Modeling land-use change with Logic Scoring of Preference Method, GIS and Cellular Automata

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THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE

in the
Department of Geography
Faculty of Environment

Approval

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Degree: **Master of Science (Geography)**

Title of Thesis: ***Modeling land-use change with Logic Scoring of Preference Method, GIS and Cellular Automata***

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Date Defended/Approved: August 21, 2012

Abstract

Multicriteria Evaluation (MCE) has been used as a land suitability method and is often coupled with Cellular Automata (CA) for land-use and urban growth modeling. MCE, however, exhibits limitations including data loss and insufficient logical requirements. The Logic Scoring of Preference (LSP) is an alternative approach that can overcome these issues. LSP is a soft computing system evaluation method efficient in nonlinear aggregation with flexible logic requirements. The main objective of this research study was to develop an integrated LSP and geographic information system (GIS) methodology for modeling land-use change. Moreover, the LSP method was further integrated into a CA to model urban growth. The LSP methodology was tested with geospatial datasets of coastal BC, Canada and several scenarios of future land-use change were generated. This research contributes to the field of spatio-temporal modeling with a novel integration of LSP, GIS, and CA for land-use suitability analysis and modeling.

Keywords: Cellular Automata; Fuzzy Logic; Land-Use Change; Logic Scoring of Preference; Suitability Analysis

Dedication

For Leah and Bodi

Acknowledgements

I would like to acknowledge the Natural Sciences and Engineering Research Council of Canada (NSERC) for full support of this study under the Discovery Grant Program awarded to Dr. Suzana Dragićević. I would like to extend thanks to Jodi Wilson of the Engineering Department, City of Nanaimo, who provided access to several datasets used for this study.

This research study would not have been possible without the assistance, patience and critical insight offered by my senior supervisor Dr. Suzana Dragićević over the past two years. I would like to thank Dr. Shivanand Balram and Dr. Margaret Schmidt for reviewing an initial draft and providing valuable comments. My special thanks go to Dr. Jozo Dujmović, Professor, San Francisco State University for his contributions to the second chapter. Acknowledgements are also extended to my fellow graduate students in the Geography Department and the Spatial Analysis and Modeling Laboratory for their support and friendship.

I would like to thank my parents for supporting my decision to become a student once again after many years. Thanks to Leah for her amazing meals and making our home a warm and inviting place. I thank Bodi who came into this world midway through my program, for his wonderful smiles at the end of the day.

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Chapter 1: Introduction

1.1. Introduction

Explaining and understanding urban growth with mathematical models has been an active area of research since the beginning of the quantitative revolution in geography (Batty 2005). The post WWII urban planning field became influenced by two bodies of thought: systems theory and the then rediscovered field of locational theory (Hall 2002). The pioneering Garin-Lowry model predicted land-use patterns based on transportation and employment data (Hall 2002). Early approaches considered the city as an entity in equilibrium with well-defined linear relationships between inputs and outputs (Torrens 2000). Many of these models, however, failed to account for complexity of human-environmental interactions that comprise real world urban systems. Over the past two decades, research efforts have been made to describe cities as *complex systems* that share the dynamic properties of ecological systems (Tomalty 2009). Urban models employing complexity theory address the limitations of early approaches.

Studying cities as complex systems has led to the development of specialized modeling approaches that attempt to capture the spatial and temporal processes of urban development (Torrens & O'Sullivan 2001). Computational models of complexity such as cellular automata (CA) and agent-based models (ABMs) linked to geographic information systems (GIS) have been used with success to simulate processes of land-use change and urban growth (White 2000).

Cellular Automata (CA) are a class of spatially explicit modeling approaches used for studying spatial and temporal change based on local interactions. Tobler's (1970) model of Detroit, Michigan, USA, was the first CA to be used in a geographical context (as cited by Batty 1997). Modellers from a range of disciplines working in CA have employed different theoretical frameworks for predicting cities of the future (Torrens 2000).

Some CA approaches relied on simplified, abstract representations of cities consisting of, for example, two competing land uses or social groups represented as different cell states. Portugali et al. (1994) and Portugali & Benenson (1995) developed CA models demonstrating emergent residential spatial patterns. CA were shown to be capable of generating realistic results, such as fractal structures seen in real cities (White & Engelen 1993; Batty & Xie 1996). CA linked with GIS and geospatial data were used to forecast future urban development (White et al. 1997; Clarke et al. 1997). Constraining the dynamics of urban CA using GIS signified a major step towards geographic realism (White & Engelen 1994; Takeyama & Couclelis 1997; Batty et al. 1999). Urban growth has been modeled using a range of hybrid and more improved GIS-CA structures including neural networks (Li & Yeh 2001), principle components analysis (Li & Yeh 2002) and data mining procedures (Li & Yeh 2004). CA also has the potential to augment spatial decision support systems (SDSSs), however, research on CA and SDSS integrated tools is still limited. For example, White et al. (2004) described a CA based Decision Support System (DSS) used for land-use forecasting. Advances in addressing the needs of operational modeling and model testing have been an active area of research as well. The effects of resolution and neighbourhood size have been explored (Menard & Marceau 2005). Model assessment has also been addressed with spatial metrics (Herold et al. 2005) and sensitivity analysis (Kocabas & Dragićević 2006). More recent CA modeling approaches have incorporated ant colony optimization (Liu et al. 2007) and load balancing (Li et al. 2010), and also was used to explain historical patterns of growth in Metropolitan London, UK (Stanilov and Batty 2011).

Spatial multicriteria evaluation (MCE) is a decision making approach often used in suitability analysis within SDSSs. MCE approaches linked with GIS constituting an SDSS framework were proposed in the literature for a range of land-use decision problems (Carver 1991; Laaribi et al. 1996; Jankowski et al. 2001). GIS-MCE approaches score locations from a set of alternatives for a variety of land-use and land allocation decision-making tasks (Malczewski 1999). The analytical capabilities of MCE have been harnessed to guide the state transitions of urban CA models. Wu and Webster (1998) developed a MCE-based CA model for alternative land-use growth under scenarios of different economic conditions for an urbanizing region of China. MCE methods can be used to characterize a policy or development preference, while a linked CA can be used to forecast future development resulting from these preferences.

Several approaches for modeling optimized urban growth exist in the literature. Ward, et al. (2003) developed a CA-based method employing a land-use allocation analytical engine for simulating compact development in a fast-growing region of Australia. Ligman-Zielinska, et al. (2008) apply an iterative optimization approach under the conditions of compact growth. An optimization and simulation system employing CA and agent-based modeling techniques is described by Li, et al. (2010).

1.2. Research Problem

The behaviour of cities is perceived as a complex system; their macro-level behaviour and growth is driven by local processes and activities (Allen 1997). City systems, however, are not entirely local by nature. Global factors exist, economic and cultural, that shape the trajectory of urban growth patterns (Batty 2005). Conceptual approaches to defining global factors for modeling urban growth with geographic CA include neural networks (Li & A. Yeh 2002a) and ant colony optimization (Liu et al. 2007). These approaches attempt to represent growth patterns based on past data and are useful for making accurate predictions. GIS planning and decision models such as MCE are yet another approach to defining global factors. Variables such as municipal policies that control the built environment in a city can be formalized as part of a decision model that in turn feeds into an urban CA. A GIS-CA integrated with a decision model is a way to go for creating models useful for urban and land-use planners and therefore serves as the lead idea for this research.

A GIS based CA using a decision model (such as MCE) may be parameterized to develop cell suitabilities and define the trajectory of urban growth over time. Simple MCE-CA models of urban growth operating on raster GIS data consist of "developed" and "undeveloped" land units or cells. Additionally, each cell is given a suitability score ranging from 0% to 100% (or 0 to 1). This score communicates the attractiveness of a land unit for future development. Therefore, cells that have a higher score will convert to a developed state before cells that are less attractive. This conceptual structure offers flexibility for researching policy and possible future states of urban systems. Expert knowledge and/or the input of different competing stakeholders could be employed to collaboratively shape an optimal pattern of urban growth. Modeling different land-use planning strategies could be presented as a series of "what if" scenarios. Despite its utility, MCE approaches have two significant drawbacks.

The first problem is that an MCE approach is meaningful only for a limited number of inputs. This is related to the linear additive rule used to calculate a global suitability score known as the *weighted linear combination* (*WLC*). In a WLC operation each input is weighted and added; the weights reflect “importance” or rank among the other inputs. This is referred to as a cardinal weighting system in which all weights sum to unity. Under this approach, a small number of data inputs gives the user a fair amount of flexibility to distribute weights and represent the “tradeoff” between different factors. As inputs increase the weights employed are necessarily thinned out as they are distributed to each factor (Dujmović & De Tré 2011). This results in a reduced significance of factors, and as a consequence, a loss of detail.

The second drawback of MCE approaches generally is related to the decision logic associated with the linear additive rule. MCE by default uses a fixed average logic that is positioned between AND and OR (conjunction and disjunction). Average logic is necessary for the “tradeoff” function in MCE. Real decision-making however is shaped by variety of conditions including *mandatory*, *optional*, and *sufficient* requirements(Dujmović & Scheer 2010). The mathematical approach used in MCE does not accommodate a system for representing a spectrum of different requirements.

An appropriate method, therefore is required that minimizes the loss of input data and represents logical requirements needed for evaluation. While MCE-CA has been shown to be effective for developing transition rules for urban systems, an alternative decision model coupled with a CA that addresses the key shortcomings of linear additive rules does not exist. Therefore this research study examines the use of the Logic Scoring of Preference (LSP) approach and its usefulness in integration with a GIS-based CA in order to overcome the drawbacks of MCE-GIS. LSP can be used to define the global variables of urban growth.

LSP is an alternative multicriteria suitability analysis approach that allows decision makers to combine multiple criteria. The LSP method, unlike MCE approaches, express flexible logic conditions observed in human decision-making such as the optional or mandatory nature of criteria. The inherent flexibility of the LSP approach overcomes issues related to MCE aggregation (combination) rules based on linear additive rules. LSP-derived solutions are justifiable and model human reasoning and decision-making processes (De Tré et al. 2009; Dujmović et al. 2009). LSP integration with a GIS has been defined; however, the LSP method currently has not been fully integrated in a GIS using raster based geospatial data in a practical application, nor used as an input for urban CA models of land-use change.

Dujmović et al.(2009) states that the strength of the LSP method relies on its resemblance to observable patterns of human reasoning. The assertion that the complexity of human behaviour can be fully computed is philosophically rooted in rationalism. Therefore, this thesis assumes a rationalist position through a structured research enquiry.

1.3. Research Objectives

The main goal of this thesis is to develop an integrated LSP methodology that uses a GIS framework and CA for the purpose of modeling urban land suitability, land-use change and for simulations of different scenarios of future urban growth. The specific objectives of the thesis are as follows:

1) Implementation and testing of the LSP method in a raster GIS environment in order to apply the LSP-GIS approach on real geospatial data sets for land-use suitability analysis;

2) Assessment of an integrated GIS-LSP and commonly used GIS-MCE methods for land-use suitability analysis;

3) Development of a LSP-CA model for land-use change and its implementation in real urban-rural settings.

This study extends the existing research efforts on land-use suitability modeling and CA modeling. Urban growth is a spatial process and is well handled by the mechanics of CA. The LSP approach leverages the power of multiple geospatial data layers and returns highly detailed results. The LSP approach functions as a selective and flexible method for defining land-use suitabilities and CA transition rules.

1.4. Study Sites and Data

Two different geospatial datasets of study sites located in coastal British Columbia, Canada were selected to accomplish the objectives of this research study (Figure 1-1). The GIS-LSP integrated prototype was tested on geospatial data of the Municipality of Bowen Island, BC, Canada. The LSP-CA approach was tested on comprehensive geospatial data sets representing the City of Nanaimo on the coast of Vancouver Island, BC, Canada.

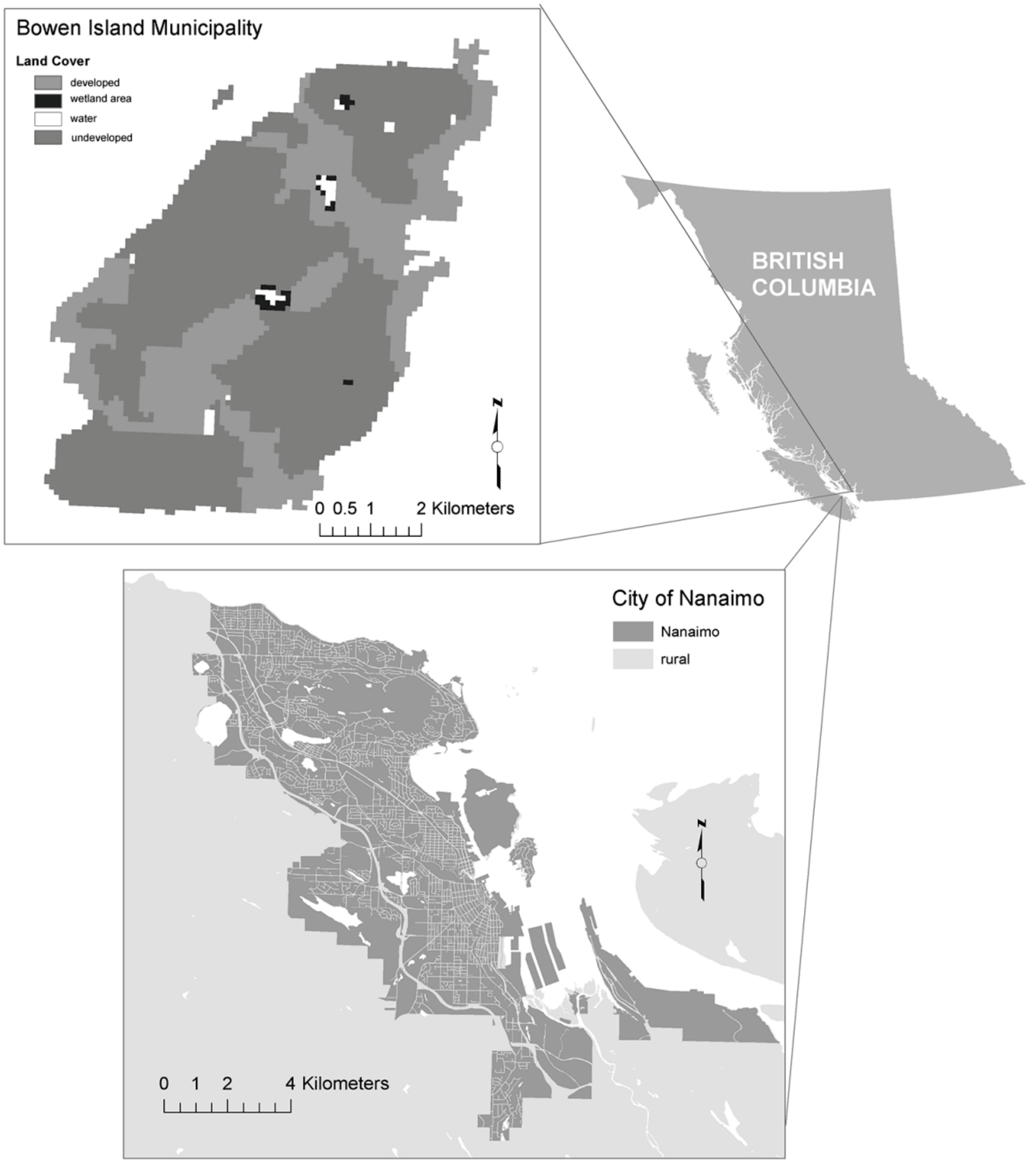

Figure 1-1. Study areas: Bowen Island Municipality, BC, Canada, and Nanaimo, BC, Canada

1.5. Background

The Logic Scoring of Preference (LSP) is a general multicriteria decision modeling approach with origins in soft computing, or computing with values that are a matter of degree. The LSP method has been applied to software, web and GUI interface evaluation

(Dujmović & Nagashima 2006), and more recently theorized for spatial applications (De Tré et al. 2009). While GIS frameworks and geospatial datasets have not been employed, LSP analysis has been implemented in a Google Maps environment (Dujmović & De Tré 2011) Additionally, a non-spatial assessment of conservation planning policy has been performed using LSP methods (Allen et al. 2011).

