with the Clayton-Cloverdale being one of its fastest growing neighborhoods. Clayton-Cloverdale has a strong vision for community design, with an extensive neighbourhood concept plan (NCP) (Condon and Johnstone 2003). These two factors make Clayton-Cloverdale an interesting study site for urban growth.

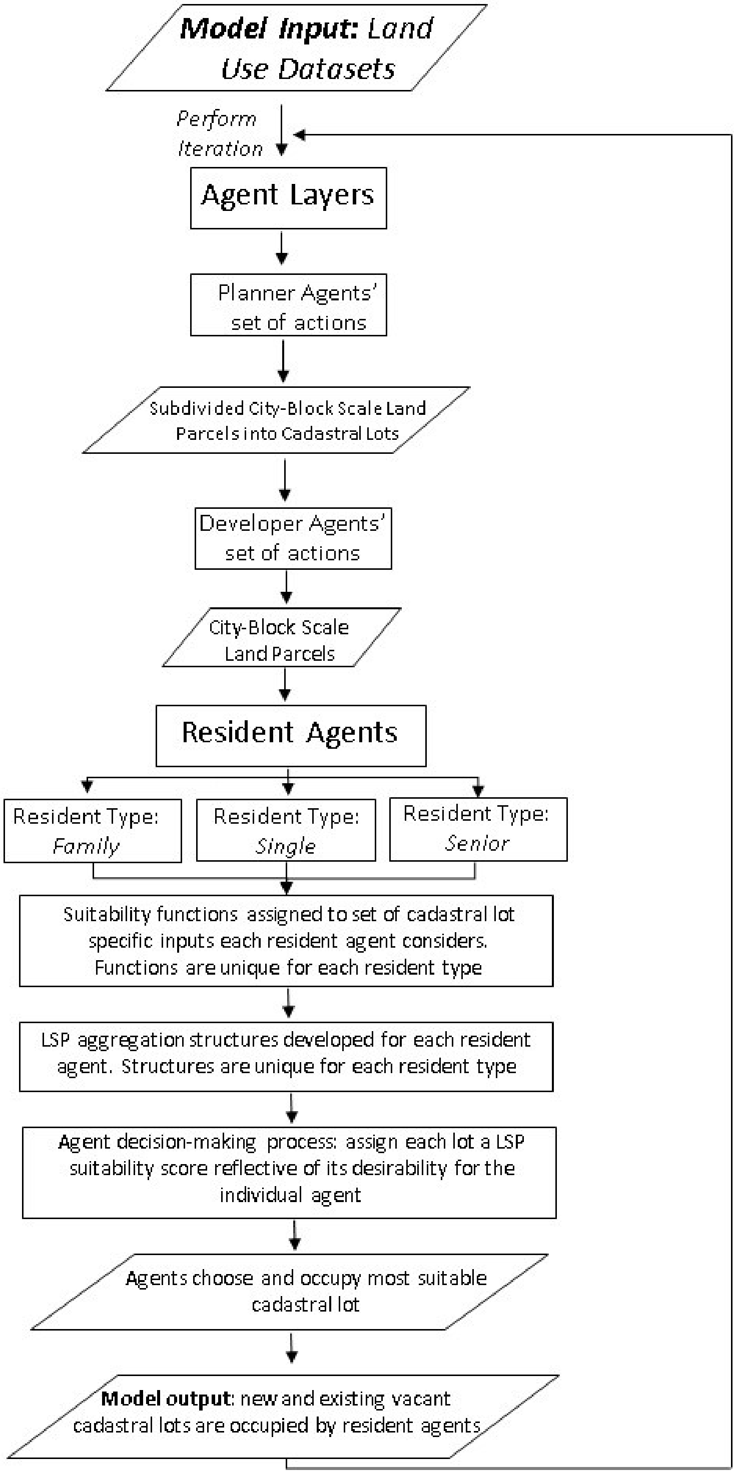

Figure 4-2. Flowchart of LSP-ABM structure with the *planning*, *developer, and resident agents*

Input Land Use Datasets

Several geospatial datasets are used for the proposed LSP-ABM. Input datasets are land-use data consisting of information on the following land categories: parks, commercial sites, schools, proposed park sites, proposed commercial sites, proposed school sites, and cadastral land parcels. With the exception of cadastral land parcels, these layers remain static throughout the simulation. Each cadastral parcel has values for all the attributes that the *resident agent*s base their decisions on. Cadastral lots are assigned as either vacant or occupied. Once occupied, cadastral lots remain occupied throughout the simulation. Over time throughout the simulation process, *resident agent*s choose desirable vacant cadastral lots, and the chosen lots then become occupied. Cadastral lots are also designated as either high density (such as a low rise apartment), medium density (such as townhouses), and low density (such as a single family home), with density established based on the number of occupants per meter squared.

4.4.1. Agent Descriptions

City Planner Agent

City planner agent ensure that a set of established development guidelines for the study area are followed. First, *developer agent*s act by proposing to develop tracts of land within the study area. These tracts vary in size, but are usually on the scale of a city-block (or one side of the street of a city-block), encompassing between five and twenty single family homes, or a single low rise apartment. Based on established development guidelines, city planners react by either permitting the proposed development, or denying the proposal, requiring the *developer agent* to choose a different tract (or density of tract) to develop. City planners deny *developer agent*s proposals in two ways. The first is by restricting development of lots of any type of density (high, medium, or low) at a particular spatial location. For example, if a spatial location is zoned as a park they may deny the proposal for development, or if a location is zoned purely for agriculture they may deny the proposal. The second way planners restrict development is through restricting lots of a particular density (high, medium, and/or low) at certain spatial locations. For example, an area close to major freeways or intersections may be restrict to the development of medium and high density lots (rather than low density single family homes). If a *developer agent*'s proposal is accepted, the tract of land is then subdivided into individual cadastral lots. The main purpose of city planners within the model is to ensure logical development principles are followed given the anticipated population growth over the next several years within the study site.

Developer Agents

The flowchart for *developer agent* reasoning is presented in Figure 4-3. *Developer agent*s make decisions on areas within the study site to purchase for future development, as well as what type of lot to develop in a study site. These decisions are influenced by three factors. The first is the number of *resident agent*s anticipated to be searching for a new home. This is based on the number of agents that came to the study area and searched for a home in the previous year, multiplied by a predicted growth factor. The second factor is the type of *resident agent*s anticipated to search for homes in the study area, which is also based on previous year data. Different *resident agent* types have different ranges of preferences, especially when concerning which land-use (high, medium, low density) type they prefer. *Developer agent*s attempt to fill the market demand by developing new sites in areas that fit *resident agent*'s land-use preferences. The third factor that *developer agent*s focus on is the cost. Cost is represented as the sum of the lot cost, as well as the anticipated cost to provide improvements to the land. For example a low density single family lot is cheaper to develop than a high density apartment building. After choosing desired land parcels to develop, developers are restricted by the planning proposals set forth by the presiding council of the study area.

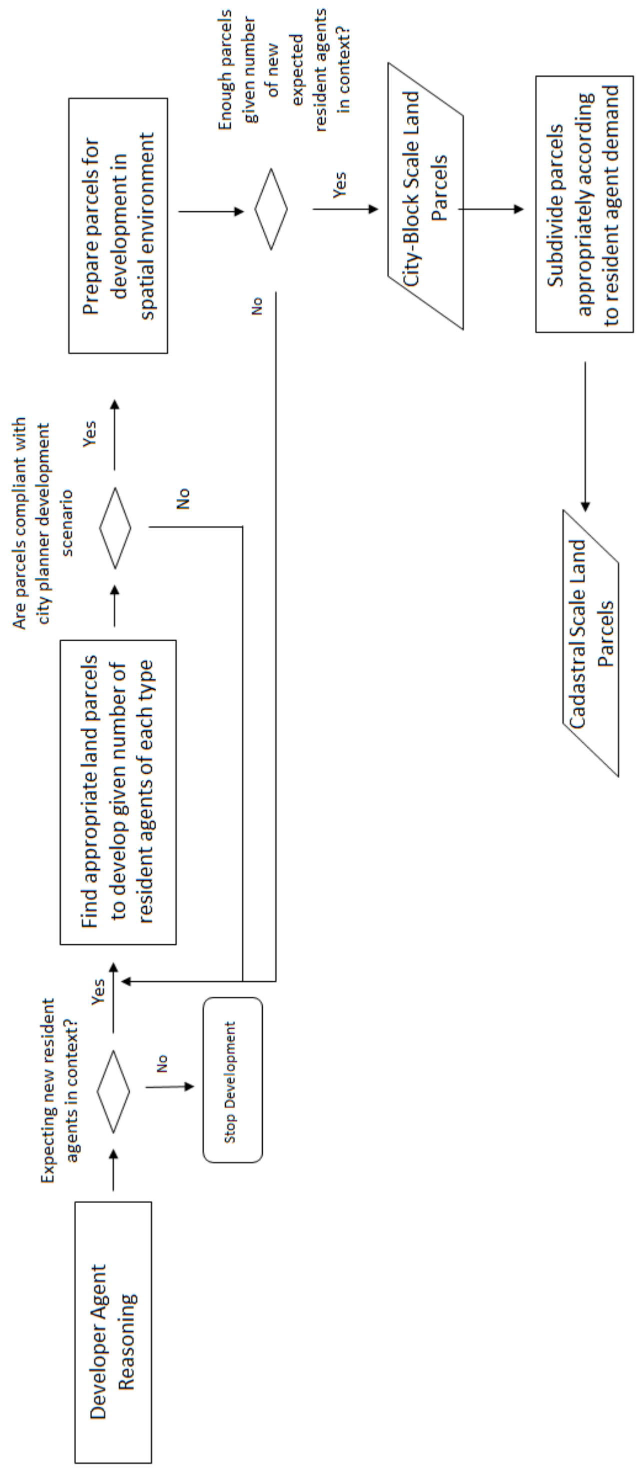

Figure 4-3. Flowchart of *developer agent* decision-making process.

Developer Agent Decision Making Algorithm

*Developer agent*s have a primary goal of profit. This comes through building the most valuable and desirable land parcels. Each iteration, the developer attempts to fill the demand for housing in two steps. Firstly, developers determine an adequate number of parcels, L_n to develop:

$$L_n = G_{fam}R_{fam} + G_{sin}R_{sin} + G_{sen}R_{sen} + C_{fam} + C_{sin} + C_{sen}$$

where R_{fam}, R_{sin}, R_{sen} are the number of family, single, and senior *developer agent*s respectively that were added in the previous iteration, G_{fam}, G_{sin}, G_{sen} are growth factors for each of the three resident classes, and C_{fam}, C_{sin}, C_{sen} are the number of *resident agent*s of each class that were added before the previous iteration, but are still in the environment looking for adequate housing.

Secondly, developers determine the total number of new high density, H_n, medium density, M_n, and low density, L_n, land parcels to develop, given by:

$$H_n = \frac{\alpha_{Hfam} G_{fam} R_{fam} + \alpha_{Hsin} G_{sin} R_{sin} + \alpha_{Hsen} G_{sen} R_{sen}}{\beta_{Hfam} G_{fam} R_{fam} + \beta_{Hsin} G_{sin} R_{sin} + \beta_{Hsen} G_{sen} R_{sen}}$$

$$M_n = \frac{\alpha_{Mfam} G_{fam} R_{fam} + \alpha_{Msin} G_{sin} R_{sin} + \alpha_{Msen} G_{sen} R_{sen}}{\beta_{Mfam} G_{fam} R_{fam} + \beta_{Msin} G_{sin} R_{sin} + \beta_{Msen} G_{sen} R_{sen}}$$

$$L_n = \frac{\alpha_{Lfam} G_{fam} R_{fam} + \alpha_{Lsin} G_{sin} R_{sin} + \alpha_{Lsen} G_{sen} R_{sen}}{\beta_{Lfam} G_{fam} R_{fam} + \beta_{Lsin} G_{sin} R_{sin} + \beta_{Lsen} G_{sen} R_{sen}}$$

where α_i, β_j are coefficients corresponding to the suitability for high, medium, and low density housing for each of the three *resident agent* classes.

Once land parcel number and type has been established for the current iteration, the *developer agent* searches for candidate land parcels. Developers choose among the available parcels for development, and decide which areas would be most suitable for high, medium, and low density, based upon which parcels would give the most total profit. Each land parcel has a cost (measured in total dollars), as well as an associated cost of providing amenities to that parcel for a particular density (low, medium, or high). Each land parcel is then assigned a value according to the following:

$$Cost_{dev} = \frac{\text{Total Cost} \; + \; \text{Cost of Providing Amenities}}{\text{Total number of occupants that can live in parcel}}$$

There is also a small amount of stochasticity associated with the developer's lot choice, meaning $Cost_{dev}$ can stochastically fluctuate in value, however *developer agent*s are more inclined to develop lots that provide the lowest cost per occupant (lowest $Cost_{dev}$). Once a candidate site for a particular land parcel type (high, medium, low density) is chosen, that parcel is made visible in the environment, and made available for *resident agent*s to potentially subdivide, and later occupy.

Resident Agents

The urban residential environment is developed in part due to the actions of the *resident agent*s. *Resident agent*s look to occupy potential property (cadastral) lots built within the study site. Through their relocation into the study area, *resident agent*s drive the demand for new lots as well as densification of lots. *Resident agent*s are added at each iteration of the simulation, and attempt to find suitable housing by querying the set of vacant cadastral lots in the study area.

As can be seen in figure 4-2, the decision making process for *resident agent*s' occurs in a number of steps. First, *resident agent*s are represented by three groups: *family*, *single*, and *senior,* each with their own set of preferences and properties. These three classes represent the three most dominant groups of individuals and are the drivers of different types of urban change seen in the study site. Next, a set of attributes is evaluated for each vacant cadastral lot, such as distance to roads, schools, and urban residential density type (low, medium, or high). These attributes are then transformed through the use of suitability functions, such that each input attribute is represented on the same standardized scale representing suitability (with respect to one of the three *resident agent* groups trying to find housing) from zero to one inclusive. Each *resident* *agent* then combines the set of standardized attributes through the use of their own unique LSP aggregation structure (seen in figures 4-5, 4-6, and 4-7). *Resident agent*s assign each cadastral lot an LSP suitability score, based on the combination of the lot's standardized attributes. *Resident agent*s then query the entire set of vacant lots and occupy the most desirable lot: the lot with the highest LSP suitability score with respect to that individual agent. If the LSP suitability scores of all of the unoccupied lots are below a particular threshold, the agent will leave the study site (and assumingly go search for housing elsewhere, outside the study site).

Incorporating LSP suitability index for Resident Agents

*Resident agent*s determine whether to occupy a cadastral lot depending on their own preferences. Local amenities have a large importance in explaining demand for housing as well as housing prices, with proximity to parks and highways being especially significant (Mcleod, 1984). In this model several local amenities are chosen that affect *resident agent*s demand for a particular cadastral lot. Each of the cadastral lots within the study site has an attribute value for each of the pertinent spatial variables *resident agent*s consider. These variables are as follows:

Accessibility: distance to highways, distance to transit lines, and distance to major collector roads. Residents of the greater region of the study area, Surrey, BC, spend an average of 31 minutes commuting to work, with only 12.8% of those using public transportation (National Household Survey, 2011). For this reason, distance to highways and major collector roads play an important role in housing choice. Additionally, there is a proposed high-speed transit station to be built in the study area, which will provide influence on homebuyers.

Amenities: distance to commercial outlets, distance to schools, distance to other educational facilities. Distance to commercial outlets play a significant role in the growth of cities (Batty and Longley, 1994). Families with children seeking suburban housing are concerned about adequate schools nearby and are more likely to buy suburban homes with greater accessibility to primary and secondary schooling (Varady, 1995). In the suburban Cloverdale neighborhood of Surrey, BC at least 65% of the population resides in a household of 3 or more people (Statistics Canada, 2006), making accessibility to schools and other educational facilities very important factors.

Distance to Parks: Residential properties near parks and green spaces are at a premium. Natural and constructed amenities such as parks are valuable attributes in housing demand (Cho et al., 2013).

Aspect: The direction that a lot is facing plays a role in determining house choice. Differentiation in the direction that a home is facing affects the amount of sunlight that a home receives throughout the day. Generally, a south facing home gets the most sun throughout the day. Additionally, north facing homes in the study area have views of local mountains and are also preferred.

Economic: year built, and type of lot (apartment, single family occupancy, senior housing facility, etc.). Housing consumers overwhelmingly prefer single-family suburban homes to any other residential alternative (Myers and Gearin 2001), however future planning regimes and demographic changes may lead to a greater demand of medium and high density housing. This is reflected in the model through different *resident agent* types having differing preferences for low density (single family homes), medium density (such as townhouses, and high density (such as apartment complexes, low rise, and high rise apartments). Agents also have concern for the year that a lot, and especially the lot value.