The first step in implementing a LSP approach involves the construction of an *attribute tree* that organizes the decision problem and contains all the relevant attributes and parameters (Dujmović & Scheer 2010). Attribute trees must accurately reflect the needs and knowledge base of the decision-maker and represent the problem at hand. *Elementary criteria* function as the basic elements of the attribute tree and each should be relevant and non-redundant (Dujmović et al. 2009). Redundancy refers a condition in which a mitigating factor is duplicated (Malczewski 1999).Careful study of all possible factors and their relevancy should be assessed as a means of verifying the non-redundancy of inputs. Elementary criteria are defined using fuzzy membership functions with suitability indicated by a continuous value (0-1).

The attribute tree facilitates the design of an *aggregation structure.* An aggregation structure is composed of a linked series of *LSP aggregators* and describes the parameterization and step-wise combination of inputs. LSP aggregators combine inputs based on logical requirements and a weighting parameter. LSP aggregators express *mandatory* and *optional* requirements associated with input criteria. Modeled logic requirements are represented as a spectrum of conditions between *full disjunction* and *full conjunction*. Requirements are referred to in terms of fuzzy degrees of *ANDness* and *ORness*. LSP aggregators are theoretically based on the *Generalized Conjunction*

Disjunction (*GCD*) function and computed using a *weighted power mean (WPM)* operation as follows (Dujmović et al. 2010):

$$S = \left(\sum_{i=1}^{n} w_i x_i^r \right)^{1/r}, 0 < w_i < 1,\ 0 \le x_i \le 1, \quad i = 1,\ldots,n,$$
$$\sum_{i=1}^{n} w_i = 1, \quad -\infty \le r \le +\infty, \quad 0 \le S \le 1 \qquad \text{(eq.1-1)}$$

where *s* represents the suitability degree, *W* is the user defined criteria weight, *r* is the parameter that determines the logical behaviour of the function and expresses a user selected degree of mandatory or optional satisfaction.

Values for the *r* parameter represent the range of logical requirements needed for evaluation (Figure 1-2) (Dujmović et al. 2010). LSP aggregators can be used as building blocks for the construction of *compound operators* to suit a range of special cases used in routine evaluations. The aggregation of a *mandatory* input with an *optional* input is one such case and may be approached with the construction of a *conjunctive partial absorption (CPA)* aggregator employed to combine asymmetrical or logically incompatible inputs (De Tré et al. 2009). Figure 1-2 depicts seven cases of ANDness and ORness (adapted from (De Tré et. al 2009)). As many as 17 cases exist (Dujmović & Nagashima 2006) and their use depends on the needs of the decision-maker.

operator	symbol	r	
Full Conjunction (and)	C	$-\infty$	simultanaety
Strong Partial Conjunction	C+	- 3.510	
Weak Partial Conjunction	C-	0.261	
Arithmetic Mean	A	1	neutral
Weak Partial Disjunction	D-	2.018	replaceabilty
Strong Partial Disjunction	D+	9.521	
Full Disjunction (or)	D	$+\infty$	

Figure 1-2. LSP aggregators and parameters

Generally, the aggregation structure design is arbitrary and entirely dependent on the conditions specified in the decision problem. Decision problems are, however, theorized to fall under several identifiable patterns. These patterns are referred by Dujmović and De Tré (2011) as *canonical aggregation structures* (CAGs), and are useful as a starting point for building up and structuring the LSP analysis.

Computing a comprehensive suitability score involves the aggregation of each elementary criteria as defined and parameterized in the aggregation structure. Elementary criteria are aggregated in stages until the structure terminates. Termination returns a global suitability score. Scores representing suitability are measured on a continuous scale from 0% to 100% (or 0 to 1) where 0 is “not suitable,” and 1 is “most suitable.” In *fuzzy set theory* variables are expressed as degrees of membership between 2 or more sets (Robinson 2009). The LSP approach relies on inexact definitions of suitability based in this theory to account for uncertainty in the decision-making process.

1.6. Overview

This thesis contains four chapters. The Introduction section outlines the theoretical and conceptual framework for the study. The second chapter describes the development of the integrated GIS-LSP method. The prototype was designed and tested on raster geospatial data of Bowen Island Municipality, BC, Canada, to derive a suitability map for residential development based on a number of input criteria. Model input criteria were selected and an aggregation structure containing LSP operators was designed and implemented in a raster GIS framework. The LSP approach was compared to a similarly structured MCE approach using a linear additive rule. Output maps are presented and compared. The primary purpose of this section is to test the ability of integration of the LSP approach in a raster GIS environment. This provides the basis for further development of the method that integrates LSP and GIS into a CA model of an urban land-use change system.

Chapter three describes the development of the integrated LSP-GIS-CA structure for modeling different urban growth scenarios. A series of CA simulations were constructed employing an LSP approach for assessing cell suitability for residential development based on numerous input criteria. The CA was calibrated to produce different outcomes and alter model behaviour by systematically adjusting the LSP parameters. As a result, several simulation scenarios of possible urban growth at the urban-rural fringe of the City of Nanaimo, BC, Canada were generated.

Chapter four is the Conclusion section and presents a summary of the thesis results and insights into additional applications for this research study. Contributions to the field of computational spatial modeling are discussed as well as future directions for this research work.

1.7. References

Allen, P.M., 1997. Cities and Regions as Self-organizing Systems: Models of Complexity, Taylor and Francis. London 300p

Allen, W., L. III et al., 2011. Identifying and selecting strategic mitigation opportunities; criteria design and project evaluation using Logic Scoring of Preference and optimization. *Journal of Conservation Planning*, 7, pp.61–68.

Batty, M. & Xie, Y., 1996. Preliminary evidence for a theory of the fractal city. *Environment and Planning A*, 28(10), pp.1745 – 1762.

Batty, M., Xie, Y. & Sun, Z., 1999. Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems*, 23(3), pp.205–233.

Batty, M., 1997. Cellular Automata and Urban Form: A Primer. *Journal of the American Planning Association*, 63(2), pp.266–274.

Batty, M., 2005. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*, Cambridge, Mass: MIT Press.

Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. *International Journal of Geographical Information Systems*, 5(3), p.321.

Clarke, K C, Hoppen, S. & Gaydos, L., 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design*, 24(2), pp.247–261.

Dujmović, J. & Scheer, D., 2010. Logic aggregation of suitability maps. In *2010 IEEE International Conference on Fuzzy Systems (FUZZ)*. 2010 IEEE International Conference on Fuzzy Systems (FUZZ). IEEE, pp. 1–8.

Dujmović, J. & Tré, G.D., 2011. Multicriteria methods and logic aggregation in suitability maps. *International Journal of Intelligent Systems*, 26(10), pp.971–1001.

Dujmovic, J.J. & Nagashima, H., 2006. LSP method and its use for evaluation of Java IDEs. *International Journal of Approximate Reasoning*, 41(1), pp.3–22.

Dujmović, J.J., De Tre, G. & Dragicević, S., 2009. Comparison of Multicriteria Methods for Land-use Suitability Assessment. *IFSA/EVSFLAT Conference*.pp. 1404-1409.

Dujmović, J.J., Tré, G. & Weghe, N., 2010. LSP suitability maps. *Soft Computing*, 14(5), pp.421–434.

Eastman, J.R. et al., 1995. Raster Procedures for Multi-Criteria/Multi-Objective Decisions. *Photogrammetric Engineering and Remote Sensing (PE&RS)*, 61(5), pp.539–547.

Hall, P.G., 2002. *Cities of Tomorrow: An Intellectual History of Urban Planning and Design in the Twentieth Century* 3rd ed., Malden, MA: Blackwell Publishers. 576p.

Herold, M., Couclelis, Helen & Clarke, Keith C., 2005. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems*, 29(4), pp.369–399.

Jankowski, P., Andrienko, N. & Andrienko, G., 2001. Map-centred exploratory approach to multiple criteria spatial decision making. *International Journal of Geographical Information Science*, 15(2), pp.101–127.

Kocabas, V. & Dragicević, S., 2006. Assessing cellular automata model behaviour using a sensitivity analysis approach. *Computers, Environment and Urban Systems*, 30(6), pp.921–953.

Laaribi, A., Chevallier, J.J. & Martel, J.M., 1996. A spatial decision aid: A multicriterion evaluation approach. *Computers, Environment and Urban Systems*, 20(6), pp.351–366.

Li, X. & Yeh, A.G., 2001. Calibration of cellular automata by using neural networks for the simulation of complex urban systems. *Environment and Planning A*, 33(8), pp.1445–1462.

Li, X, Chen, Y., et al., 2010. Concepts, methodologies, and tools of an integrated geographical simulation and optimization system. *International Journal of Geographical Information Science*, 25(4) pp.633-655

Li, X,, Zhang, X., et al., 2010. Parallel cellular automata for large-scale urban simulation using load-balancing techniques. *International Journal of Geographical Information Science*, 24(6), pp.803–820.

Li, X. & Yeh, A.G.-O., 2004. Data mining of cellular automata's transition rules. *International Journal of Geographical Information Science*, 18(8), pp.723–744.

Li, X. & Yeh, A.G.-O., 2000. Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, 14(2), pp.131–152.

Li, X.,& Yeh, A.G.-O., 2002a. Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, 16(4), pp.323–343.

Li, Xia & Yeh, A.G.-O., 2002b. Urban simulation using principal components analysis and cellular automata for land-use planning. *Photogrammetric Engineering and Remote Sensing*, 68(4), pp.341–351.

Ligmann-Zielinska, A., Church, R.L. & Jankowski, P., 2008. Spatial optimization as a generative technique for sustainable multiobjective land-use allocation. *International Journal of Geographical Information Science*, 22(6), p.601.

Liu, X. et al., 2007. Discovery of transition rules for geographical cellular automata by using ant colony optimization. *Science in China, Series D: Earth Sciences*, 50(10), pp.1578–1588.

Malczewski, J., 1999. *GIS and Multicriteria Decision Analysis*, New York: John Wiley. 408p.

Malczewski, J., 2000. On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches. *Transactions in GIS*, 4(1), pp.5–22.

Menard, A. & Marceau, D.J., 2005. Exploration of spatial scale sensitivity in geographic cellular automata. *Environment and Planning B: Planning and Design*, 32(5), pp.693–714.

Portugali, J & Benenson, I, 1995. Artificial planning experience by means of a heuristic cell-space model: simulating international migration in the urban process. *Environment and Planning A*, 27(10), pp.1647–1665.

Portugali, J., Benenson, I. & Omer, I., 1994. Sociospatial Residential Dynamics: Stability and Instability within a Self-Organizing City. *Geographical Analysis*, 26(4), pp.321–340.

Robinson, V.B. Fuzzy Sets and Spatial Analysis. In *The Sage Handbook of Spatial Analysis*. eds. P. Rogerson and S. Fotheringham, Sage Publishing. pp.204-219.

Stanilov, K. & Batty, Michael, 2011. Exploring the Historical Determinants of Urban Growth Patterns through Cellular Automata. *Transactions in GIS*, 15(3), pp.253–271.

Takeyama, M. & Couclelis, H., 1997. Map dynamics: integrating cellular automata and GIS through geo-algebra. *International Journal of Geographical Information Science*, 11(1), pp.73–91.

Tobler, W. 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* 26:234-240

Tomalty, R., 2009. The Ecology of Cities. *Alternatives Journal*, 35(4), pp.19–21.

Torrens, P.M., 2000. How cellular models of urban systems work.

Torrens, P.M. & O'Sullivan, D., 2001. Cellular automata and urban simulation: where do we go from here? *Environment and Planning B: Planning and Design*, 28(2), pp.163 – 168.

De Tré, G., Dujmovic, J. & Van De Weghe, N., 2009. Supporting Spatial Decision Making by Means of Suitability Maps. In J. Kacprzyk, F.E. Petry & A. Yazici, eds. *Uncertainty Approaches for Spatial Data Modeling and Processing*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 9-27.

Ward, D.P., Murray, A.T. & Phinn, S.R., 2003. Integrating spatial optimization and cellular automata for evaluating urban change. *The Annals of Regional Science*, 37(1), pp.131–148.

White, R, 2000. High-resolution integrated modelling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, 24(5), pp.383–400.

White, R. & Engelen, G., 1993. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. *Environment & Planning A*, 25(8), pp.1175–1199.

White, R. & Engelen, G., 1994. Cellular dynamics and GIS: modelling spatial complexity. *Geographical Systems*, 1(3), pp.237–253.

White, R., Engelen, G. & Uljee, I., 1997. The use of constrained cellular automata for high-resolution modelling of urban land-use dynamics. *Environment and Planning B: Planning and Design*, 24(3), pp.323–343.

White, R, Straatman, B. & Engelen, G, 2004. Planning Scenario Visualization and Assessment: A Cellular Automata Based Integrated Spatial Decision Support System. In *Best Practices in Spatially Integrated Social Science*. New York: Oxford University Press, pp. 420–442.

Wu, F. & Webster, C.J., 1998. Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B: Planning and Design*, 25(1), pp.103–126.

Chapter 2: GIS-based Logic Scoring of Preference (LSP) Method for Suitability Analysis

2.1. Abstract

Multicriteria Evaluation (MCE) is a common approach for building suitability maps in raster based geographic information systems (GIS). MCE aggregation can be performed by a linear additive model also known as the Weighted Linear Combination (WLC) or simple additive scoring. MCE methods see a decrease in factor significance with an increase in the quantity of inputs and do not reflect logical requirements needed for decision making. The Logic Scoring of Preference (LSP) approach is presented here as an alternative to MCE models. The LSP approach features an efficient nonlinear system for suitability aggregation, and allows the expression of a spectrum of logical requirements. The objective of this research study is to integrate the LSP method into a raster–based GIS in order to (a) test the approach within a GIS framework and by using real geospatial datasets, and (b) compare the GIS-LSP approach to a GIS-MCE approach. The two approaches were applied to a land-use suitability analysis problem using GIS data for Bowen Island Municipality, Canada. Obtained results indicate that the integrated GIS-LSP approach is a flexible and useful approach for suitability analysis. The GIS-LSP approach outperformed the GIS-MCE approach with respect to selectivity and level of detail present in the output.

A version of this chapter is in preparation for submission to the International Journal of Geographic Information Science under the title: GIS-based Logic Scoring of Preference (LSP) Method for Suitability Maps and coauthored with S. Dragićević and J.Dujmović

2.2. Introduction

In the context of geographic information systems (GIS), decision-making is an iterative and interactive process geared towards understanding the problem, objectives, tradeoffs and uncertainties in identifying a solution or choice from a set of alternatives. Decision-making can be conceptualized as *structured* or *unstructured* (Malczewski 1999). The terms refer to the level of computability associated with the problem. A problem with a high degree of computability is one in which all factors can be exhaustively decomposed and accounted for (Malczewski 1999). Spatial Decision Support Systems (SDSSs) facilitate spatial decision-making research for *semi-structured* decision tasks, involving a special hybrid computational and expert knowledge approach (Densham 1991). SDSS frameworks combine spatial data management, analytical modeling, visualization, and require the interaction of a decision-maker analyst or group of stakeholders. SDSSs may function as stand-alone software tools customized for a narrow domain and application or integrated within a GIS framework (Church, et al. 2000). Broadly defined, GIS comprises spatial data input, storage, retrieval, output and analysis (Goodchild 1987). A GIS-SDSS integration methodology builds on the visualization, data processing and database management capabilities of fully developed GIS applications. Integration was recognized as an appropriate approach for implementing SDSS methods and more particular *multicriteria evaluation* (*MCE*) procedures, first implemented in raster GIS by Carver (1991).

Spatial multicriteria evaluation (MCE) is a general term given to decision modeling approaches that can be used within SDSSs operating on geospatial data (Malczewski 2010). A spatial MCE approach consists of a set of mapped choice alternatives (locations), a set of preference criteria, and a means of evaluating each choice alternative based on the criteria set (Jankowski 1995). Alternatives are given cumulative suitability scores presented spatially as a mapped *suitability index* or *suitability map*. Suitability maps are the product of a suitability analysis used for the visualization of preference, likelihood, or consequences surrounding a phenomenon, or activity (Hopkins 1977).