Prior to inputs in the LSP attribute tree being combined in the aggregation structure, they must be standardized. This is achieved through the use of fuzzy suitability functions. Fuzzy suitability functions transform each input from their original units onto a continuous scale of increasing suitability from 0 to 1 with 0 being completely unsuitable and 1 being completely suitable. The fuzzy suitability functions for the attributes that each of the three *resident agent* classes consider are shown in Figure 4-4.

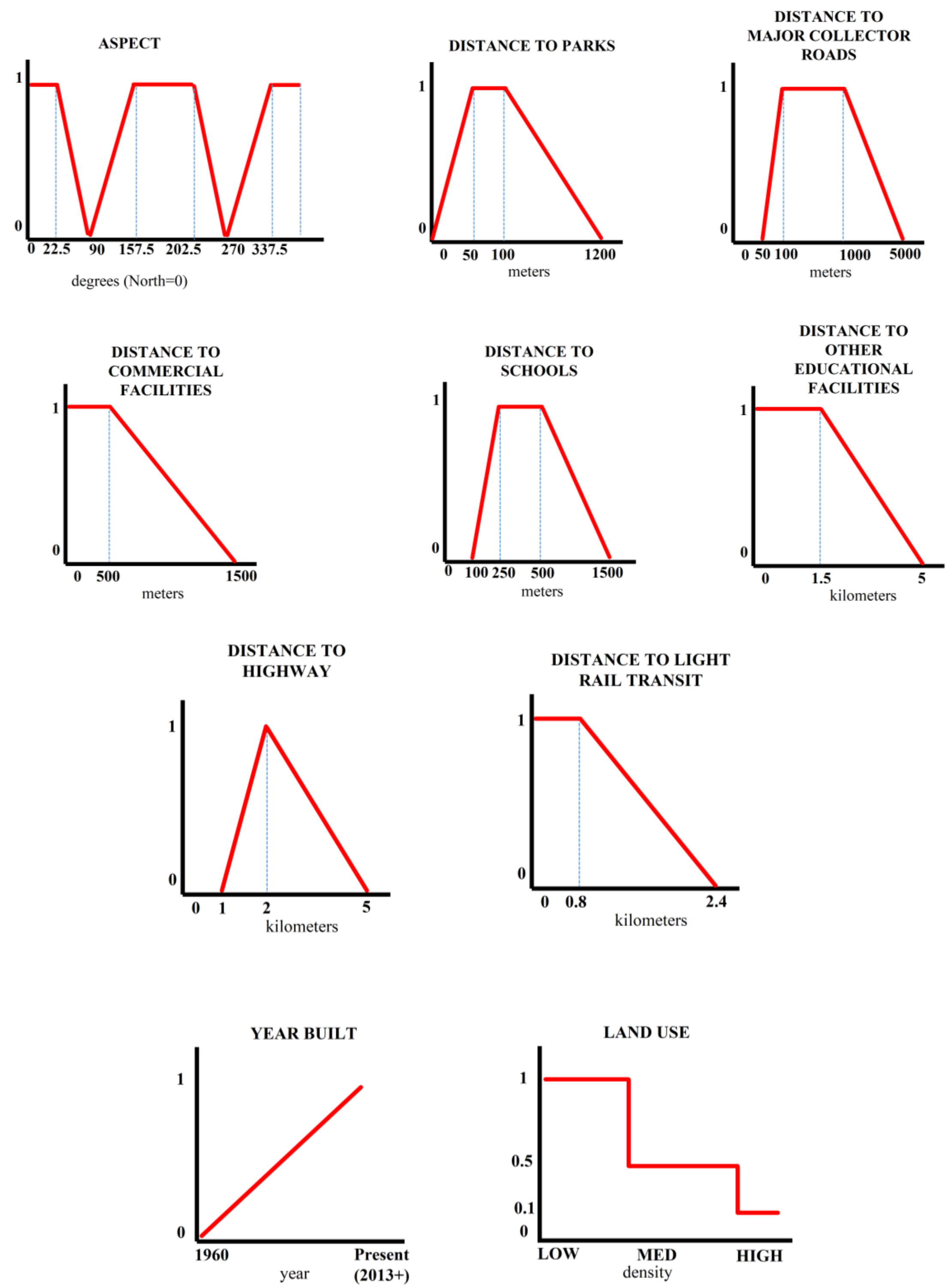

Figure 4-4. Criteria functions for LSP aggregation structures.

After standardizing the inputs, the attribute tree is created. Inputs are placed into one of following categories: Terrain and Environment, Amenities, Transportation, or Economic. The step-wise combination of inputs is then determined, and LSP aggregators are assigned each time two or more inputs are combined. Figure 4-5 depicts the LSP aggregation structure for *family resident agent*s, Figure 4-6 depicts the structure for *senior resident agent*s, and Figure 4-7 depicts the structure for *single resident agent*s. LSP aggregators combine inputs together through the use of the GCD and CPA (equations 1 and 2 respectively) equations associated with LSP. For each agent, the individual weights of preference when combining two standardized inputs can vary ±0.1 from the values given in Figures 4-5, 4-6, and 4-7, and the LSP aggregators can vary by one degree of simultaneity more or one degree of replaceability more than given in the aggregation structures. LSP Aggregators for each aggregation structure (Figures 4-5,4-6,4-7) are chosen in order to develop a *canonical aggregation structure* (Dujmovic and De Tre, 2011): one wherein the level of *simultaneity* increases as the number of inputs combined in an individual aggregator increases. Weights used when combining inputs were determined based on weighting schemes used in previous MCE/LSP studies (Dujmovic et al., 2009), as well as based on the desired level of influence each input has on the overall suitability for each scenario, and the desired level of influence on each input when combined with other inputs. When all input criteria are combined in the LSP aggregation structures the LSP suitability score for a particular agent is obtained, with respect to a particular cadastral lot.

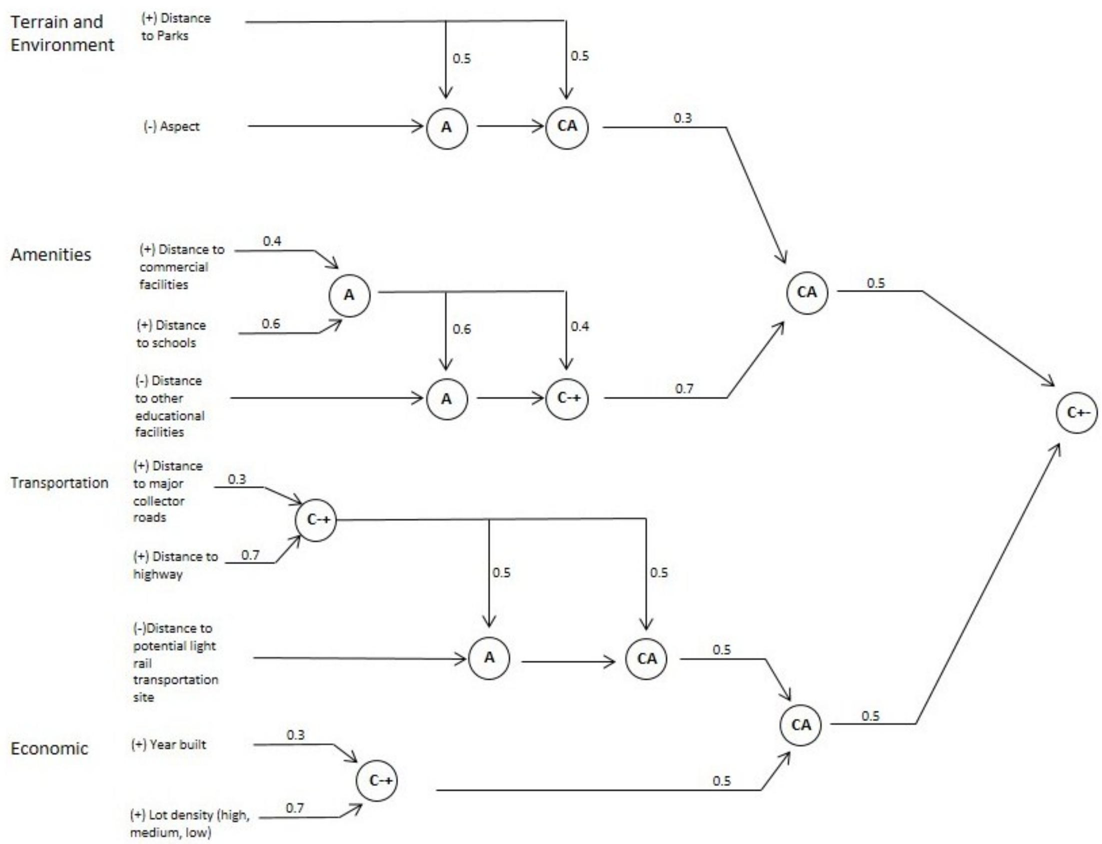

Figure 4-5. LSP aggregation structure for *family resident agents*.

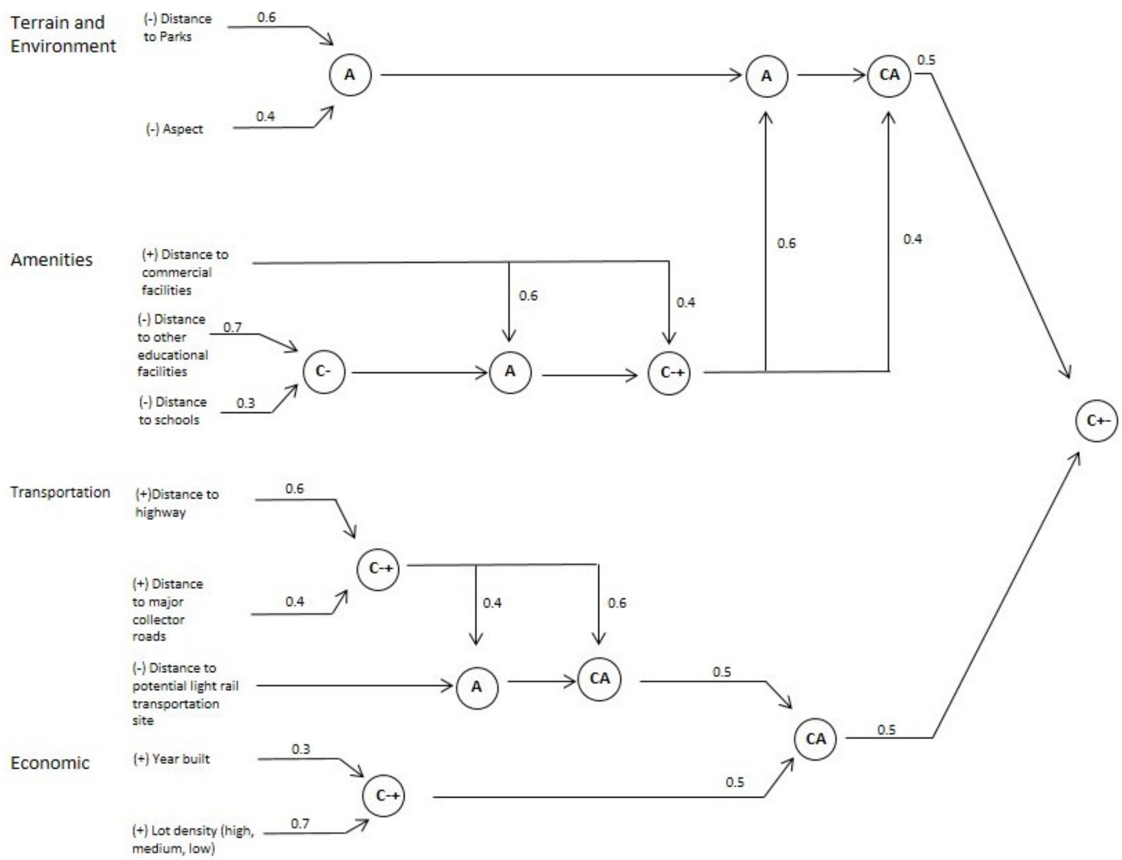

Figure 4-6. LSP aggregation structure for *senior resident agent*s.

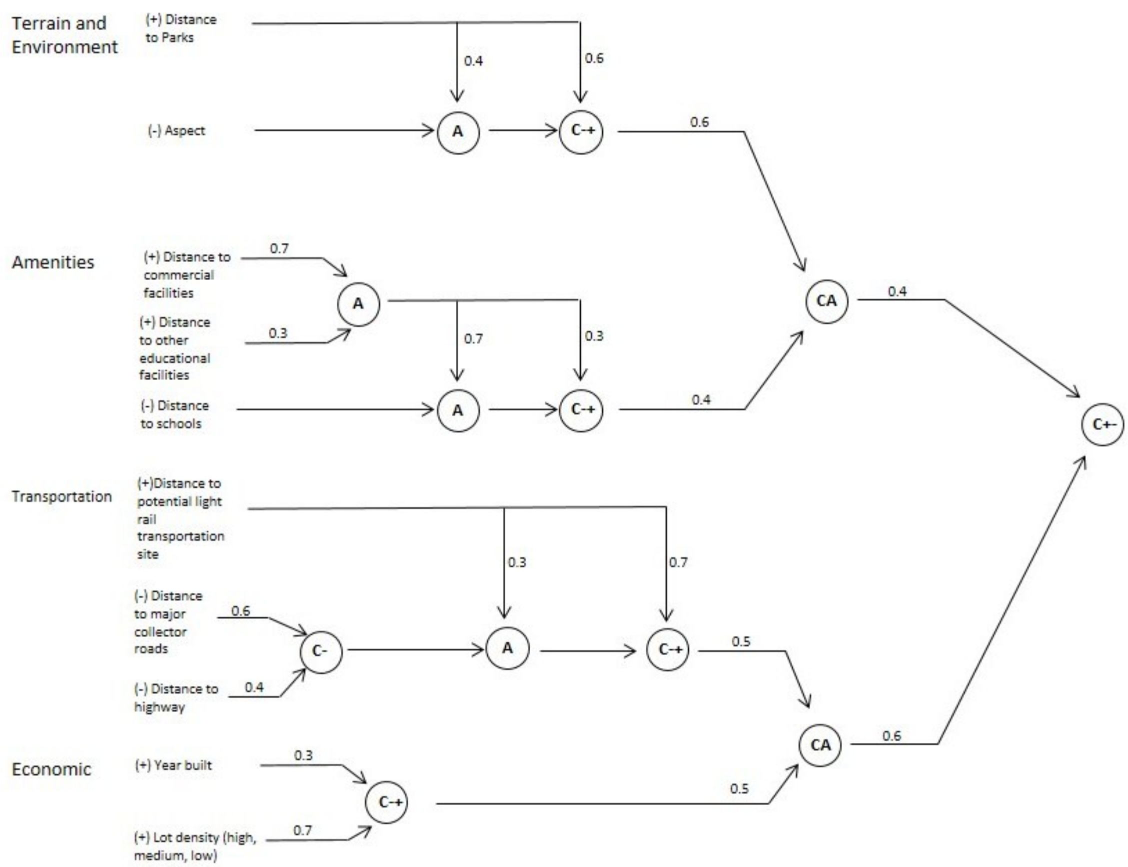

Figure 4-7. LSP aggregation structure for *single resident agent*s.

The LSP method used has the goal of determining suitable locations for residential development based on the combination of the small number of factors given. Cadastral lots are assigned a suitability value reflecting their appropriateness for occupation with respect to an individual *resident agent*, based on their output from that particular *resident agent*'s LSP aggregation structure. *Resident agent*s iterate over the entire set of vacant lots and choose the lot with the highest LSP suitability score. If two or more *resident agent*s choose the same lot, one is randomly assigned that lot, with the other agents then having to choose from the remaining most suitable lots.

4.5. Model Implementation

The ABM was developed within the Recursive Porous Agent Simulation Toolkit (REPAST), Simphony edition, an object oriented programming framework capable of integrating real geospatial data (North et al., 2013). The model consists of numerous components (Figure 4-2), each acting independently, performing a specific task in the model, with all the components integrated to form the entire model. The model environment operates over a cadastral-scale neighborhood, with each cadastral parcel having its own individual properties and land-use type, such as: school, park, commercial, low density residential, medium density residential, or high density residential.

The model runs iteratively, with land parcels changing from a vacant state to occupied state as *residential* agents choose to move in. At each iteration, more *resident agent*s are added to the model according to demographic data provided by the City of Surrey (City of Surrey Open Data Catalogue, 2013).