Different types of MCE exist in the GIS literature and include but are not limited to a Boolean approach used with a maximum or minimum operators (Jiang & Eastman 2000), a Fuzzy MCE (FMCE) approach based on fuzzy, continuous variables employing a linear additive rule (Eastman, et al 1995), and MCE augmented with Ordered Weighted Averaging used to evaluate the level of risk associated with a decision model outcome (Malczewski 2006). The term MCE as used in this study refers specifically to the FMCE approach employing fuzzy inputs encoded as a spectrum of varying degrees ranging from 0 (not suitable) to 1 (most suitable) (Eastman et al. 1995). In *fuzzy set theory*, such continuous variables belong to more than one set and are defined by a function used to address vague or incomplete knowledge (Robinson 2009). MCE used in this way accommodates a flexible and inexact definition of suitability.

Numerous linked MCE and GIS approaches have been proposed that represent a wide range of spatial decision-making objectives including species habitat suitability (Store & Kangas 2001), agricultural suitability analysis (Ceballos-Silva & Lopez-Blanco 2003), risk and hazard assessment (Aceves-Quesada et al. 2007), and infrastructure planning (Rybarczyk & Wu 2010). MCE as an analytical approach for land-use planning forms a large area of research. A prototype urban planning support tool based on MCE was developed for the Queensland region of Australia (Pettit & Pullar 1999). Joerin, et al. (2001) introduced MCE to study residential suitability under the conditions of environmental noise pollution. Hill et al. (2005) document an operational decision support system (ASSESS) used for agricultural land-use policy analysis in Australia.

In addition to different applications, researchers have also focused on preferences of decision makers and modeling optimal solutions among competing planning objectives. Rinner and Taranu (2006) developed an interactive tool for MCE-based decision making. Proctor and Dreschler (2006) developed and tested an MCE approach for collaborative planning. A GIS-MCE approach was used to study competing goals in forest conservation planning in Malaysia (Phua & Minowa 2005). Wood and Dragićević (2007) employed a multi-objective GIS decision support framework for identifying optimal marine protection locations based on criteria representing the conflicting objectives of conservation and resource extraction.

Spatial MCE approaches based on linear models, however, fall under criticism for producing an oversimplified representation of human reasoning and decision-making that is difficult to interpret (Dujmović et al. 2009; Malczewski 2006). Linearized MCE has two significant methodological issues: (a) the number of data inputs that may be combined to produce meaningful results is limited and (b) the decision logic employed does not reflect logic conditions needed for decision problems. These two issues are related to the linear aggregation process that is used in MCE. A linear additive combination rule is used, known as the *Weighted Linear Combination* (*WLC*) rule. In a WLC procedure, criteria are first assigned a weight and summed returning suitability scores used to make a suitability map (Eastman et al. 1995):

$$S = \sum_{i=1}^{n} w_i x_i, \; 0 < w_i < 1, \; i = 1, \ldots, n, \quad \sum_{i=1}^{n} w_i = 1, \qquad \text{(eq. 2-1)}$$

where S is the aggregated overall suitability, w is an array of positive normalized weights representing the relative importance of elementary decision criteria. The WLC rule is compensatory; a low criteria score may always be compensated by higher criteria scores in the same location. By selecting a different distribution of weights a different outcome may be produced (Malczewski 2000).

The amount of inputs *n* in such a system is limited; the compensatory relationship between MCE factors functions well if the inputs are minimized. As the number of input factors increase, the significance of each input decreases. Because the total sum of factor weights must sum to unity, the mean value of weights is 1/n and it can become insignificant for large numbers of input attributes. For WLC systems the total impact of input x_i is $\delta_i = S(x_1,...,x_{i-1},1,x_{i+1},...,x_n) - S(x_1,...,x_{i-1},0,x_{i+1},...,x_n) = w_i$ Obviously, the average impact is $\overline{\delta} = (\delta_1 + ... + \delta_n)/n = 1/n$ and as n increases the average impact becomes negligible. This problem relates to the amount of detail that can be transmitted through MCE/WLC methods.

MCE/WLC models also exhibit limitations with respect to decision logic. In many cases decisions require the application of logical requirements to compare and select a set of locations over the alternatives. Traditional logic operators model simultaneity (AND) and replaceability (OR). AND denotes partial or full conjunction and is similar to a minimum function, whereas OR denotes partial or full disjunction and is similar to a maximum function. The WLC approach yields a fully *neutral* decision logic that is neither AND nor OR. Neutral logic is only one of necessary logic aggregators. According to Dujmović et al., (2009) logical requirements such as *conjunctive, disjunctive*, *mandatory, nonmandatory, sufficient, optional*, and others are necessary for real-world decision-making. In order to accommodate real-world reasoning for decision-making, the Logic Scoring of Preference (LSP) method is necessary as a new approach capable of overcoming WLC-based MCE limitations.

The Logic Scoring of Preference (LSP) approach is a multicriteria approach to decision-making with origins in soft computing (computing with variables that are matter of a degree). The LSP approach features nonlinear attribute criteria and aggregation structures that model decision requirements. These features make LSP an appropriate method for researching complex spatial problems requiring numerous data inputs (attributes) and a high level of detail. LSP has been used primarily as a utility for evaluating software and web interfaces. Spatial applications and LSP method have been proposed, but full GIS integration using geospatial data sets has not yet been implemented.

Therefore the main objective of this study is to develop an integrated GIS and LSP model for the purpose of defining land-use suitability. Suitability was expressed as raster suitability maps representing a geographic study area. The model was built primarily to test the LSP approach in a spatial context using geospatial data in a raster GIS framework. The LSP approach was also compared to a MCE/WLC structured approach. A comparison served two purposes: (a) to address the limitations of MCE/WLC suitability maps and (b) to highlight the relevant qualities of LSP (nonlinear aggregation and flexible logic aggregators) in addressing those limitations. The LSP approach was tested in a residential land-use suitability analysis procedure using geospatial data attributes of Bowen Island Municipality, BC, Canada.

2.3. Logic Scoring of Preference Approach: Theoretical Background

2.3.1. Background

The Logic Scoring of Preference (LSP) is presented here as a novel approach for researching semi-structured spatial decision problems in a GIS framework. LSP was originally conceived as a general multicriteria approach and has been used for evaluating complex software development environments, web browsers and user interfaces (Dujmović & Nagashima 2006). More recently the approach has been extended to the evaluation of complex spatial systems (Dujmović et al. 2009). De Tré et al. (2010) describe a framework for building LSP suitability maps, also often called *s-maps*. LSP suitability maps have been described using empirically derived data for a hypothetical optimal home location siting (Dujmović and Scheer 2010). Dujmović and De Tré (2011) develop this research problem and describe an interactive, dynamic web-based LSP system integrated with Google Maps (SEAS 2012). A spatial LSP system may be configured to provide analysis on the financial components and costs related to a decision strategy (De Tré et al 2010). De Tré et al. (2009) have proposed suitability maps that express bipolar satisfaction representing degrees of satisfaction and dissatisfaction of decision criteria incorporating LSP aggregators.

2.4. Elements of the LSP approach

The LSP approach comprises a set of components: (i) *elementary criteria*, (ii) an *attribute tree*, (iii) an *aggregation structure*, and a computed *global suitability score*. Elementary criteria function as the inputs of an LSP evaluation. Criteria are scaled using a fuzzy membership function to define suitability. An attribute tree is used to organize the elementary criteria for the purpose of structuring the problem. Criteria must be organized categorically and non-redundantly. For example, a category such as “access to transit” in a decision problem may contain bus, train, and street car accessibility factors. Factors may also be categorized based on logic requirements.

The expression of logic requirements is a key feature of the LSP approach. In many cases criteria may require *mandatory* satisfaction, or reflect a requirement that is merely *optional*. For example, a slope criterion must be satisfied for many land-use decision problems. However, satisfying a “view criteria” may be entirely optional. Ultimately, if the mandatory slope criteria is not satisfied (assigned a 0 score on a scale of 0 to 1) in any location, the result will be a null score for that location. An optimal view criteria with an *optional* satisfaction requirement is more replaceable. A null score of an optional criterion will not disqualify the location. Mandatory and optional requirements are modeled in terms of fuzzy degrees or strengths. For example, a mandatory criteria is modeled as a degree of *ANDness*, and an optional requirement is conversely modeled as a degree of *ORness*. ANDness and ORness occur on a continuum between logical AND and OR. The two types of logic have an inverse relationship. Therefore a strong mandatory requirement (strong ANDness) is equivalent to a weak optional requirement (weak ORness), and vice versa.

Structuring the criteria categorically by fuzzy logical requirements and problem domain facilitates the mathematical *aggregation* or combination of inputs. Categorically defined inputs are introduced into a hierarchical stem and leaf *aggregation structure.* The aggregation structure combines smaller categories into more comprehensive suitability layers. For example, in a hypothetical evaluation, the “transit” category is first aggregated, and then this comprehensive suitability is subsequently combined with “road, highway, and airport” accessibility into generalized “transportation” suitability. Aggregation is performed mathematically using *LSP aggregators*. LSP aggregators accept a set of inputs and weight and logical strength parameters are applied. Aggregators are based in the *generalized conjunction disjunction* (*GCD*) function (Dujmović et al. 2009, Dujmović and Larsen 2007). GCD provides the means for combining or *aggregating* criteria scores to model different strengths of satisfaction requirements (i.e. mandatory or optional) needed by the analyst. GCD is a theoretical structure that can be mathematically implemented through different approaches including a *logarithmic mean*, a *counter-harmonic mean* or a *weighted power mean* (*WPM*) (Dujmović 2008). In this research study the GCD function is computed with a *WPM* and is used to calculate an aggregated suitability score as follows:

$$S = \left(\sum_{i=1}^{n} w_i x_i^r \right)^{1/r}, 0 < w_i < 1,\ 0 \le x_i \le 1, \quad i = 1, \ldots, n,$$
$$\sum_{i=1}^{n} w_i = 1, \quad -\infty \le r \le +\infty, \quad 0 \le S \le 1 \qquad \text{(eq. 2-2)}$$

where S represents the aggregated suitability score, x_i denotes an input attribute suitability score, w_i is the user defined attribute weight reflecting the relative importance of the selected input, and *r* is the parameter that determines the logical behaviour of the function and expresses a user selected degree of mandatory or optional requirements. The LSP aggregator "nodes" of the aggregation structure systematically combine the categorically grouped inputs and the system terminates returning a global suitability map. The map ranks each location with a score ranging from 0 not suitable to 1 most suitable.

The set of methods under the LSP approach handles input data more efficiently than the MCE approach and result in more data-rich and expressive suitability models. The nonlinear method of aggregation permits an unlimited amount of inputs to be included in an evaluation with a minimization of data loss. The LSP aggregators employing the *WPM* facilitate aggregation and allow modeling of different types of conditional logic needed to conceptualize suitability. A more in-depth review of fuzzy models of preference logic follows in the next section.

2.4.1. Models of Preference Logic

The LSP approach models fuzzy ANDness (*conjunction*) and ORness (*disjunction*) with models of *simultaneity* and *replaceability* (Dujmović & Nagashima 2006). Figure 2-1 describes different levels of simultaneity and replaceability, and their associated unit intervals, *r* parameters, and symbolic notation. LSP aggregators used in evaluation include (i) *full conjunction* (*C*) and *partial conjunction* (*PC*) for modeling simultaneity between inputs; (ii) the *mean average* (*A*) to model balanced neutrality; (iii) *full* (*D*) and *partial disjunction* (*PD*) for modeling replaceability among inputs; and (iv) specially configured aggregators designed to combine *mandatory and desired/optional* inputs, and *sufficient and desired /optional* inputs.

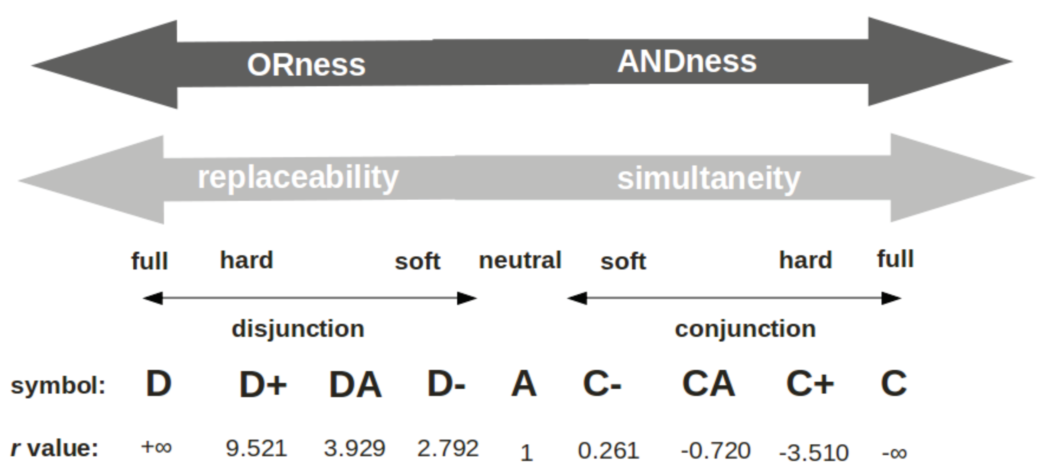

Figure 2-1. Different levels of simultaneity and replaceability

Selecting a LSP aggregator is a matter of determining the strength of logical requirements needed to evaluate criteria. To model a stronger, more restrictive simultaneity, a *hard partial conjunction* (*HPC*) *or full conjunction* (*FC*) operator may be selected. A defining feature of the *HPC* operator is that any null criteria input will return a 0 output. This property of the *HPC* aggregator makes it appropriate for combining criteria with mandatory satisfaction requirements. Alternatively, a less restrictive satisfaction requirement may be appropriate, such as a *soft partial conjunction* (*SPC*). Likewise, different intensities of replaceability modeled with disjunction may be represented as either *hard partial disjunction* (*HPD*) or *soft partial disjunction* (*SPD*). A *HPD* operator will output a score of 1 to any input that is fully satisfied. The mean average (A) is another model that represents logical *neutrality*. Neutrality refers to a logic that is expresses neither ANDness nor ORness. Non-mandatory criteria may be aggregated using a *SPC*, A, *SPD*, or *HPD* operator. A strong model of replaceability will give a high score to locations in which at least one of the inputs is satisfied, representing trade-off of non-mandatory criteria. The strength of one criteria score may replace or compensate for the absence of the weaker criteria score.

The approach was designed for flexibility and LSP aggregators may be configured to handle special situations such as the aggregation of logically incompatible inputs. The aggregation of a mandatory input and an optional input is approached using a *conjunctive partial absorption* (*CPA*) aggregator (Dujmović & De Tré 2011). A CPA aggregator is built with basic LSP operators: models of partial conjunction and partial disjunction or neutrality along with a preference weighting structure. In a hypothetical LSP evaluation, a *CPA* aggregator is used to combine mandatory input x and desired input y. If the mandatory input (x) is 0, then the corresponding output preference (z) is 0. However, if the desired input y is 0 and falls on the range of $0 < x \leq 1$ then a *penalty* is applied. In other words, the null satisfaction of the mandatory criteria eliminates the location under evaluation, whereas the null satisfaction of the desired input merely detracts from the overall suitability score. In the case of the desired input $y = 1$, and the mandatory input x is greater than 0, a *reward* is applied. If a desired input is fully satisfied (1), given that the mandatory input is also satisfied, the desired input compensates the output score. A lookup table may be employed (Dujmović 1979) or specialized software for selecting penalty and reward pairs (De Tré et al. 2009).

It is theorized that system evaluations follow identifiable patterns. Dujmović & De Tré (2011) refers to these evaluation patterns as *canonical aggregation structures* (*CAS*). In an LSP system, criteria are aggregated and combined in a stepwise, nonlinear fashion. With increasing degree of aggregation the cumulative strength of aggregators increases. Dujmović and De Tré (2011) refer theoretically to the accumulation of logical strength as a *shadow* defined as the quantity of inputs and aggregated inputs that accumulate in an aggregation structure and influence the output. Aggregators, for example, positioned at the beginning of the aggregation structure may have 2 inputs, and the output is influenced by a shadow of size 2. As more input attributes are combined into subgroups, their collective importance and logical strength increases resulting in a larger shadow of size *n*. A *conjunctive CAG,* for example, uses less restrictive logical operators at lower levels in the aggregation structure. As additional criteria merge into larger aggregates, the level of ANDness increases. Stronger conjunctive aggregators are needed to reflect stronger requirements, requiring a hard partial conjunction or full conjunction operator to derive the final solution. In the case of a conjunctive CAG, the model of simultaneity (ANDness) needed is directly related to the size of its shadow. A full discussion of less commonly applied CAG structures and their applications are presented in Dujmović & De Tré (2011).