4.6. Simulation Results

4.6.1. Datasets

Spatial information consists of several GIS datasets (ESRI shapefiles) available through the Surrey Open Data Catalogue. The first of these datasets is a cadastral-scale land-use map, which contains data on the lot value, the value of improvements to the lot, the vacancy status, the development type, the year constructed, among other attributes. Data obtained from the City of Surrey are all current up to and including the year 2012. Neighborhood concept plans for West Clayton were digitized into a GIS. Transportation and road network data provided by the City of Surrey were also used. Extensive census data was used from both the 2006 and 2011 Canadian census provided by Statistics Canada. All data used in this study are in in vector GIS format.

There are several layers that appear in the output of the model at some point of the simulation. These layers are either static, or dynamic. The static layers consist of: park and proposed park school sites, as well as a creek and buffer around the creek.

The dynamic sites, commercial and proposed commercial sites, schools and proposed layers consist of: existing cadastral lot housing, split into high, medium and low density categories, potential sites for large tracts of high, medium, and low density housing, as well as the subdivision of those land tracts.

4.6.2. LSP-ABM Model Simulation

Two different model simulation Scenarios were developed to reflect separate population trends in the study site. Scenario 1 follows projected growth rates established by the city of Surrey, BC for the Cloverdale town center (a superset of the Clayton-Cloverdale neighborhood). Scenario 2 doubles the projected growth rates of Scenario 1. Both of the Scenarios involve perturbations to the number of agents that are added into the model at each iteration. The Cloverdale neighbourhood's projected growth rates are as follows: 2013-2016, 2.28%, 2017-2021: 2.41%, 2022-2026: 2.32%, 2027-2031: 3.21%, 2032-2036: 2.48%, 2037-2041: 1.15% (City of Surrey Open Data Catalogue, 2013). These growth rates are used in Scenario 1 to help determine the number of *resident agent*s to add each iteration. Population statistics for the Clayton-Cloverdale neighborhood (City of Surrey open data catalogue, 2013) were also used to determine the total number of agents to add into the simulation at each iteration. Given a total number of agents, demographic data provided by the city of Surrey for the Cloverdale region is then used to determine the number of each of the three *resident agent* types to add into the model at each iteration. As of 2013, Cloverdale consists of approximately 75.6% families (households consisting of three or more people), and 5% total seniors, with the remaining 19.3% considered single adults, or married without children. These three percentages are used to split up the total number of agents into each of the three *resident agent* categories: family, single, senior. Scenario 2 considers extreme rapid growth: the growth rates are doubled compared to their values in Scenario 1. Table 4-2 depicts the number of *resident agent*s added in each of the first 28 years of the simulation for both scenarios. The total number of *resident agent*s added each year can be multiplied (and rounded up to the nearest integer) by 0.756, 0.05, and 0.193 to determine the total number of *family*, *senior*, and *single* agents that are added in each iteration respectively.

Table 4-2. Number of agents added in each of the first 28 years of simulation for Scenario 1 and Scenario 2.

	Scenario 1		Scenario 2	
Year	*Growth Rate (%)*	*Total Number of Resident Agents Added*	*Growth Rate (%)*	*Total Number of Resident Agents Added*
2013	2.28	138	4.56	276
2014	2.28	141	4.56	282
2015	2.28	144	4.56	288
2016	2.28	148	4.56	296
2017	2.41	151	4.82	302
2018	2.41	163	4.82	326
2019	2.41	167	4.82	334
2020	2.41	171	4.82	342
2021	2.41	175	4.82	350
2022	2.32	180	4.64	360
2023	2.32	177	4.64	354
2024	2.32	181	4.64	362
2025	2.32	185	4.64	370
2026	2.32	190	4.64	380
2027	3.21	194	6.42	388
2028	3.21	275	6.42	550
2029	3.21	283	6.42	566
2030	3.21	293	6.42	586
2031	3.21	302	6.42	604
2032	2.48	312	4.96	624
2033	2.48	248	4.96	496
2034	2.48	255	4.96	510
2035	2.48	261	4.96	522
2036	2.48	267	4.96	534
2037	1.15	274	2.3	548
2038	1.15	130	2.3	260
2039	1.15	132	2.3	264
2040	1.15	133	2.3	266
2041	1.15	135	2.3	270

The temporal resolution of each simulation is one year, with simulations beginning in the year 2012, and *resident agent*s added in beginning in the year 2013. Figures 4-8 and 4-9 depict the spatial changes at 5-iteration snapshots, with figure 4-10 providing a comparison of the simulations of the two scenarios at three temporal snapshots.

Figures 4-8 and 4-9 depict the spatial distribution of cadastral lots and developed land parcels for scenarios 1 and 2 respectively. Because each of the scenarios only perturb the number of agents added to the model at each iteration, there is not an extreme amount of disparity in the spatial distributions of land parcels built. For example, the high density land parcels built first in Scenario 1 are for the most part the same as the high density land parcels built first in Scenario 2. This is due to the *developer agent* logic being the same for both scenarios: they try to develop the most profitable parcels of land given the number and type of *resident agent*s added into the simulation. However, what is seen are differences in the rate of development of land parcels in the two scenarios, as well as differences in the rate of occupation of cadastral lots by *resident agent*s in both the scenarios.

Some common features can be observed in the spatial distribution of development in both scenarios (Figure 4-10). First, there are planning constraints that prevent the northwest region of the study area from being developed. As a result, the low density lots in the northwest region of the study site remain unchanged throughout the simulations. Additionally, a limited amount of new low density housing is permitted in the study region, and its primary location of development is in the far northwest region of the study area, where "low density occupied" (figure 4-8) lots are developed. The reasoning behind low density development in this area is due to its presence far from major freeways, intersections, and existing transportation lines: areas where higher density developments are more desirable for planners and profitable for developers. The western boundary of the study site is delimited by the Fraser highway, a major freeway that funnels traffic into the central business district of Vancouver. One implication of this is that most of the major transportation routes throughout the study area eventually funnel out into downtown Vancouver by means of the Fraser highway. As a result, a large proportion of high density housing is located on the western edge of the study site. Newly developed medium density housing is located mostly in the middle of the study site due to many of the major streets running east to west along the study site, providing ideal candidate sites for medium density development.