2.5. Methodology

This section is divided into three parts. The first part presents the framework of an integrated GIS-LSP prototype model. The second part describes the prototype used in a suitability analysis case study. The third part describes a GIS-MCE structured approach to facilitate comparison of the GIS-LSP and GIS-MCE approaches.

2.5.1. Integration of raster GIS with the LSP method

The LSP approach described assumes a tight integration with a raster GIS. A GIS-LSP framework uses geographically referenced GIS data layers as input, and relies on existing GIS operations to standardize and define elementary attributes, implement LSP operators, and calculate suitability scores for each choice alternative. The GIS-LSP integrated approach may be used to formulate a suitability index, or alternatively select the top ranked locations in the study site. Inputs and results may be visualized in map form.

Using map visualization, users may perform model validation, a sensitivity analysis, or create a series of alternative decision scenarios. By changing different features (the attribute tree, factor weights, LSP aggregators, and the aggregation structure) of the LSP system a series suitability scenarios may be generated.

The integrated GIS and LSP model is built in the following stages: (i) elementary criteria definition (ii) development of an attribute tree (iii) aggregation structure selection and (iv) computation of a global suitability score.

2.5.2. Elementary Criteria Definition

Elementary criteria are the basic elements of the attribute tree as designed by the decision-maker. The spatial application of LSP suitability maps proposed by De Tré et al.(2009) specifies a field-based model, therefore the approach described is implemented using a raster GIS data model. Furthermore, raster cells are well suited for the representation of *fuzzy sets* used to express vague definitions of suitable distances related to spatial accessibility (Malczewski 1999). Each elementary criteria is defined as a spatial attribute pertaining to a user preference value. Preferences are specified using natural language and formalized with a continuous membership function. This procedure is similar to the standard approach used in fuzzy GIS-MCE approaches. For each mapped criteria layer, each cell or raster at (x,y) location is ranked and assigned a continuous value (0-1) related to a suitability score for a specific purpose required by the decision-maker or analyst. For example, a trapezoidal linear function may be used to model a preference of housing location, for example, corresponding to the level of spatial accessibility to a major airport. Data conversion procedures using linear transformation functions are necessary; yet do not eliminate the possibility of using nonlinear and more realistic functions to represent meaningful decision-maker preferences.

2.5.3. The Attribute Tree

The first step in creating an LSP suitability map involves the construction of an attribute tree that organizes the decision problem and contains all the relevant attributes. Within the structure of the attribute tree, elementary criteria are defined by problem domain and with qualities of decision logic. All attributes that share a similarity or relationship within the decision problem are grouped accordingly. Structuring the decision problem facilitates the mathematical aggregation of criteria.

2.5.4. The Aggregation Structure

The second step involves selecting an appropriate aggregation structure to combine criteria. Elementary criteria structured within the attribute tree described above are fed into a user designed aggregation structure. The structure employs LSP aggregators based in the *GCD* function and implemented using the *WPM*. The aggregation structure combines criteria according to the categorization of the attribute tree. Categorically grouped inputs are then aggregated. Aggregation structure design is relatively arbitrary and dependant on the application domain. A *CAS* may be used as a template to model decision making. Each elementary criterion is then aggregated in sequence determined by the attribute tree and aggregation structure resulting in a suitability map. Each location in the study area given a suitability score measured on a continuous scale (0 to 1, or 0% - 100%).

2.6. The Case Study - GIS-LSP Prototype

The Municipality of Bowen Island, BC, Canada was chosen as a test study site for the implementation of the GIS-LSP method. The Idrisi Taiga GIS software (Clark Labs 2012) was used given its raster-based functionalities.

2.6.1. Study Area and Datasets

Bowen Island (Figure 2-2) is comprised of over 5050 hectares of rugged bedrock-dominated terrain situated at the entrance of Howe Sound, Canada (Block 1978). It is in close proximity to the fast growing and densely populated Metro Vancouver Region and is a popular location for vacation cottages and outdoor recreation (Bowen Island Municipality 2002). Under the pressures of intensified residential development, Bowen Island has experienced significant changes in its natural environments. Raster GIS data sets used in this study were acquired from Hectares BC (2012), a collaborative pilot project between The Nature Conservancy of Canada and Biodiversity BC. Layers used for the development of the elementary criteria included a digital elevation model (DEM), roads, and land-use. The extent of the study area under analysis was a 14 x 14 km area encompassing Bowen Island Municipality.

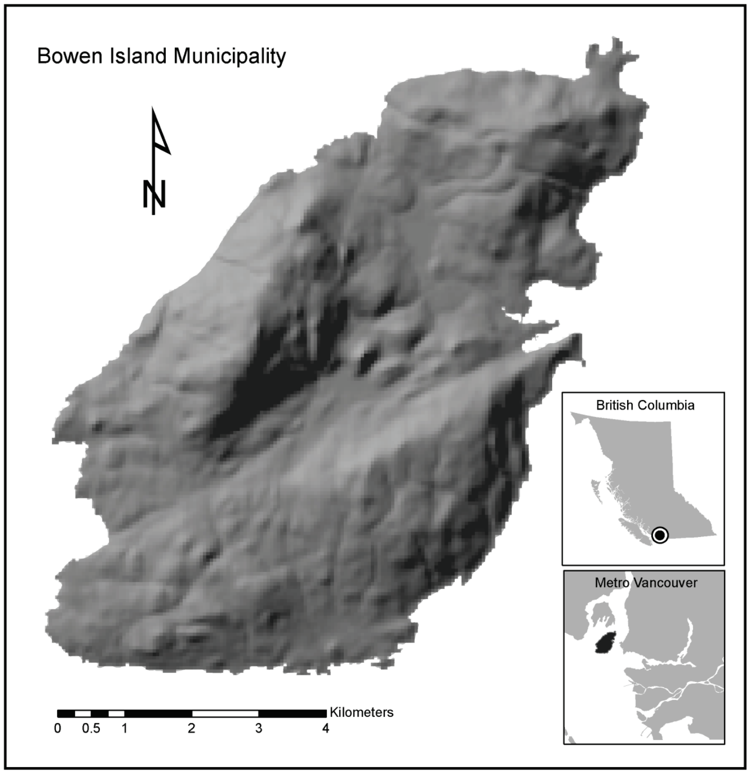

Figure 2-2. Map of Bowen Island Municipality with surface elevation visualized as shaded relief

2.6.2. Step 1. Elementary Criteria Definition

Six input criteria were selected for the GIS-LSP prototype and developed using GIS operations, namely (i) *slope,* (ii) *aspect,* (iii) *road access,* (iv) *water access,* (v) *ferry terminal access,* and (vi) *park access.* Development on Bowen Island favors vacation cottages and seasonal homes. While the set of factors is not comprehensive they serve the purpose of testing the GIS-LSP approach. The input layers are summarized and justified below in Table 2-1. Additional factors that may be useful may be view shed, terrain, and soil drainage. Municipal planning documents could be used as a means of developing highly detailed suitability maps that account for bylaws that determine the nature of development in different locations based on environmental, economic, or social planning objectives.

The input criteria used for the LSP evaluation were derived from GIS data and standardized. *Slope* and *aspect* were obtained from a DEM data set. The *road access*, *ferry terminal access*, and *park access* were obtained through the application of a raster-based GIS Euclidian distance function. Linear trapezoidal functions were applied in the fuzzification of data measurements for the purpose of representing suitability. As this study investigates novel methodological approaches, criteria variables were chosen arbitrarily. The descriptions and justifications for the selected functions are summarized in Table 2-1 in the following section. Figure 2-3 shows the functions applied to the GIS raster data sets, and Figure 2-4 shows the series of individual criteria input layers used in this study.

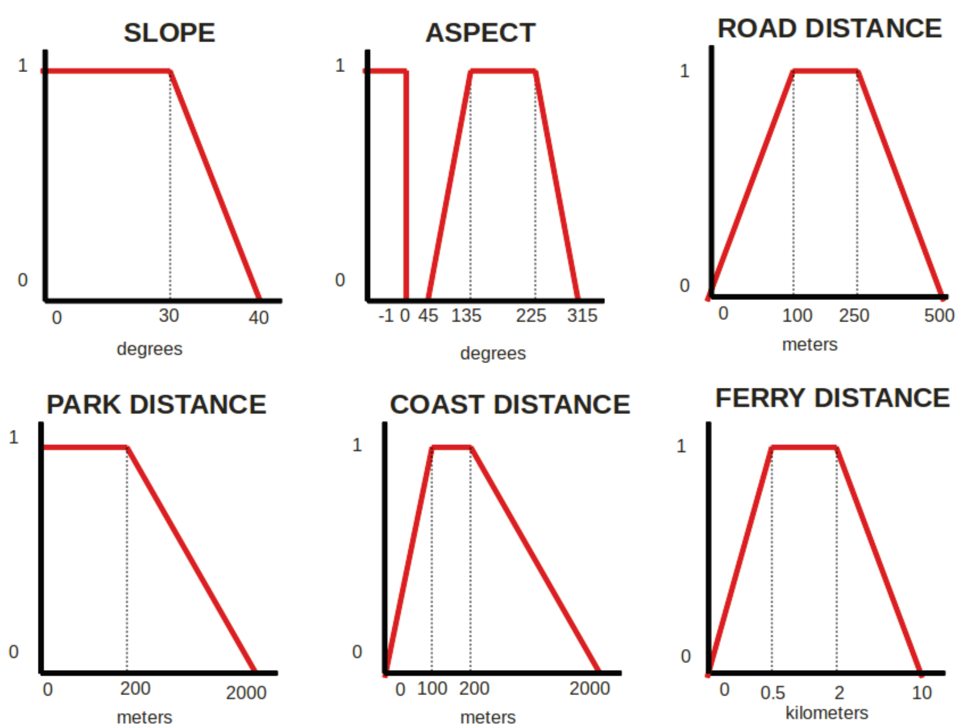

Figure 2-3. Fuzzy transformation functions for criteria definition.

Under the ASPECT function the variable -1 refers to level ground or locations without a measurable degree of slope.

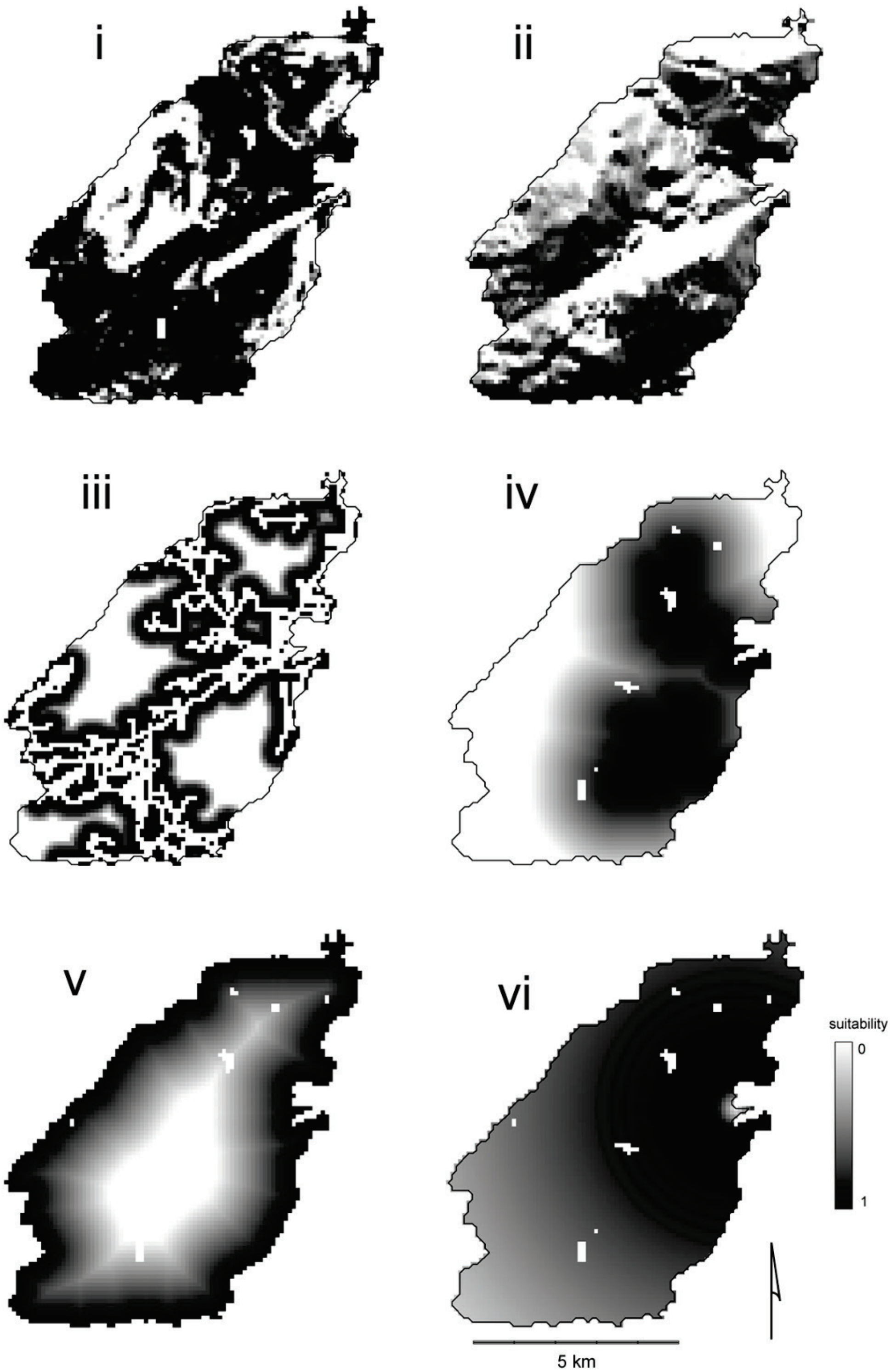

Figure 2-4. Elementary criteria maps: (i) slope, (ii) aspect, (iii) road access, (iv) park access, (v) coast access, and (vi) ferry terminal access.

2.6.3. *Step 2. Attribute Tree*

To structure the decision problem, the criteria were arranged hierarchically into an attribute tree and first grouped according to problem domain (Table 2-1). Three domain categories were designed: (i) *site*, (ii) *transportation* and (iii) *amenities*. *Slope* and *Aspect* are grouped under *site*; *ferry terminal access*, and *road access* are grouped under *transportation*; and *coast access* and *park access* are arranged under the *amenities* category.

Logical requirement	Category	Criteria
Mandatory	Site(+)	**Slope (+)**: 0 - 30 degrees = 100%, 40 degrees = 0%; Reflects the relative costs of residential development on steep graded slopes as opposed to level surfaces. Slopes from level (0 degrees) up to 30 degrees are considered suitable, with monotonically decreasing suitability to 40 degrees. Grades above 40 degrees are considered too costly and unsuitable.
		Aspect (-) : 0 degrees – 45 degrees = 0%, 135 degrees – 225 degrees = 100%, 315 degrees – 360 degrees = 0%; Reflects the desirability of south-facing sites for development for the objective of maximizing sunlight exposure. Aspect refers to the direction in which a slope faces measured in decimal degrees (180 degrees = south).
	Transportation(+)	**Road access (+)**: 0m = 0%,100 m – 250m = 100%, 500m = 0%; Locations adjacent to road features are unsuitable with increased suitability to 100m. Car ownership is high in the municipality and many residents use them daily for their commute. Areas with the highest suitability are areas within 100m and 250m of roads with monotonically decreasing suitability from 250 to 500 m. Areas at a distance of 500m are the least suitable and locations beyond that distance are considered unsuitable.
		Ferry terminal access(+): 0km = 0%, 0.5km – 2km = 100%, 10km = 0% Locations with a greater access to the ferry terminal under 0.5 km are less suitable and coincide with higher noise and traffic levels. Locations between 0.5 and 2km are highly suitable. Distances beyond 2km decrease in suitability to a maximum of 10 km. Distances farther than 10km are considered unsuitable. The ferry terminal is the Municipality's link to Metro Vancouver for residential commuters.
Optional	Amenities(-)	**Park access(-)**: 0m – 200m = 100%, 2km = 0% Reflects a desirability of sites with access to parks for recreational purposes. Locations within walking distance (0m -100m) are valued higher than areas at a greater distance that would require cycling or motor vehicles.

		Coast access(-): 0m -100m = 100%, 2km = 0% Relates to the desirability and value placed on residential locations with access to coastlines and related amenities. Locations adjacent to the coast are considered high risk in terms of home construction, with increasing suitability up to 100m. Locations ranging from 100 m to 200 m represent optimal distances with a gradual decrease in suitability up to 2km.

Table 2-1. Attribute tree

Criteria were then grouped by the nature of logical requirements. Three of the four criteria contained in the subcategories *site* and *transportation* were classified with mandatory requirements. Any unsuitable (0) location within the mandatory elementary criteria was expected to remain unsuitable in the final evaluation score. It is important to note that *aspect* however, was classified as *optional* under the mandatory *site* category. Mandatory and optional inputs are denoted in Table 2-1 with (+) and (-) respectively. While the elementary criteria *Aspect* is optional it also falls under the mandatory *Site* category. Logically asymmetrical inputs are allowable and in this case aggregation is facilitated with a *conjunctive partial absorption* (*CPA*) operator resulting in a mandatory *Site* output (see Figure 2-5).

Criteria that were grouped under the *amenities* category were classified as optional. *Coast access* and *park access* refer to the value placed on locations in proximity to areas with a high aesthetic value. Because they are optional, a null or low value is not necessarily expected to return a 0 or low score in the comprehensive suitability score. If a number of mandatory criteria are satisfied in a particular location, a low suitability score in an optional criteria coinciding with this location *will not negatively affect the score* in that location.

2.6.4. Step 3. Aggregation structure

A series of connected LSP aggregators were implemented with the WPM to mathematically combine each elementary criteria into a comprehensive suitability score. Parameter values *r* correspond to the different levels of modeled logical requirements and are as follows: -3.510 (C+ or hard partial conjunction); 1 (A or mean average); and 9.521 (D+ or hard partial disjunction). The land-use suitability assessment was conducted using an *aggregated mandatory/optional CAS* and used as a template for modeling the decision problem. This form of *CAS* was selected due to (1) the small amount of criteria, and (1) the need to aggregate mandatory and optional criteria (Dujmović & De Tré 2011).

First the categories by defined by problem domain were aggregated. The *park access* and *coast access* categories were aggregated using an LSP aggregator representing *SPD* (D-) to reflect the optional/replaceable nature of these inputs. The road and ferry access criteria were aggregated with a *HPC* (CA) aggregator reflecting a mandatory requirement. Aggregation of the *slope* and *aspect* criteria was accomplished with the application of a *CPA* structure built from a neutral aggregator (A) and a *HPC* aggregator (CA). In this case, the full satisfaction of the optional criteria (*aspect*) augments the non-zero score of the mandatory criteria with a *reward*, and a null *aspect* score assigns a *penalty* to the mandatory criteria. Ultimately, if the *mandatory* criterion (slope) is not satisfied, the *optional* criterion has no compensatory power, and the aggregator returns a zero value. The final aggregator applied is another *CPA* structure to combine the mandatory and optional categories using the A and C+ aggregators. The LSP aggregation structure is presented in Figure 2-5. The gradual increase in logical strength (from weaker to stronger requirements) in this aggregation structure is consistent with the theoretical *shadow* of aggregation logic.

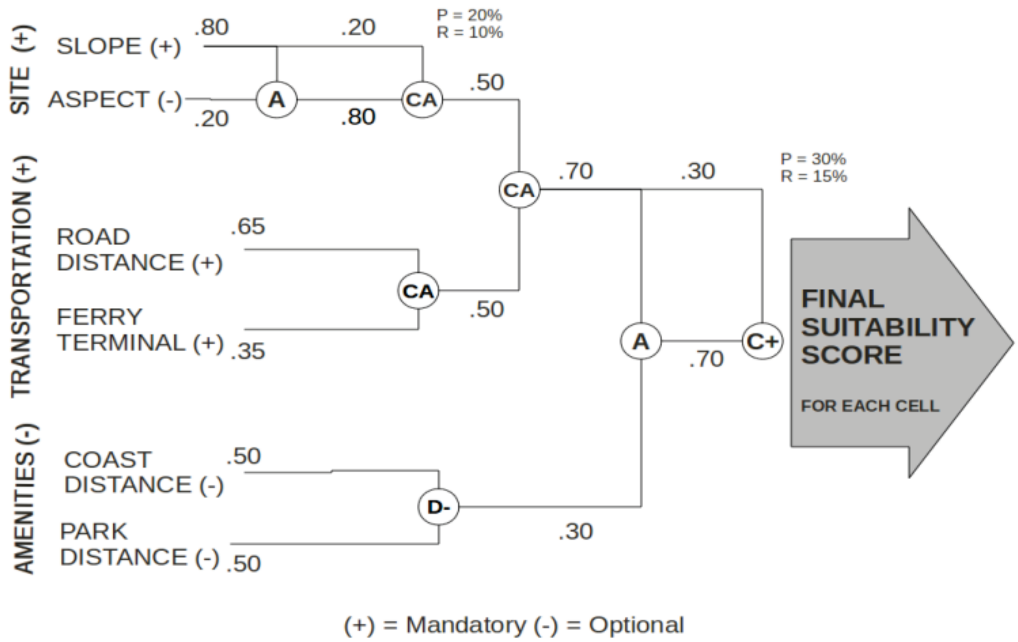

Figure 2-5. Aggregation Structure

2.7. Results

2.7.1. GIS and LSP Integration

Integration of the LSP method with GIS was performed with the IDRISI desktop GIS software. More specifically, the key elements of the LSP method, including aggregation structures, and LSP logic operators were constructed and executed entirely in IDRISI's visual geoprocessing environment Macro Modeler. Aggregators function as the basic units of a complete LSP aggregation structure and were implemented using IDRISI's core raster processing modules, primarily SCALAR (for mathematical calculations) and OVERLAY. Data processing with these modules facilitated the implementation of LSP logic aggregators calculated with the *weighted power mean*. In this research study LSP aggregators were built, encapsulated, and nested in a modelled aggregation structure.

Figure 4-1 below details the basic design of the LSP aggregator and arrangement in a modeled aggregation structure. The first diagram (i) shows an IDRISI Macro Model of an LSP aggregation structure. The second diagram (ii) depicts the arrangement of a nested LSP aggregator calculated with a *weighted power mean* where r represents logical strength, x is an input layer, w is the weight parameter, and S is the calculated suitability score.

As the modules used are by no means unique to IDRISI, integration may be performed similarly in other common raster GIS Desktop environments (ESRI, ArcGIS, GRASS, etc.).

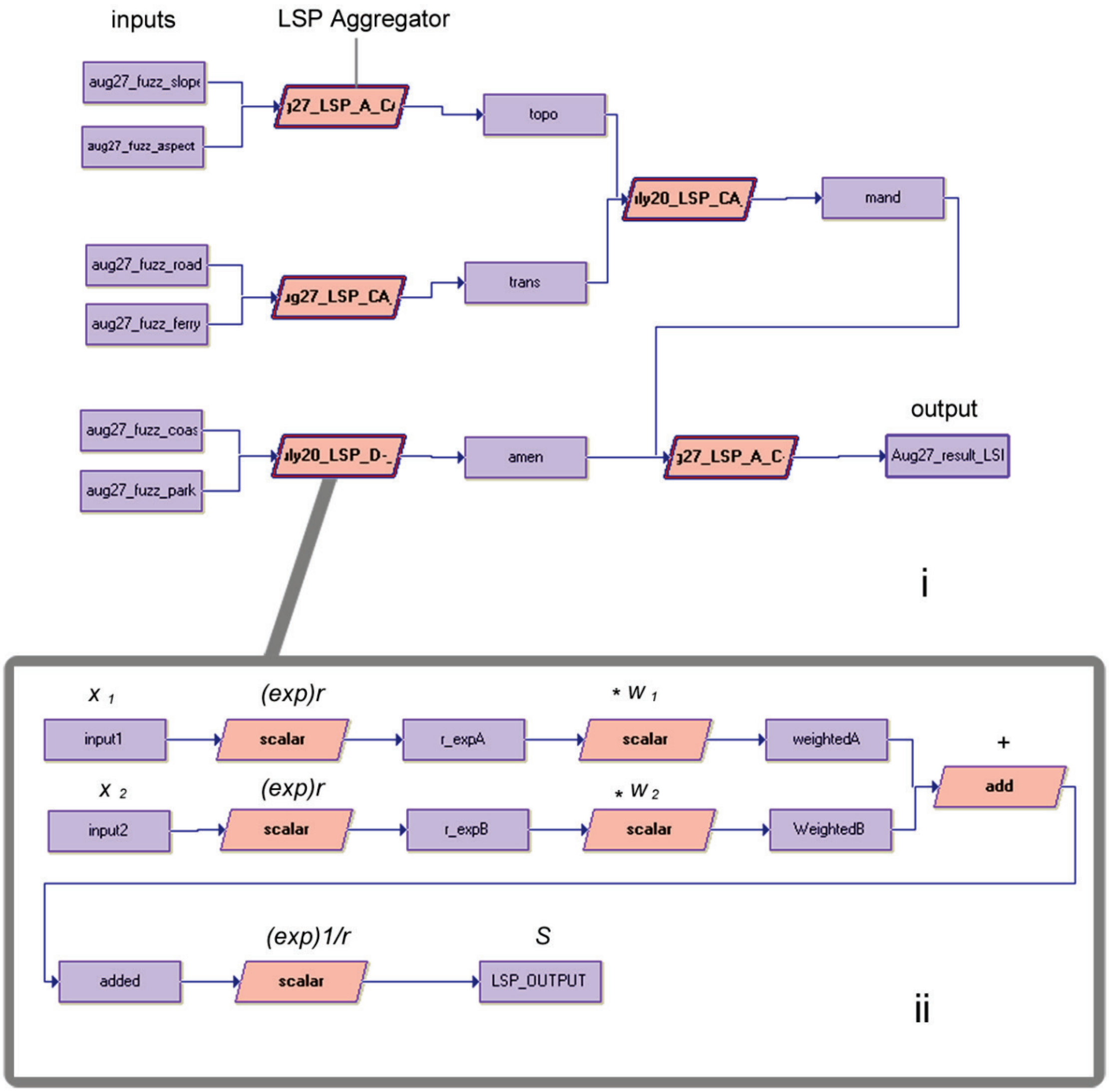

Figure 2-6. Integration of LSP in IDRISI's Macro Modeler environment

2.7.2. LSP suitability map output

Following the stepwise nonlinear aggregation of each of the raster criteria layers, a LSP suitability map was generated (Figure 2-6). Each location was assigned a suitability score ranging from 0 to 1. The resulting map based in logic requirements displays regions that are scored and regions that are unsuitable (0%).

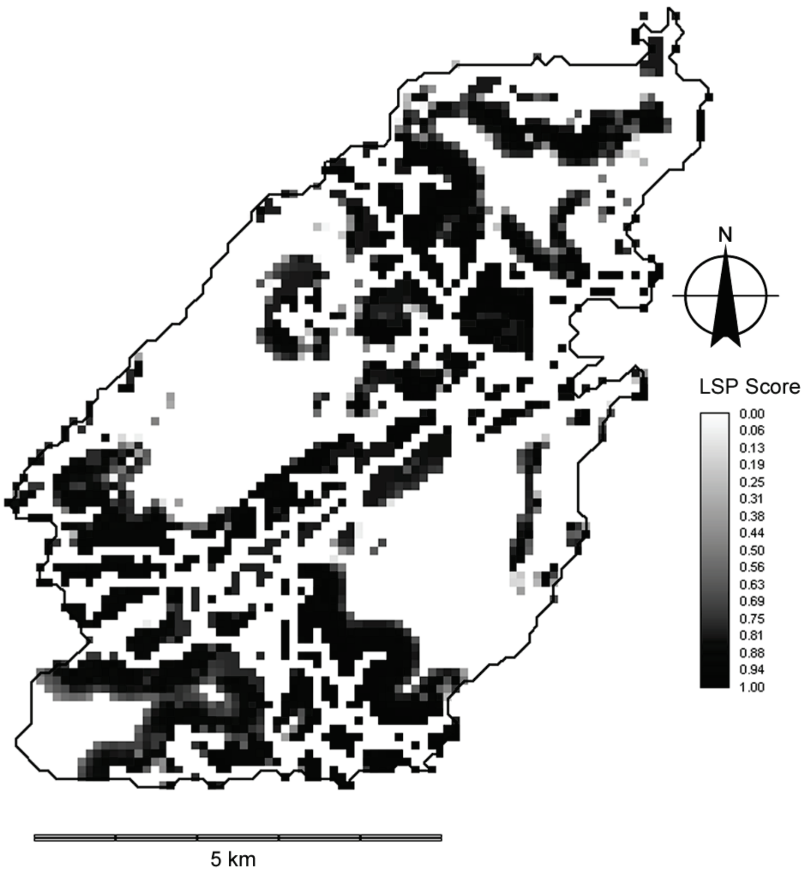

Figure 2-7. LSP suitability map

2.7.3. Comparison of MCE and LSP Approaches

As a means of evaluating the initial results of the GIS-LSP prototype, a second residential land-use suitability map was calculated using a GIS-MCE approach employing a weighted linear combination (WLC) rule. To facilitate a comparison of the two approaches the MCE approach was implemented in a GIS raster environment in two parts. The first part involved the acquisition of a set of standardized criteria. The GIS-MCE used the same fuzzy criteria map inputs that were employed in the LSP approach: *slope*, *aspect*, and *access to roads,* and *water, parks* and *ferry terminals* (Figure 2-4). In the second stage, each criteria was multiplied by a weighting value reflecting the importance or level of tradeoff within the decision problem. Under the conventions of the WLC rule, all weights must sum to unity. The assigned weights were selected for each criteria layer: *slope* (.30), *aspect* (.10), *road access* (.30), *coast access* (.15), *park access* (.05), *ferry terminal access* (.10). A diagram of the GIS-MCE structure is shown in Figure 2-6. Following the application of weights the criteria were summed, resulting in a comprehensive MCE suitability map and presented in Figure 2-7

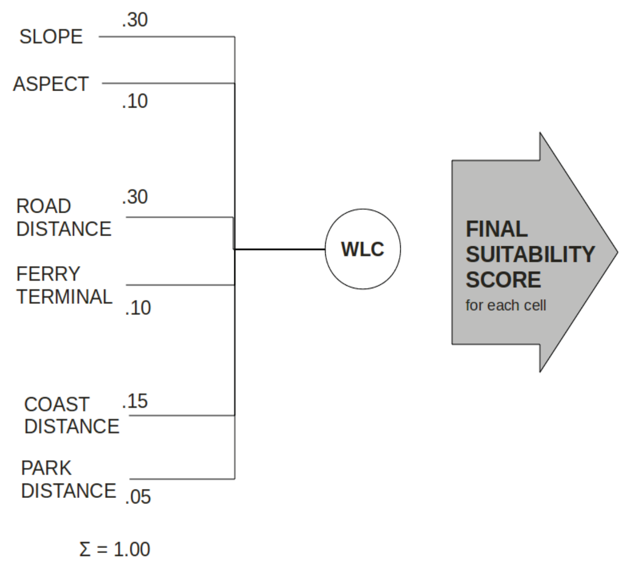

Figure 2-8. MCE diagram

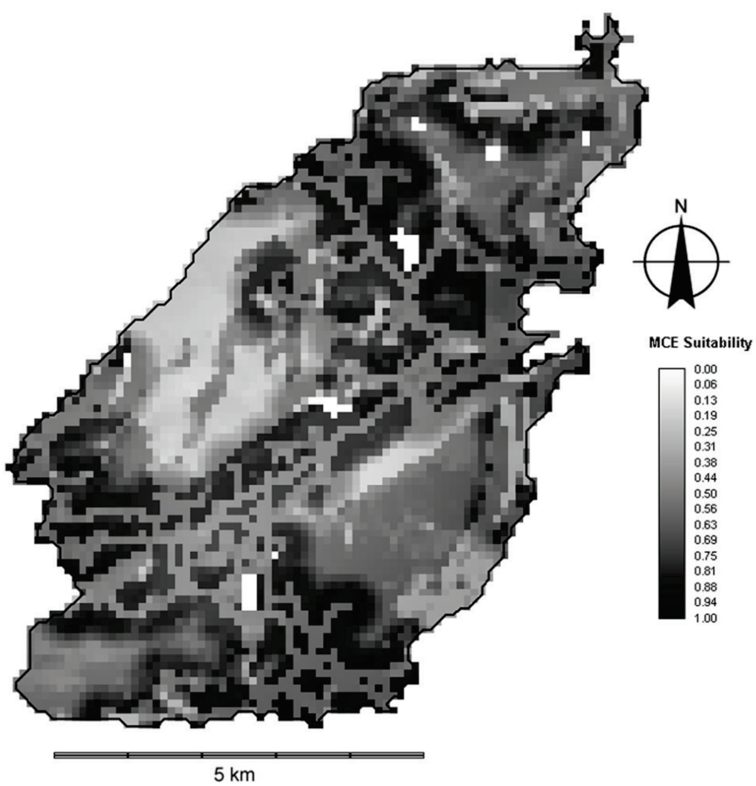

Figure 2-9. MCE suitability map

The results demonstrate that the LSP approach can be integrated within a raster GIS framework and can be used to create a land-use suitability map. The question remains: do LSP suitability maps outperform their MCE counterparts? In addressing this question it must be considered that LSP and MCE approaches employ different conceptualizations of human decision-making. Because of this fact the two approaches will yield very different measurements of suitability. MCE approaches assume all inputs are non-mandatory, whereas the LSP approach considers inputs as mandatory or non-mandatory. The LSP suitability map illustrates specific advantages in terms of (1) logical expression and (2) aggregation efficiency.