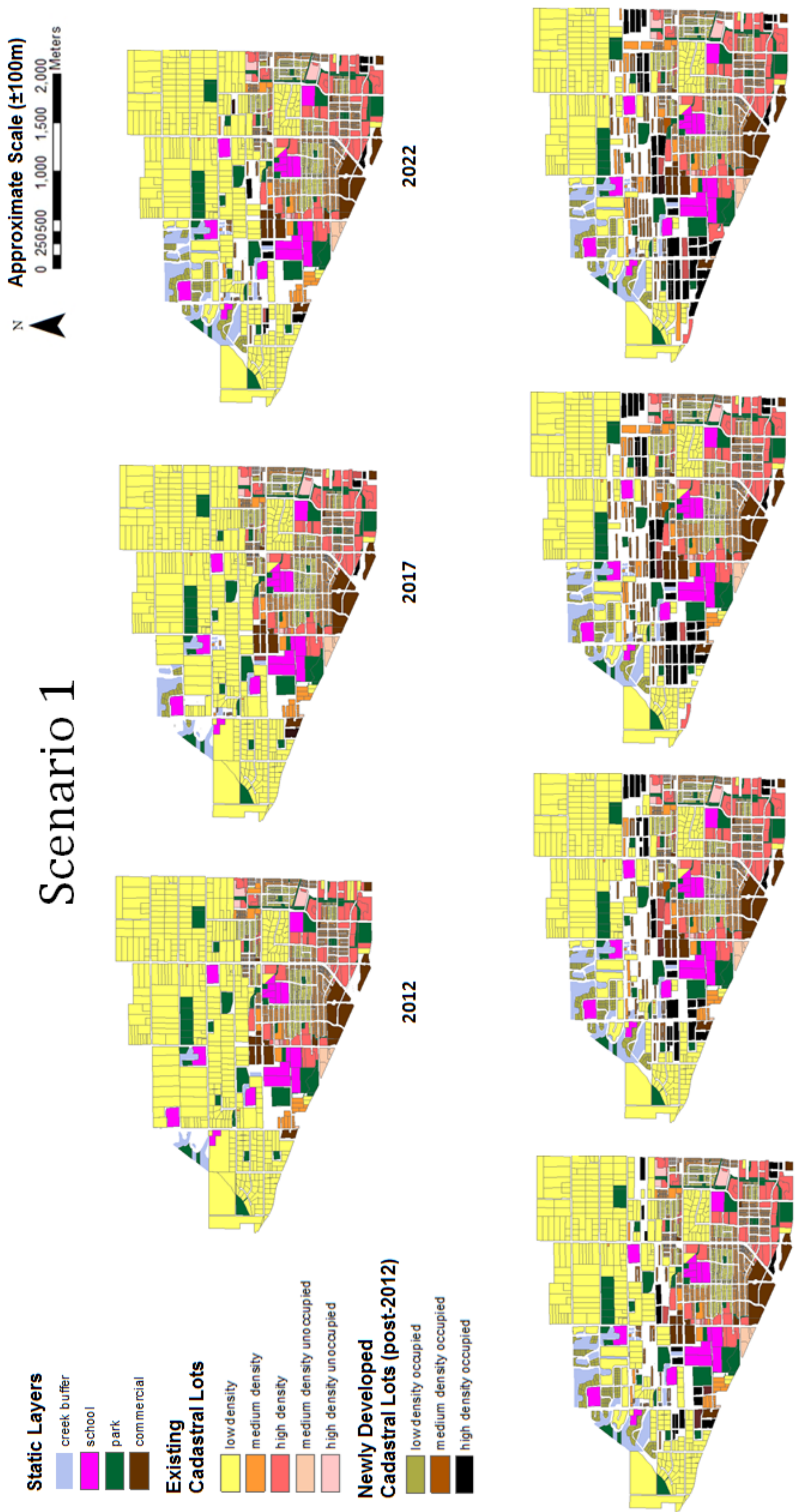

Figure 4-8. Spatial distribution of cadastral lots and developed parcels for Scenario 1 at five year snapshots

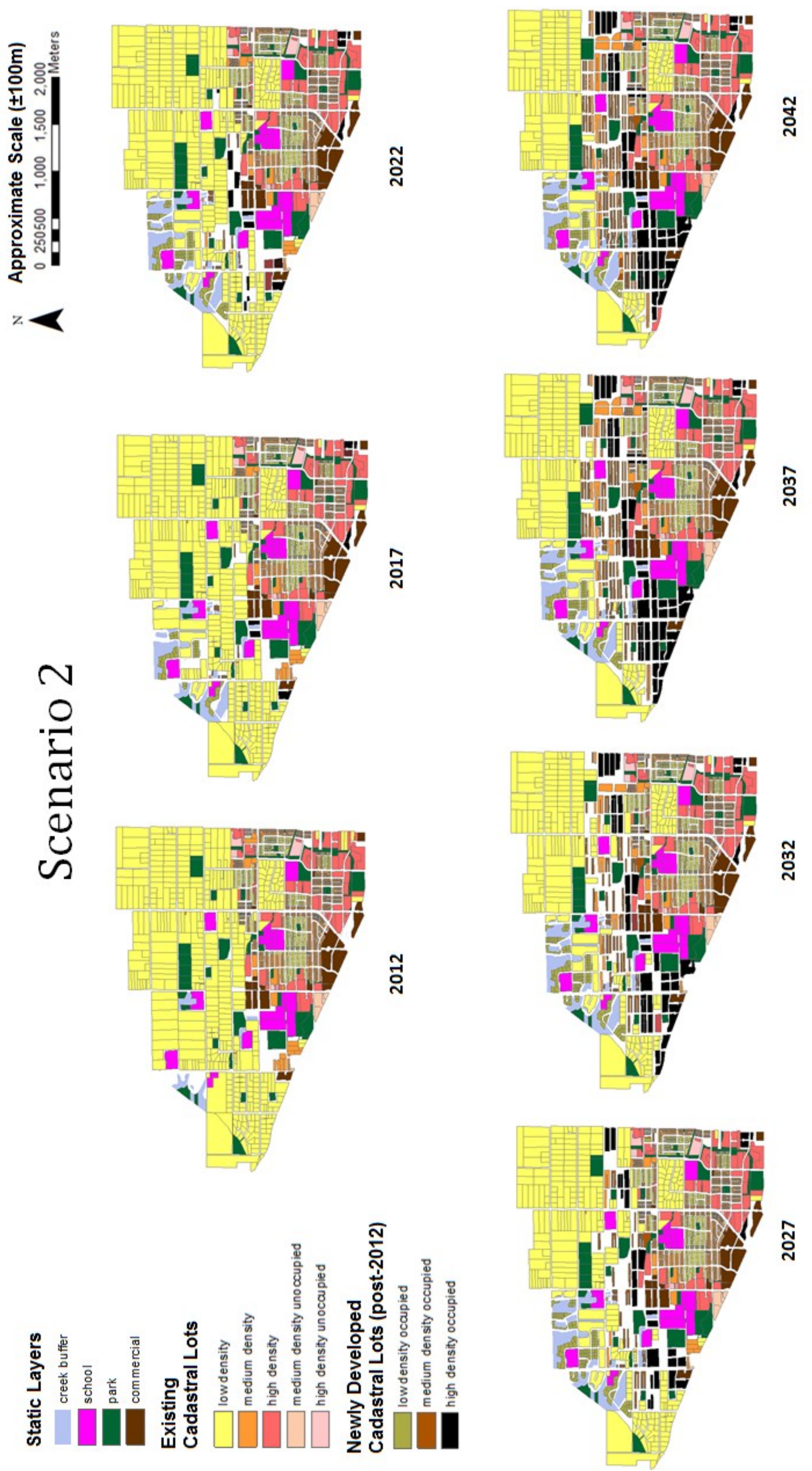

Figure 4-9. Spatial distribution of cadastral lots and developed parcels for Scenario 2 at five year snapshots

Figure 4-10. Comparison of Scenarios 1 and 2 at 2027, 2032, and 2042

Figures 4-11 depicts the total number of newly developed high and medium density land parcels created by developed agents after each iteration. Figure 4-12 depicts the total number of newly developed low density land parcels, as well as the sum of the total number of low, medium, and high density land parcels created by *developer agent*s after each iteration. For each Scenario, the number of low density land parcels reaches a maximum at some point between iteration 8 (2021) and iteration 12 (2024); reflective of city planners only allowing a small amount of newly zoned land to be used for low density lots, such as single family homes to accommodate future anticipated growth. Due to Scenario 2 simulating rapid growth, and thus many more *resident agent*s added in each iteration, many more medium and high density lots are developed each iteration in comparison to Scenario 1. For Scenario 1, 113 tracts of land (where tracts are usually the size of one side of the street on an average city-block in the study area) are developed after 25 years, allowing for a total new occupancy of 9238 *resident agent*s. Scenario 2 has 153 tracts developed after 25 years, allowing for 14309 *resident agent*s. Each *resident agent* represents an individual household (such as a family, or a couple) occupying one lot. The average household size for the Cloverdale neighbourhood is 2.9 (City of Surrey open data catalogue, 2013). Assuming this size remains constant, this implies that 26,790 new persons are added to the study site in Scenario 1 after 25 years and 41,496 in Scenario 2. With the area in which new development occurs being approximately 4 km^2, this leads to a population density of roughly 6500 persons per km^2 in Scenario 1 and 10,000 persons per km^2 in Scenario 2. Comparing this to densities of 11,577 persons per km^2 in the city of Vancouver, these results are within the realm of possibility for providing enhanced density into the study area.