A map comparing the LSP suitability map and the MCE suitability map results is presented in Figure 2-9 below. A visual comparison of the outcomes of the LSP and MCE procedures demonstrate significant differences in the selective power of LSP. Many locations (1715 hectares total) in the LSP suitability map are unsuitable compared to identical locations in the MCE output. This is expected under the logical mandatory conditions stated in the LSP aggregation structure: *any low or null mandatory input will result in a resulting low or null score in the output*. The input criteria in the MCE are uniformly treated as non-mandatory, which implies that any location that is not satisfied by an input may still be considered suitable. Some areas in the MCE suitability map are scored as high as 50% whereas the same locations are unsuitable in the LSP suitability map. LSP excludes locations based on mandatory conditions and is therefore a more realistic model of decision-making that voices logical requirements.

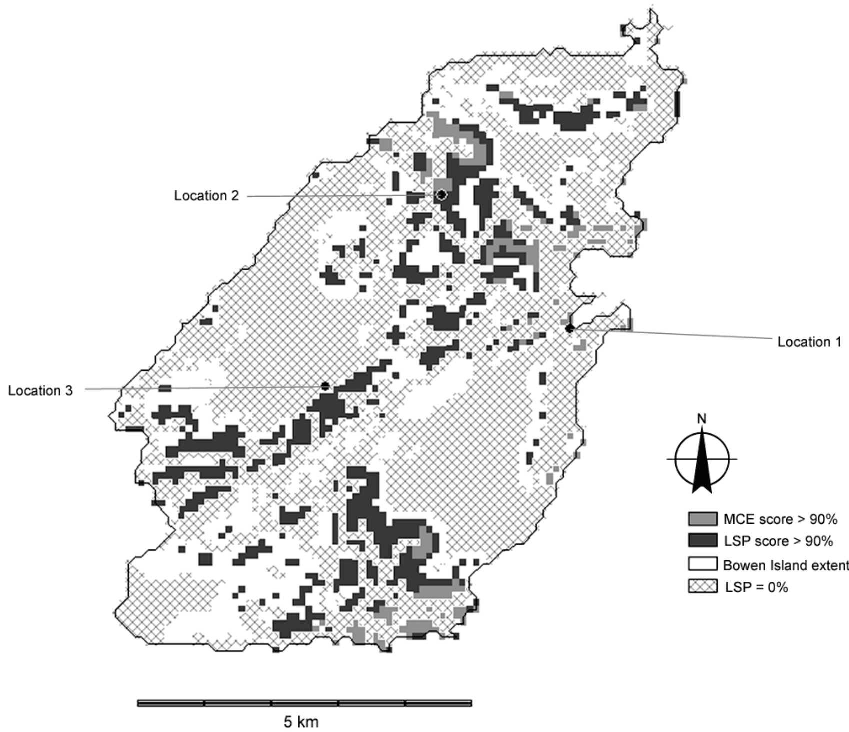

Figure 2-9. A comparison of LSP and MCE suitability map results

Locations 1-3 indicated on this map are described in detail in Table 2-2

The LSP and MCE suitability maps also differ in their representation of areas classified as suitable. The LSP map displays 900 hectares scoring greater than 90% and the MCE ranks only 185 hectares above 90%. This difference in the LSP suitability map is attributed primarily to the method of aggregation. In the LSP approach inputs are hierarchically categorized and combined in stages. The results also reflect the relationships based on logical requirements. For example, the inputs grouped under *transportation* and *site* were combined with strong conjunctive aggregators; areas that contain a measure of satisfaction of *all* these factors *simultaneously* will yield a greater suitability score in the final outcome. It is important to note that factors such as coastline access and park access are treated as optional and their level of non-satisfaction does not negatively impact locations with high-scoring mandatory inputs.

The MCE approach simply combines and averages all six inputs without conditions. In this case the global suitability score is primarily affected by the use of a weighting system (WLC) that must be distributed among all six criteria. The impact of some inputs will necessarily suffer from a loss of significance. The high scoring areas in MCE/WLC maps are more influenced by *idempotency*, or the coinciding location of high ranking scores in all inputs (Dujmović and Scheer 2010). This principle explains the results from the MCE procedure.

Table 2-2 compares the input and output scores used in both models that characterize three different locations. In location 1, the MCE and LSP methods return similarly high scores (91% and 99% respectively). The high score awarded by the LSP analysis results from satisfaction of all three mandatory inputs. The MCE score (91%) is a result of the principle of idempotency described above. In location 2, The LSP analysis returns a 0% score and the MCE procedure scores this location differently at 50%. The unsuitable score given by the LSP analysis reflects the mandatory requirement of the *slope* input. This criteria was not satisfied *simultaneously* with the other mandatory inputs. In Location 3 the LSP suitability score returned a 90% compared to an 83% score assessed with MCE. Again, The LSP score is derived from a measure of satisfaction of the mandatory inputs. The lower MCE score reflects the negative impact of the lower scores attributed to negative impact of the logically optional *aspect* criteria.

	Mandatory			Optional			Output	
criteria	Slope	Road access	Ferry access	Coast access	Park access	Aspect	LSP	MCE
Location 1	100%	100%	93%	41%	100%	100%	99%	91%
Location 2	0%	100%	76%	0%	49%	100%	0%	50%
Location 3	100%	100%	100%	100%	100%	0%	90%	83%

Table 2-2. Input scores and comprehensive scores for the LSP and MCE suitability maps.

Locations 1 -3 are indicated in Figure 2-9

The quality of a suitability map is related to how well it reflects the needs and objectives of the decision-maker. A comparison of the two suitability maps suggests that MCE procedures lack the mathematical sophistication for modeling human reasoning in a realistic way. LSP suitability maps outperform MCE/WLC maps in this respect. Ultimately, an assessment of any suitability map requires the user to perform a visual check to validate the map (Dujmović & Scheer 2010). Modifying the strength of logic aggregators and aggregation structure will influence the suitability map outcomes. Therefore an LSP map will benefit from a sensitivity analysis procedure to maximize its usefulness.

2.8. Conclusion

The selection of logic qualifiers and aggregators is highly subjective and unique to the decision problem and expertise of the decision-maker. Model output is sensitive to the decision-makers choice of aggregation structure, weights, and aggregators used. While the MCE has a very intuitive way of combining criteria, the LSP model is not as readily accessible and requires specialized training for effective use. As an academic prototype, the GIS-LSP approach functions as a means of exploring the mechanics and possibilities of LSP. The approach merits further development in terms of criteria design. Municipal planning documents could be used as a means of developing highly detailed suitability maps that account for bylaws that determine the nature of development in different locations based on environmental, economic, or social planning objectives.

In this study it has been demonstrated that the LSP approach and GIS can be integrated. A GIS-LSP approach was successfully tested on geospatial data for land-use suitability analysis. Additionally, the LSP approach addresses the limitations of MCE and the WLC through the application of modeled logic requirements resulting in more selective and detailed suitability maps. The LSP approach offers many possibilities to explore highly complex relationships among factors and multiple objectives in the analysis of complex land-use suitability problems.

2.9. Acknowledgements

The Natural Sciences and Engineering Research Council (NSERC) of Canada provided full support of this study under a Research Discovery Grant awarded to Dr. Suzana Dragićević. Special thanks to Biodiversity BC and the Nature Conservancy of Canada for providing the data sets used in this research study through the collaborative pilot project Hectares BC.

2.10. References

Aceves-Quesada, J.F., Diaz-Salgado, J. & Lopez-Blanco, J., 2007. Vulnerability assessment in a volcanic risk evaluation in Central Mexico through a multi-criteria-GIS approach. *Natural Hazards*, 40(2), pp.339–356.

Block, J., 1978. Bowen Island: A Resource Analysis for Land Use Planning, Victoria, B.C: Islands Trust, Ministry of Municipal Affairs and Housing.

HectaresBC, 2012. Data Catalogue. Biodiversity BC, and the Nature Conservancy of Canada, Available at: http:// www.hectaresbc.org [Accessed August 4, 2012]

Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. International Journal of Geographical Information Systems, 5(3), p.321-339

Ceballos-Silva, A. & Lopez-Blanco, J., 2003. Evaluating biophysical variables to identify suitable areas for oat in Central Mexico: A multi-criteria and GIS approach. *Agriculture, Ecosystems and Environment*, 95(1), pp.371–377.

Church, R.L. et al., 2000. Support system development for forest ecosystem management. European Journal of Operational Research, 121(2), pp.247-258.

Densham, P., 1991. Spatial Decision Support Systems. In Longman, pp. 403-412.

Dujmović, J.J. 1979. Partial Absorption Function. *Journal of the University of Belgrade, EE Dept., Series Mathematics and Physics*, No. 659, pp 156-163.

Dujmovic, J.J., 2008. Characteristic forms of generalized conjunction/disjunction. In *IEEE International Conference on Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence)*. IEEE International Conference on Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence). IEEE, pp. 1075–1080.

Dujmović, J.J.& Nagashima, H., 2006. LSP method and its use for evaluation of Java IDEs. International Journal of Approximate Reasoning, 41(1), pp.3-22.

Dujmović, J.J. & Larsen, H.L., 2007. Generalized conjunction/disjunction. International Journal of Approximate Reasoning, 46(3), pp.423-446.

Dujmović, J.J. & Scheer, D., 2010. Logic aggregation of suitability maps. In IEEE, pp. 1-8.

Dujmović, J.J., De Tré, G.D. & Dragićević, S., 2009. Comparison of Multicriteria Methods for Land-use Suitability Assessment. IFSA World Congress 8 EVSFLAT Conference, Lisbon, Portugal. Pp. 1404-1409.

Dujmović, J.J., De Tré, G. & Weghe, N., 2009. LSP suitability maps. *Soft Computing*, 14(5), pp.421–434.

Dujmović, J.J. & De Tré, G.D., 2011. Multicriteria methods and logic aggregation in suitability maps. *International Journal of Intelligent Systems*, 26(10), pp.971–1001.

Eastman, J.R. et al., 1995. Raster Procedures for Multi-Criteria/Multi-Objective Decisions. Photogrammetric Engineering and Remote Sensing (PE&RS), 61(5), pp.539-547.

Goodchild, M., 1987. A spatial analytical perspective on geographical information systems. International Journal of Geographical Information Science, 1(4), pp.327-334.

Hill, M.J. et al., 2005. Multi-criteria decision analysis in spatial decision support: the ASSESS analytic hierarchy process and the role of quantitative methods and spatially explicit analysis. Environmental Modeling & Software, 20(7), pp.955-976.

Hopkins, L., 1977. Methods for Generating Land Suitability Maps: A Comparative Evaluation. Journal of the American Planning Association, 43(4), pp.386-400.

Jankowski, P., 1995. Integrating geographical information systems and multiple criteria decision-making methods. International Journal of Geographical Information Science, 9(3), pp.251–273.

Joerin, F., Theriault, M. & Musy, A., 2001. Using GIS and outranking multicriteria analysis for land-use suitability assessment. International Journal of Geographical Information Science, 15(2), pp.153-174.

Malczewski, J., 1999. GIS and Multicriteria Decision Analysis, New York: John Wiley. 576p.

Malczewski, J., 2000. On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches. *Transactions in GIS*, 4(1), pp.5–22.

Malczewski, J., 2010. Multiple Criteria Decision Analysis and Geographic Information Systems. In M. Ehrgott, J. R. Figueira, & S. Greco, eds. Boston, MA: Springer US, pp. 369-395

Malczewski, J., 2006. Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis. International Journal of Applied Earth Observation and Geoinformation, 8(4), pp.270-277.

Pettit, C. & Pullar, D., 1999. An integrated planning tool based upon multiple criteria evaluation of spatial information. Computers, Environment and Urban Systems, 23(5), pp.339-357.

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

Proctor, W. & Drechsler, M., 2006. Deliberative multicriteria evaluation. *Environment and Planning C: Government and Policy*, 24(2), pp.169–190

Rinner, C. & Taranu, J.P., 2006. Map-based exploratory evaluation of non-medical determinants of population health. Transactions in GIS, 10(4), pp.633–649.

Robinson, V.B. Fuzzy Sets and Spatial Analysis. In *The Sage Handbook of Spatial Analysis.* eds. P. Rogerson and S. Fotheringham, Sage Publishing. pp.204-219.

Rybarczyk, G. & Wu, C., 2010. Bicycle facility planning using GIS and multi-criteria decision analysis. Applied Geography, 30(2), pp.282–293.

SEAS. 2012. LSPmap. Available at: http://www.seas.com/LSPmap/index2.php [Accessed August 23, 2012].

Store, R. & Kangas, J., 2001. Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modelling. Landscape and Urban Planning, 55(2), pp.79–93.

De Tré, G., Dujmovic, J. & Van De Weghe, N., 2009. Supporting Spatial Decision Making by Means of Suitability Maps. In J. Kacprzyk, F.E. Petry & A. Yazici, eds. Uncertainty Approaches for Spatial Data Modeling and Processing. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 9-27.

De Tré, G. et al., 2009. Heterogeneous bipolar criteria satisfaction handling in geographical decision support systems: an LSP based approach. In *Proceedings of the 2009 ACM symposium on Applied Computing*. *SAC '09*. Honolulu, Hawaii: ACM, pp. 1704–1708.

Wood, L. & Dragićević, S., 2007. GIS-Based Multicriteria Evaluation and Fuzzy Sets to Identify Priority Sites for Marine Protection. *Biodiversity and Conservation*, 16(9), pp.2539-2558.

Chapter 3: Urban Growth Simulations with Logic Scoring of Preference Method and Cellular Automata

3.1. Abstract

Geospatial modeling approaches using linear additive rules, such as multicriteria evaluation (MCE) are used to compliment cellular automata (CA)-based urban growth models. Such approaches have limitations with respect to the expression of decision logic and the allowable number of factor inputs. The Logic Scoring of Preference (LSP) approach exhibits unique aggregation capabilities that allow numerous inputs without loss of significance and the expression of continuous decision logic such as ANDness and ORness. The main objective was to use the LSP approach as an input for an urban CA. Integration of the LSP approach with geographic information systems (GIS) and CA techniques were developed and implemented. Geospatial datasets of the City of Nanaimo, Canada were used as a case study to develop, implement and test the model. Several simulation scenarios were developed to predict urban growth (i) transportation oriented, (ii) growth in environmentally sensitive areas, (iii) compact growth, (iv) accelerated and slow dynamics, and (v) asynchronous growth. Map comparisons of simulation results demonstrate that CA is highly sensitive to different LSP parameterization. Results obtained from the LSP-CA approach has demonstrated improvement over existing MCE-CA modeling approaches

A version of this chapter is in preparation to be submitted to Transactions in GIS under title: An Integrated Logic Scoring of Preference and Cellular Automata Approach for Urban Growth Simulation and coauthored with S. Dragićević

3.2. Introduction

The science of complexity and its body of theory provides a framework for explaining and understanding real world natural and social systems. Complex phenomena exhibit properties such as hierarchical aggregate structures, emergence, path dependence, self-organization, chaos-oriented behaviour, and geometric signatures (such as fractals) (Manson 2001). Complexity science offers a universality that has attracted the attention of researchers a range of disciplines in the social and physical sciences (O'Sullivan 2009). A central concern in complexity studies is the concept of global structures that evolve from individual autonomous units. This particular behaviour of complex systems is termed "bottom-up," as opposed to "top-down," as illustrated in applications of complex system modeling approaches (White & Engelen 2000).

The concept of localized "bottom-up" processes giving rise to the generation of larger scale pattern and structure has been embraced by researchers for the purpose of studying urban and regional systems (Torrens & Benenson 2005). Complexity science offers a powerful framework for analyzing urban systems characterized by unstable nonlinear growth rooted in the individual actions of households, developers and the configuration of different land uses (Batty 2005). Studying urban growth is a difficult task given the limits of geographical and temporal scales. For this reason, computational simulation models are well suited for the study of complex urban and regional systems.

A two-dimensional cellular automaton is a common approach for modeling cities as complex spatial systems (Santé et al. 2010). CA are self-reproducing computational structures used to present as Toffoli and Margolus (1987) assert, a "stylized" depiction of the universe. Each individual unit or cell is assigned a state that changes or remains unchanged as a result of simple rules based on the collective states of neighbouring cells. A classical CA introduced by mathematician John Conway known as the “Game of Life” requires a regular lattice of cells, a neighbourhood function, a temporal element, in addition to cell states and transition rules (Gardner 1970). Cellular automata simulation applied to geographical systems was first pioneered by Tobler (1970), however, Lathrop and Hamburg (1965) and Chapin and Weiss (1968) theorized CA-like approaches for urban modeling (as cited by Batty 1997). The past few decades have seen much of the development of Geographic CA in urban systems research (Torrens & Benenson 2005). CA has been used to caricature social and structural systems by presenting a hypothetical image of how cities, regions and social structures self-organize in geographic space. Semboloni (1997) modeled the hypothetical development and evolution of human settlements. Portugali, et al., (1994) developed a spatial cellular automata system designed to represent dynamic social aggregation in an urban system. Researchers began simulating fractal (self-similarity at different scales) morphologies seen in real cities (M. Batty & Xie 1996; White & Engelen 1993; White & Engelen 1994). The “classical” “Game of Life” structure is generally too rigid, requiring modification in order to represent and model phenomena that operate within diverse and richly patterned geographic landscapes (Couclelis 1985). In an attempt to capture the growth of real urban systems CA has been used in conjunction with geospatial datasets and geographic information systems (GIS).

GIS is used for the management, creation, storage, analysis and visualization of geospatial data (Goodchild & Haining 2004). Raster based GIS offers many features to enhance CA models with the necessary realism to represent urban growth. Most importantly, the raster data structure, and neighbourhood functions are routine, universal GIS operations and are compatible with the requirements of CA (White & Englen 2000). In addition to compatibility, high resolution data in the form of remotely sensed images contain a wealth of information needed to represent the conditions of real study areas (White & Engelen 1994). GIS based CA models have been used extensively since the 1990's to model urban growth. White et al. (1997) simulated development in Cincinnati, OH, USA using historical GIS datasets. Batty et al.'s (1999) work with a standalone CA simulation system was used to simulate growth and decline in North American Rust Belt cities. The SLEUTH CA simulation modeling system was also developed to simulate historical patterns of growth in the San Francisco Region using multiple layers of geospatial data (Clarke et al. 1997). GIS and CA structures have been prototyped as a part of Spatial Decision Support Systems (SDSSs) featuring different types of configurations and applied to different regions globally. A multi-scale simulation and decision-support system was developed to simulate regional growth in The Netherlands (White & Engelen 2000). Ward et. al. (2003) approach combined spatial optimization and CA for modeling sustainable development in Australia. Optimization and CA were also coupled recently to study policy surrounding industrial development in a rapidly growing region in China (Li et al. 2011). Stanilov and Batty (2011) have also used CA as an approach to discover pre-existing conditions for urban growth using London as a case study.

Additionally a variety of techniques has been applied for developing improved transition rules including artificial neural networks (Li & Yeh 2001; Yeh & Li 2003; Almeida et al. 2008), and ant colony optimization (Liu et al. 2007). Multicriteria Evaluation (MCE) based transition rules were used to model different growth scenarios in a rural region in China (Wu & Webster 1998). MCE offers the advantages of a rich body of applied research in the geographic information science literature, and a conceptually simple structure.

MCE is a GIS-based approach for modeling human decision-making, preferences and suitability for a given purpose with in a geographic study area (Malczewski 1999). Suitability analysis using MCE can be approached to create a suitability map ranking all locations in a study area from "most suitable" to "least suitable." Alternatively MCE can be used to map only the "optimal locations" based on a score threshold or a required number of top ranked locations (Eastman et al. 1995). While many variations of MCE exist in the literature, for the purposes of this article, the MCE approach uses raster GIS data model and, mathematically operates on continuous or fuzzy data inputs (Jiang & Eastman 2000; Malczewski 2002). GIS-MCE integrated approaches for suitability analysis were supported by many researchers in the 1990s (Carver 1991; Laaribi et al. 1996; Jankowski 1995).

Linked GIS and MCE approaches have been used as a means for studying and understanding a range of environmental issues such as marine resources management conflicts (Wood & Dragićević 2007), and defining wilderness regions (Comber et al. 2010). MCE methods have been applied towards facilitating multi-stakeholder group decision-making (Boroushaki & Malczewski 2010) and public participation in institutional planning processes (Bailey & Grossardt 2010).

Despite its advantages MCE has two significant issues that create problems with interpreting the meaning of results. In discussing these issues it is important to introduce the generic MCE decision rule known as the *weighted linear combination* rule, or *WLC*:

$$S = \sum_{i=1}^{n} w_i x_i,\ 0 < w_i < 1,\ i = 1,\dots,n, \quad \sum_{i=1}^{n} w_i = 1 \qquad \text{(eq. 3-1)}$$

Where S is the global suitability, w is the cardinal weight, and x is the factor variable. The first limitation relates to number of input factors that may be aggregated

(Dujmović et al. 2009). Each factor input representing a unique suitability is assigned a cardinal weight (the total of all weights must sum to unity). The user manipulates weight parameters representing the importance of each input layer relative to one another to define a problem and produce a desired end result. This quality known as "tradeoff" is the most important aspect of MCE; by manipulating factor weights, a different suitability maps may be created. Tradeoff is an important feature for generating MCE transition rules; if linked to a CA, an MCE system may be used to develop different initial conditions for the purposes of generating alternative urban growth scenarios. It must be noted that as the number of MCE inputs increase their individual significance within the system decreases (Dujmović & De Tré 2011). Despite the conceptual simplicity of factor tradeoff, the restriction on the number of inputs places constraints on representing the richness and complexity of a geographic region needed for spatial decision-making and analysis. Urban growth is a very complex and layered process operating on different scales with a multitude of factors. If the allowable inputs are limited or overloaded, a MCE-driven urban CA runs the risk of producing erroneous or unrealistic results.

The second problem lies in the logic implied by the linear additive rule. Typically logic is expressed in binary terms with Boolean AND, and OR to query and select observations or locations from a data based on conditions. AND functions mathematically like multiplication, and OR operates much like addition; the former is much more restrictive, while the latter is permissive. The WLC rule integral to MCE expresses an "average" logic that is neither AND nor OR. The sacrifice of logic is necessary for the existence of the tradeoff feature. As a result, suitability indices produced with "average" logic do not have the realism required to represent real decision problems (De Tré, et al.

2009). Decision making requires the expression of mandatory (ANDness) or optional (ORness) conditions of decision factors.

In Wu and Webster's (1998) urban modeling approach employing MCE, a structure was applied to the suitability layer to influence the performance of the CA model. A nonlinear scaling function applied with different strengths via a user selected coefficient. By increasing or decreasing the coefficient, the areas of higher suitability were amplified, increasing or decreasing the selectivity of the CA. It is believed that this scaling function was necessary to overcome MCE's methodological shortcomings as an input to a CA.

Therefore the objective of this study is to develop an urban GIS-based CA model that overcomes the limitations of the existing MCE-CA approach for developing transition rules through the application of an alternative suitability modeling approach, the Logic Scoring of Preference (LSP). LSP is a soft computing approach developed originally for software evaluation (Dujmović & Nagashima 2006). The approach has recently been applied to site suitability problems, yet has not been integrated with in a GIS framework (De Tré et al. 2009; Dujmović et al. 2009). To address the methodological problems with MCE derived transition rules, LSP was used because of (i) its ability to aggregate an unlimited amount of inputs, and (ii) express a wide range of flexible logic conditions between AND and OR. LSP offers users the manipulation of more inputs allowable than MCE, and the addition of logical operators without sacrificing the expressive power of a tradeoff parameterization. LSP logic operators are more efficient for affecting the selectivity of CA models and do not require additional procedures such as scaling functions to increase the performance and selective behaviour of the CA.

This study reports on a LSP-CA integrated model that was developed for the purpose of testing the utility of LSP in formulating transition rules for urban CA. Different urban growth scenarios were created using a database representation of The City of Nanaimo, BC, Canada.

3.3. LSP Theoretical Background

LSP refers to a set of methods used for system evaluation and comparison using logic that is observed in human decision-making processes that are based intuitively on preference requirements (Dujmović 2007). A decision between two or more alternatives involves an assessment of how *mandatory* or *optional* the factors are. The following example illustrates the concept of logic requirements that are fundamental to the LSP approach.

The requirements used in evaluating for example numerous parcels for the institutional acquisition of land for a given purpose are evaluated in terms of slope and directional orientation. The measured slope of different locations necessitates a narrow range of requirements in order to keep building costs down. The slope requirement is therefore considered *mandatory*. A location with unsuitable slope conditions is disqualified as a choice alternative. Additionally each candidate location permits the proposed facility to be built in a particular directional orientation. While the developers favor a south-facing orientation, an alternative orientation is just as acceptable. In this example orientation is *optional* and different locations are *replaceable.*

The significance of the LSP approach lies in its ability to model fuzzy conditional requirements. Conditional logic is traditionally represented by Boolean AND and OR. Mandatory conditions are modeled with AND and optional or replaceable conditions are modeled with OR. LSP permits a fuzzy definition of requirements; mandatory requirements can be expressed as a degree of ANDness, and optional requirements may be represented with a corresponding degree of ORness. Furthermore, requirements can be conceptualized as a spectrum of conditions between AND and OR. This implies that a requirement representing a high degree of ANDness is also expressing a low degree of ORness, and vice-versa.

The LSP approach handles fuzzy logic requirements mathematically using an application of the *Generalized Conjunction Disjunction* (*GCD*) function. The *GCD* function can be used to generate an average value of a series of inputs while imposing logic requirements. The *GCD* function is implemented using the *weighted power mean* (*WPM*) as follows (Dujmović et al. 2009):

$$\boldsymbol{GCD}(s_1 \ldots s_n) = (W_1 s_1^r + \ldots + W_n s_n^r)^{1/r} \qquad \text{(eq. 3-2)}$$

where *s* represents the suitability degree of each raster cell in the array, *W* is the user defined criteria weight, and *r* is the parameter that defines the fuzzy logic requirement.

The *GCD* implemented with the *WPM* functions as *aggregators* or *operators* within the LSP approach that is composed of *elementary input criteria* that are combined in a nonlinear fashion using a leaf and stem *aggregation structure.* Inputs are combined mathematically where they converge at nodes containing LSP aggregators. The elementary input criteria are fuzzy-scaled factors or variables used to describe suitability. The inputs are initially grouped categorically and aggregated in parallel until the processing terminates and returns a final suitability score.

The aggregation structure design is arbitrary and depends on the decision-making problem and needs of the decision-maker. Dujmović and De Tré (2011) theorize that aggregation structures fall into a set of identifiable patterns known as *Canonical*

Aggregation Structures (*CAS*). *CASs* can therefore be used as a template or starting point for designing an aggregation structure for system evaluation.

The LSP approach has been used in a wide array of routine evaluations including computer hardware design (Dujmović 1996), web services evaluations (Yip & Mendes 2005), and software design (Soni et al. 2010). Allen et al. (2011) describe a non-spatial evaluation of environmental policy assessment employing LSP. LSP suitability maps have been reported but not fully implemented in a GIS software environment (De Tré et al. 2009; Dujmović et al. 2009; Dujmović & Scheer 2010).

3.4. Methods

3.4.1. LSP-CA Model

The methodological approach to developing the urban model was conducted in two parts. The first part involved the design of the input of the LSP-CA consisting of a cell state expressing development status and development suitability. The second part dealt with development of a series of LSP-CA simulations and for the purpose of modeling different urban growth scenarios.

3.4.2. Part 1: LSP analysis

The first objective of creating the model involved the creation of an input layer encoded with cell states expressing two kinds of information. The first was a suitability score for development in the form of a continuous score ranging from 0 (unsuitable) and 1 (suitable). In addition to suitability, each cell was assigned a *developed* or *undeveloped* state. The development conditions were derived from 2012 vector GIS data layers representing cadastral parcels supplied by the City of Nanaimo.

The second objective involving model input was the creation of a suitability score for each location in the study area. Suitabilities were calculated from an application of the LSP approach. As the predominant development pattern is expected to be single family, residential homes, a series of factors were created to characterize this type of growth. An LSP system is built in the following stages: (i) selection of input factors (ii) organization of input factors into an aggregation tree, (iii) selection of appropriate LSP operators and weights, and (iv) the calculation of a final suitability score.

A series of unique input factors were developed from a series of geospatial data sets. Layers supplied by the City of Nanaimo were used to depict water bodies, urban infrastructure and zoning. A 20m resolution digital elevation model (DEM) was acquired from GeoBase (2012), a Canadian geospatial data portal, and processed to create elevation and slope data sets. And finally the current 2011 census data were used to calculate population characteristics. Following GIS processing, an appropriate scaling function was applied to each layer converting the original raw units – such as a distance measurement or slope to a new continuous value representing suitability ranging from 0 to 1. Cells coinciding with the location of water bodies, roads, and developed land areas were assigned a value of 0, disallowing growth in those cells.

The data were divided into four basic categories to characterize urban growth namely: (1) *urban factors*, (2) *topography*, (3) *environmentally sensitive areas*, (4) and *transportation*. The urban factor category was composed of three individual suitability layers. The factors *access to urban land-use* and *access to urban core* are self explanatory and were developed from applying a cost distance analysis routine using a road network layer (supplied by Statistics Canada (2012d)). The third layer was constructed from a 2011 Census Canada geographic boundary file and attribute file (Statistics Canada 2012b, 2012c) depicting total population per census dissemination unit and used to calculate population densities. The *topography* category contained an *elevation* suitability and *slope* suitability layer. *Transportation* consisted of three layers depicting *access to highways*, *access to roads* and *access to rail*. All three were calculated using a Euclidian distance function. The category *environmentally sensitive areas* included the factors, *access to coast, access to lakes*, and *access to streams*. These inputs were calculated through the application of a distance function. The selected inputs are intended as representative set for the purpose of testing the integrated LSP-CA scenario development abilities, and is by no means comprehensive. Each category represents a guiding theme of four of the seven simulations completed for this study. Additional inputs that would be of value would be layers conveying land ownership, bylaw development controls to represent growth management policy. A more sophisticated analysis of travel time could be applied in place of the cost distance analysis.The categories, inputs and scaling functions are summarized in Table 3-1.