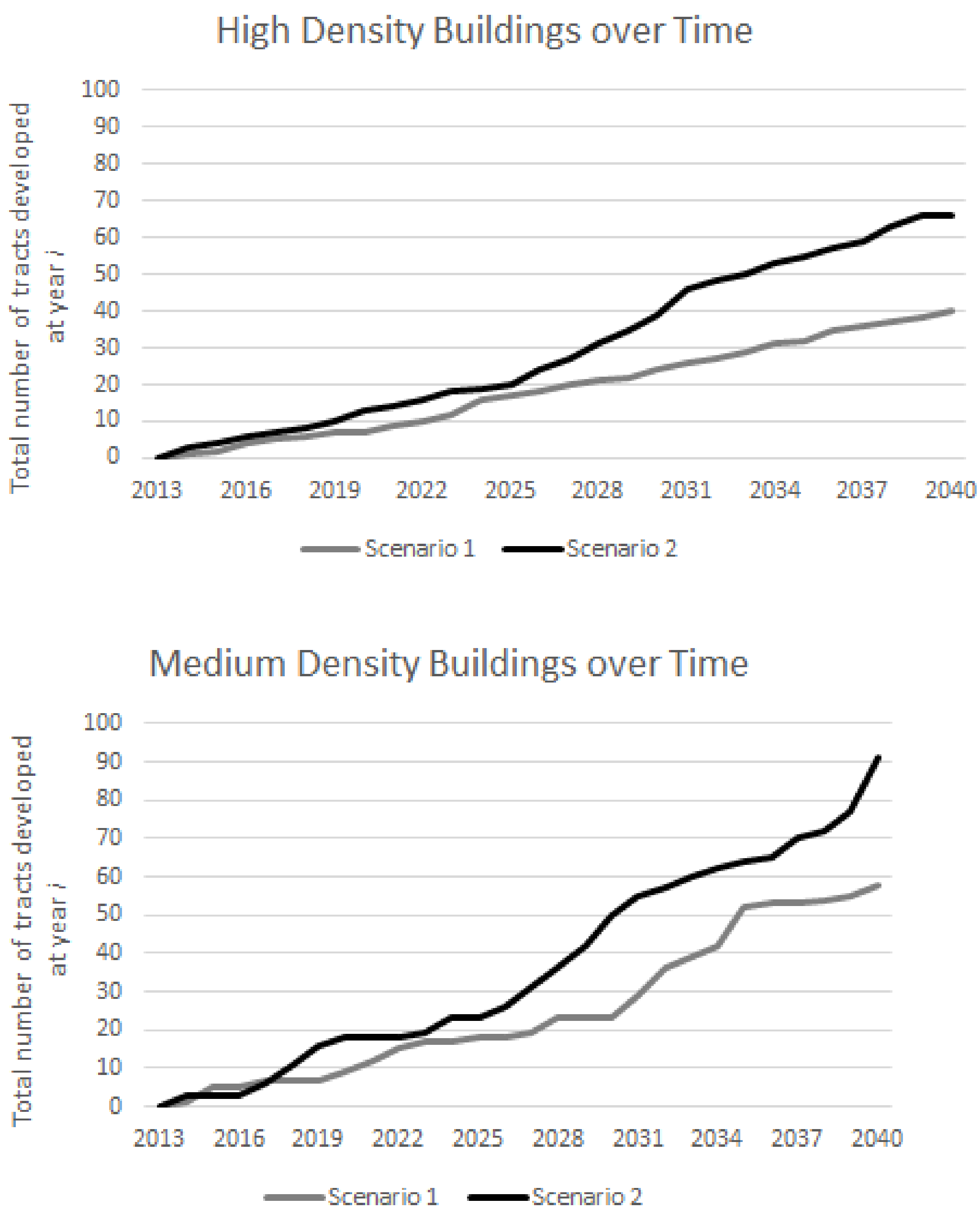

Figure 4-11. Total number of high and medium density tracts developed after each iteration (year *i,* expressed on the x-axis) in scenarios 1 and 2

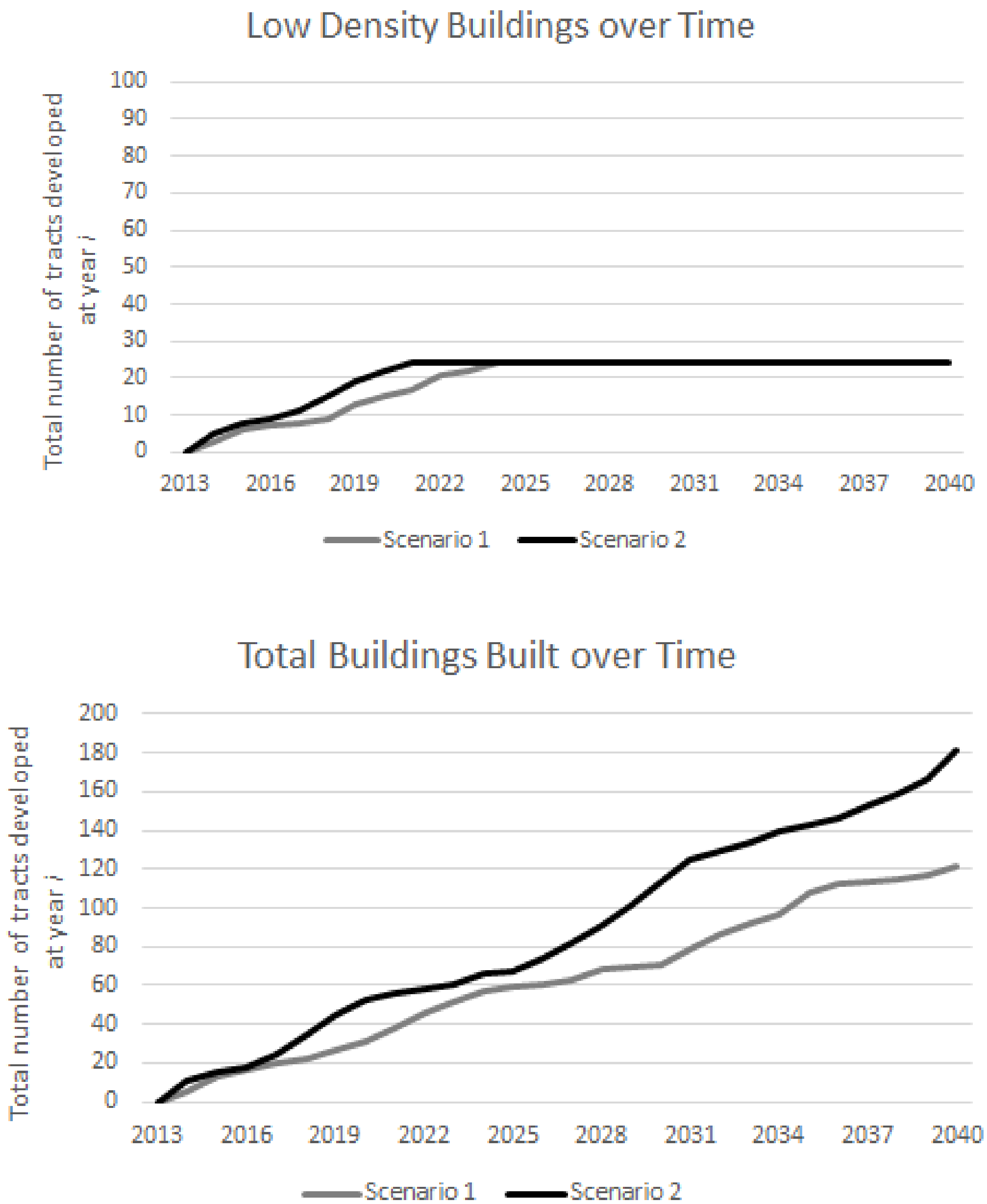

Figure 4-12. Total number of low density tracts, and tracts of each type developed after each iteration (year *i*, expressed on the x-axis) in scenarios 1 and 2

4.7. Conclusion

The agent based model developed simulates cadastral scale urban land use change. It puts primary emphasis on residents as agents who drive change in the model, as well as involving developers and city planners in the simulation process. *Resident agent*s have their decision-making logic simulated using the LSP method, wherein a set of preferences for each *resident agent* were aggregated together, and an overall suitability score for each individual land parcel was obtained. The proposed LSP method represent a novel way of modeling agents' reasoning and provides improved aggregation logic more reflective of actual human-decision making. The model was developed in the Java-based ABM environment, REPAST, with vector-based ESRI GIS used to display data for the Clayton-Cloverdale neighborhood of Surrey, British Columbia, Canada.

The simulation and prediction of fast, controlled, urban expansion following guidelines laid out by the West Clayton NCP can benefit land-use management. The simulations could benefit from improved developer decision making analysis, such as giving developers the ability to develop in un-zoned and agriculture-zoned, potentially cheaper areas near the Clayton-Cloverdale study site as to see what effects it would have on the plans laid out by the City of Surrey for the Clayton-Cloverdale neighborhood. Additionally, improved sensitivity analysis on the fuzzy suitability functions, LSP aggregation structures, as well as developer rules could benefit simulation results. The ABM helps planners because it provides a cadastral level spatial visualization of potential future urban land use change that follows development guidelines set out by city planners.

4.8. Acknowledgments

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Chapter 5.

Conclusions

5.1. Conclusions

The focus of this thesis research was to develop a set of spatial simulation approaches that model urban residential land-use change on both city-wide and neighborhood-wide scales implementing the LSP method within complex system theory and GIS. The objectives of the research were achieved by integrating the LSP method into two different types of complex system models simulating residential land-use change.

First, suitability for residential land-use change was determined for Metro Vancouver, Canada based on the aggregation of relevant input criteria within the framework of the LSP approach (Chapter 2). Suitability maps were created through the use of the IDRISI GIS: a raster based GIS software capable of manipulating geospatial datasets using a set of various operational tools. Input criteria were standardized through the use of fuzzy membership functions that transform inputs from their initial units and values onto a standardized scale from 0 to 1 representing suitability. Standardized inputs were grouped categorically and combined step-wise in LSP attribute trees. At each instance of a combination of two or more inputs in the attribute tree, a LSP aggregator was present, determining the *simultaneity* (ANDness) and *replaceability* (ORness) among the set of inputs. Three scenarios were created each with their own set of input criteria, attribute trees, and LSP aggregation structures. Outputs were represented as raster suitability maps. Results of the study indicate that the LSP method has advantages over other existing MCE methods used in previous studies. This is due to the LSP method permitting several inputs to be combined without loss of significance, meaning that each individual input included in aggregation structures used retained importance in the overall suitability output of that aggregation structure. Additionally, the LSP method allowed for the use of aggregators represented on a continuous scale of logic conditions, with varying degrees of *simultaneity* and *replaceability*.

The second component of the thesis was to integrate each of the three LSP aggregation structures developed into a cellular automata (CA) model of urban land-use change, for the purpose of generating patterns of residential urban growth. Geospatial datasets for Metro Vancouver, Canada for the years 2001, 2006, and 2011 were used to create and calibrate model simulations. The outputs from the LSP aggregation structures of each of the three scenarios were combined into a CA model. The main objective of the research was to determine the benefit of incorporating the LSP approach into a CA model that simulates residential land-use change. The results include a set of three simulation scenarios: one for each of the three LSP aggregation structures developed in the first component of the research. The integration of LSP into a CA model allows for potential new residential land-use sites to be ranked based on their suitability, such that only the most optimal sites of those determined by the neighborhood and transition rules of the CA model are chosen.

The third component of the thesis was to integrate the LSP approach into the decision making of residential agents within an agent-based model that simulates residential land-use change at a more local, neighborhood scale, and with the use of cadastral lots and vector-based GIS. The model incorporates interactions of various stakeholders: residents, developers, and city planners, each of which have separate and conflicting priorities. Each stakeholder is represented as an autonomous, decision-making agent in the model, and is governed by their own set of rules and regulations. *Resident agent*s have their decision making logic based on the LSP approach: each agent chooses between cadastral lots based on their own unique combination of attributes associated with each lot. The objective of the study was also to determine the usefulness of the LSP approach as soft computing method in the context of simulating residential land-use change on a neighborhood scale in an ABM model, achieved by observing differences in logic aggregation between LSP and existing ABM-MCE methods, such as weighted linear combination (WLC). The LSP-ABM model was operationalized using geospatial data for the Clayton-Cloverdale neighbourhood of

Surrey, BC, Canada. The REPAST ABM IDE software was used to encode simulations, agents, and visually display output scenario simulations. The LSP method's inclusion of human decision making logic proves very useful in the context of an agent-based model, where decisions need to be made on the individual, human (agent-based) level.

5.2. Contributions

The methods derived from this research contribute to the literature related to GIS-based modeling of complex and dynamic geographic systems. In particular, the methods and results contribute to research pertaining to: GIS-based CA and ABM models of dynamic systems and particularly modeling urban systems at various spatial scales. Furthermore, contributions are made related to the integration of soft computing methods, the LSP method, into modeling approaches for urban growth. With respect to modeling urban systems dynamics, MCE methods based on commonly used ordinary weighting have significant limitations in their ability to express properties of human decision making logic. This is a due to these MCE methods not operating on a scale of *simultaneity* and *replaceability* (ANDness and ORness) as LSP does. As a consequence, these methods can produce significant errors in their land-use suitability maps. Therefore, the research in the field of modeling urban land-use change can benefit from the integration of LSP based MCE techniques capable of simulating human decision-making logic.

Only recently the LSP method been used to create residential land-use suitability maps (Dujmovic and Scheer, 2007; Dujmovic and De Tre, 2011), however none of these methods operate on a large number of inputs, nor do they operate on real geospatial datasets. In this thesis the LSP approach is implemented into GIS to determine its effectiveness in producing suitability maps when presented with a large set of input criteria, and within an urban environment at a regional spatial scale. Furthermore, LSP suitability maps were integrated into a CA model of residential land-use change.

Never before has any aggregation method similar to the LSP approach been used in an agent-based model of residential land-use change. Most frequently, simple linear combinations of relevant criteria (Li and Liu, 2008; Xiao et al. 2010) are used to simulate the decision making logic of individual agents with an ABM. None of the existing methods of combining criteria for agent decision-making operate on a continuous scale of ANDness and ORness, a critical component in simulating human decision making logic. The LSP approach was used simulate the decision making process of individual resident agents within an agent based model in order to determine the effectiveness of its use on the individual, small scale level. The ABM developed operates through the use of a Java applet, wherein individual weights of preference, logic aggregators, number of agents, among other model parameters can be modified to observe changes in outputs.

5.3. Future Directions

The research presented in this paper can be extended by investigating residential land-use patterns at various scales, such as on the municipality level. The methods could be extended through the development of a residential land-use change model that integrates both multi-agent systems as well as CA in the model, rather than focusing on the two complex system modeling techniques separately, as was done for this research. An increased number of inputs into the LSP aggregation structures of individual scenarios could help further test the LSP method's effectiveness in producing suitability maps. However, scenarios implementing an even larger number of inputs than presented in Chapter two and three of this research would have to be further calibrated to ensure that each input has a reasonable level of pertinence in the overall LSP suitability outputs, and also to ensure that small changes in the aggregation structure do not have exceedingly large changes on the output suitability maps. Although several different LSP aggregators, and weights of preference were developed, only a limited number of LSP attribute trees were constructed. The LSP approaches developed could benefit from significant sensitivity testing, where a large number of LSP attribute trees are developed: with several different frameworks for combining inputs.

The development of LSP-CA and LSP-ABM models would benefit from the link to a spatial decision support system (SDSS), which can be used to assist decision-makers in site identification for new residential development. Models must be calibrated and fully tested prior to their use within an SDSS. ABMs are very complex in their nature, involving a large number of parameters, making validation quite difficult. In order to fully test developed LSP-CA and LSP-ABM modeling approaches, the following stages must occur: verification (ensuring the model matches the parameters and assumptions for the desired objective or purpose), sensitivity analysis (observing how much model results will change given perturbations to the model constraints or parameters), validation (observing accuracy of model to real datasets), credibility assessment, and qualification (assessing whether the model is suitable for the given objective). Some potential solutions can be offered to process ABM calibration and validation when a large number of model runs is needed to be performed (Li et al., 2008). Linking the model created and agent-based services described by Li et al. (2008), as well as performing further sensitivity analysis would provide benefit to the overall testing of the model.

The Java applet developed can only be run within the REPAST ABM development software. It would be of great utility if the Java applet could be provided as an online service, so that many users could modify model parameters as they see best fit, and a wide range of scenarios could be developed. Nevertheless, this would require another limitation of the developed ABM model to be resolved, which is the speed at which simulations occur. To fully develop the entire Clayton-Cloverdale study site, simulation can take as long as six hours (when simulations performed on a Dell Precision T7600 with 32GB Ram, operating on two Intel Xeon CPU E5-2630 processors), depending on the model parameters chosen and the capacity of the computer used for simulation. The proposed models developed in this study would benefit from parallel processing. Simulation times would decrease dramatically, evidenced in the parallel processing developed ABM by Tang and Wang (2009), allowing for more scenarios to be run, and allowing for further exploration, calibration, and sensitivity testing of the LSP approach. The LSP approach proved useful as an alternative to existing MCEs when used to simulate residential land-use change. Therefore, other areas of MCE analysis may also benefit from the implementation of the LSP approach, such as for modeling natural disasters (Dou et al. 2013), insect infestation (Perez et al., 2013), or evacuation (Wagner and Agrawal, 2014), as well as agent-based modellers.

In summary, the thesis research presented provides improved methods for developing the decision-making properties of agents in urban land-use change ABMs, as well as for providing land-use suitability map that can be used in CA models. Regardless of the MCE approach used, there is always going to be disparity between the actual decision-making processes of individuals, and how these decision-making processes are encapsulated in a model. The LSP approach helps narrow this disconnect by providing improved representations of actual human decision-making. The research provided here only deals with a small set of the possibilities available for the LSP approach within the fields of GIS and spatiotemporal modeling. Avenues are available to further test and integrate the LSP approach into other GIS-based modeling procedures.

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