CATEGORY	INPUT	DESCRIPTION	FUNCTION	FUNCTION BREAKPOINTS			
				a	b	c	d
TOPOGRAPHIC FACTORS	SLOPE	Measured in degrees: relates to the relative cost of development on locations with steep grades.	J	0	0	0	40
	ELEVATION	Measured in meters; relates to the desirability and cost of locations at corresponding to different elevations	Linear	0	0	0	1019
ECOLOGICALLY SENSITIVE	STREAMS	Measured in meters; reflects the desirability of locations within access to biologically diverse riparian areas for aesthetic attributes and recreational purposes.	J	50	50	50	7961
	LAKES	Measured in meters; reflects	J	50	50	50	7000

CATEGORY	INPUT	DESCRIPTION	FUNCTION	FUNCTION BREAKPOINTS			
		the desirability of locations within access to lakes for aesthetic attributes and recreation.					
	COAST	Measured in meters; reflects desirability of locations with coast and beach access.	J	150	150	150	12626
TRANSPORTATION	ROADS	Measured in meters; reflects the importance of locations situated within 50m of roads	J	50	50	50	10646
	HIGHWAYS	Measured in meters; reflects the importance of locations situated within 50m of highways	J	50	50	50	12802
	RAIL	Measures in meters; reflects the negative effect of locations situated near railroad paths and rail yards.	Linear	50	500	500	500
URBAN FACTORS	DEVELOPED AREAS	Developed through cost distance analysis; based in the assumption that areas closer to existing urban locations with develop before areas with less access.	Linear	0	0	0	1378
	URBAN CORE	Developed through cost distance analysis; based in the assumption that a locations development is influenced by its location relative to the centre of urban activity.	Linear	0	0	0	1583
	POP DENSITY	Measured in population per km^2; based in the assumption that lower densities are associated with growth in residential land development.	Linear	0	0	0	750

Table 3-1. LSP criteria inputs

A canonical aggregation structure (*CAS*) was selected to represent urban growth. The *CAS* selected is designed to aggregate inputs employing a logic that is initiated with inputs set at neutrality and as the structure converges, the system globally increases in ANDness and decreases in ORness. The reason for selecting this structure is rooted in its simplicity and theoretical strength (Dujmović & De Tré 2011). Additionally a simple aggregation structure is useful to highlight the advantages of the LSP approach over traditional MCE techniques. The advantages are the aggregation of numerous inputs, and the use of logic conditions to impose increasing or relaxed site selectivity. Using a structure with increasing ANDness and decreasing ORness ensures that the final suitabilities reflect a stringent logic for site selection and are more selective. The aggregators used along with their associated *r* values are as follows: A or average (1); C-- or soft partial conjunction (.619); C- or soft partial conjunction (.261); C-+, or hard partial conjunction (-0.148); and CA or hard partial conjunction (-0.72).

The global suitability score was then calculated through the pair-wise aggregation of categories into subcategories via the LSP aggregators using the associated weights and logic parameters. The global suitability score expresses development suitability as a real number from 0 to 1. For the purpose of this research, the LSP aggregation structure serves as an exploratory tool to create transition rules for different growth scenarios through interactively adjusting the parameters.

3.4.3. Part 2

3.4.3.1. CA Model Development

The purpose of the dynamic CA model is to characterize the growth of developed or residential urban cells at the expense of undeveloped cells over time. For the purpose of exploring different types of scenarios using the LSP approach to develop cell state transitions, three different modeling trials were created during the course of this research:

(1) *Trial 1*: the simple LSP-CA approach, (2) *Trial 2*: The LSP-CA with an annual growth constraint parameter, and (3) *Trial 3:* the LSP-CA demonstrated asynchronous urban growth.

All three operate with a 3x3 Moore neighborhood with the same cell state input layer derived from the LSP submodel and development condition data. While different neighbourhood sizes could be applied (5x5 or 7x7), it was found (through an extensive trial-and-error process) that a simple 9 cell neighbourhood configuration was sufficient and produced visually satisfying results. The temporal scale used for the three structures was one year per iteration. Trial 1 operated on a set of simple transition rules based on the LSP layer that were processed iteratively. While simulations with this type of model are useful, the structure is difficult to control in terms of dynamics. The approach used in Trial 2 was formulated to address this problem. The CA was configured to select a specified "best" number of cells for conversion and exhibited more dynamic control than the simulations generated for Trial 1. Trial 2 was used to simulate slow and accelerated urban growth. The LSP-CA approach used in Trial 2 could be used with historical data sets to calibrate a model for mimicking actual growth over a specified time period. While this approach is useful for an overall perspective of growth, in many cases urban areas grow at different rates within their boundaries, and CA models should address this (Stevens and Dragićević 2007).Therefore, Trial 3 was designed to make urban land-use change happen asynchronously; different growth rates were assigned for different sub-regions in the study area. The calibration of the LSP-CA for each trial involved and extensive trial and error process in which the parameters of the LSP structure were adjusted to increase or decrease the influence of different factors resulting in different simulation outcomes.

3.4.3.2. Simulation Scenarios

Simulation scenarios were generated in three different modeling trials and are summarized below in Table 3-2, and described in detail in the following sections.

Simulation Trial	*Trial 1*	*Trial 2*	*Trial 3*
Growth Characteristic	Simple	Growth Dynamics	Asynchronous Growth
Simulation Scenarios	• *1A*: transportation oriented; • *1B*: growth in environmentally sensitive areas • *1C*: compact growth • *1D:* control simulation	• *2A* Accelerated Growth • *2B* Slow growth	• *3A* Asynchronous Growth

Table 3-2. Simulation scenarios

The LSP-CA simulations for Trial 1 function as a set of theoretically representative urban growth patterns: (1) 1A transportation oriented growth, (2) 1B urban growth that consumes environmentally sensitive areas, and (3) 1C compact growth. The development of the LSP-CA for Trial 2 generated two scenarios that exhibited (1) 2A an accelerated rate and (2) 2B slow rate of growth. This was accomplished through setting a global development rate parameter that limits the amount of land area that converts to a developed state annually. In Trial 3 the LSP-CA was developed for the purpose of simulating asynchronously growing sub-regions of the urban system. Each sub-region was assigned a different development rate parameter that constrained the amount of cells that converted to a developed state at each cycle, and run simultaneously.

3.4.3.2.1. Trial 1

For Trial 1, three separate scenarios were created: namely *Scenario 1A*, "transportation oriented;"*Scenario 1B*, "growth in environmentally sensitive areas," and *Scenario 1C, "*compact growth." A fourth simulation, *Scenario 1D,* was produced using Average LSP aggregators and balanced weights as a control simulation to compare the effects of parameterization. To demonstrate the utility of the LSP-CA structure for generating realistic patterns, an LSP aggregation structure was created as basic template for all simulation trials. The adjustable parameters were (1) the factor weights and (2) the strength of decision logic. Factor weights were adjusted to amplify the effect of specific inputs and input categories in the global LSP score, and the decision logic strength was adjusted to increase the selectivity of the LSP system. By increasing the level of modeled simultaneity, this results in a more selective than relaxed suitability and corresponds to more discriminating CA transition rules. The LSP models used for the different scenarios are shown in Figure 3-1.

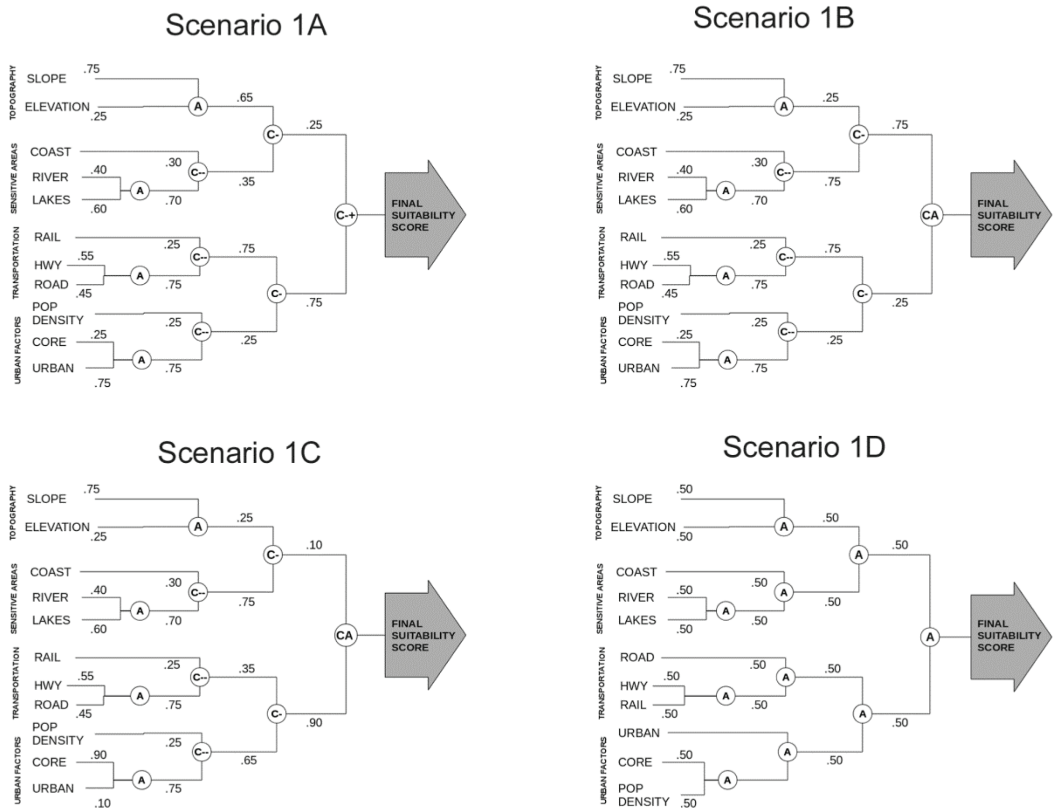

Figure 3-1. Aggregation structures used for scenario development

In addition to adjusting the LSP submodel, the local transition rules were adjusted to attain realistic hypothetical growth scenarios. Both the transition rules and the LSP adjustment were calibrated and fine tuned to produce realistic patterns through a trial and error process. This process consisted of experimenting with different parameters and gauging the outcome by employing the GIS framework to inspect results, use visual feedback, and develop simple animations.

3.4.3.2.2. Trial 2

In Trial 2, the LSP-CA model was calibrated to generate different scenarios representing accelerated and slow rates of growth (scenarios 2A and 2B). This was accomplished by specifying a global growth parameter that effectively limits the amount of land units to be converted from an undeveloped to a developed state. This approach was introduced to limit growth to a more plausible growth dynamic while increasing the discrimination of the CA transition rule. To represent an accelerated rate of growth over the course of 25 iterations (years) the global cell conversion parameter was set to 1.25 km^2 per year. Additionally a “slow” growth simulation was created using the model with the growth parameter set to approximately 1 km^2 per year. The LSP-derived input used to simulate the different rates of growth was the “compact growth” scenario used in the previously mentioned simulations.

3.4.3.2.3. Trial 3

In Trial 3 the LSP-CA was developed to simulate a region divided into three sub-regions, each growing simultaneously at different rates for a specified number of iterations. This structure operated in a similar way as the configuration used in Trial 2. The annual growth rates were specified to limit cell state conversions at each cycle. The key difference with this variation of the structure is that each sub-region was assigned a unique growth rate parameter, resulting in a global system that grew asynchronously. One simulation (3A) was generated to test the performance of this model variant. The CA model was tested using the LSP-derived “compact” growth scenario.

3.5. Results

3.5.1. Data Sets

The geospatial data used to implement the LSP-CA approach was provided by The City of Nanaimo, a mid-sized Canadian city on the eastern coast of Vancouver Island, British Columbia (Figure 3-2).

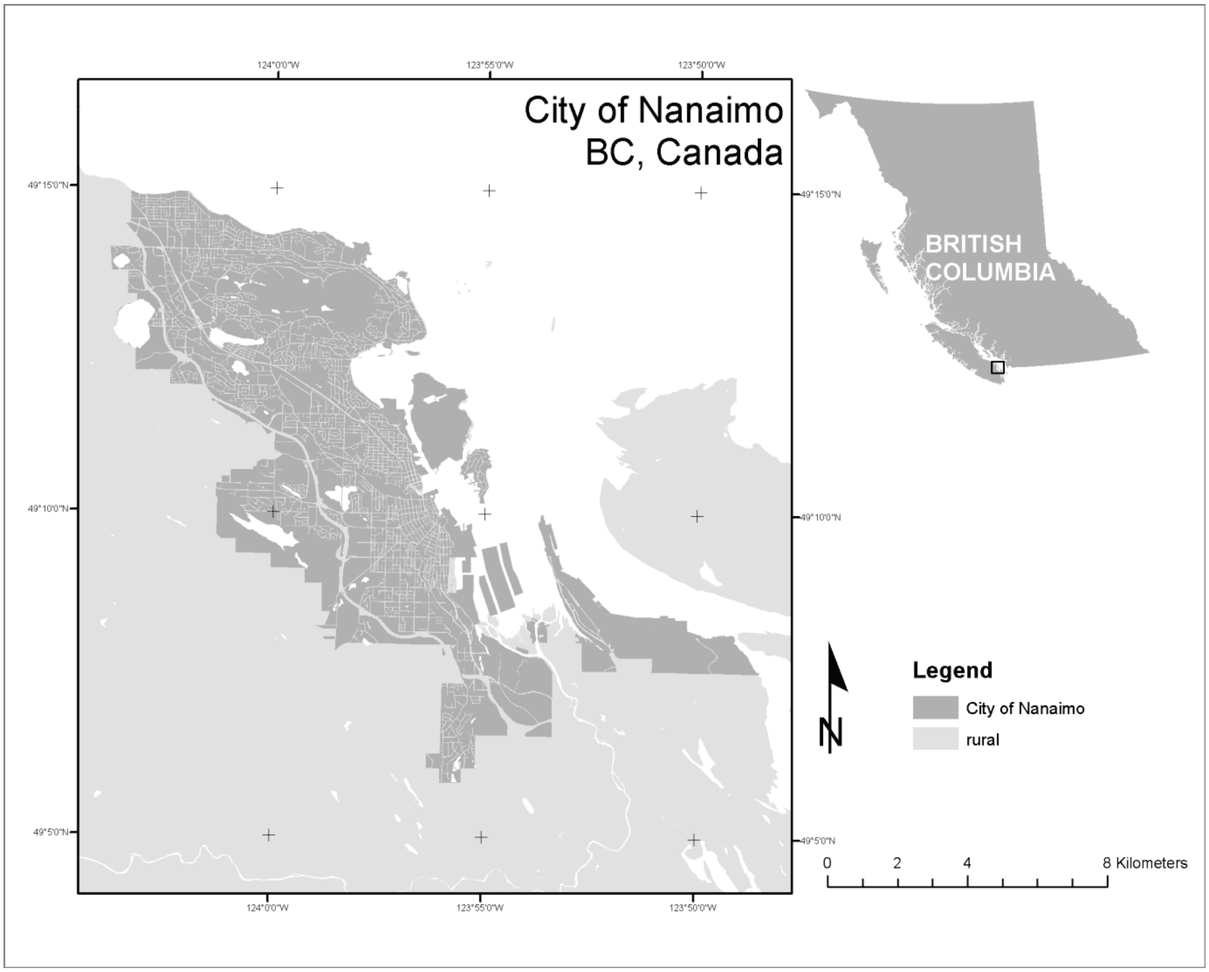

Figure 3-2. Study area

As of 2011, Nanaimo had a population of just over 83,000, with an increase of 6.5% from 2006 (Statistics Canada 2012a). Nanaimo is geographically hemmed in along the Strait of Georgia and rugged, mountains to the east. In an effort to grow the city in a sustainable way, the City has adopted a policy of enacting a growth boundary to limit services and avoid growth into predominantly rural farmlands that surround the edge of the city. According to the City of Nanaimo's official plan, the landbase is composed of mostly low-density single family dwellings and the expected growth in the next 30 years will be continued in this type of development (Nanaimo 2008).

The datasets used for the LSP analysis covered an area of 20km by 18km at 25m resolution. The individual spatial units (cells) cover an area of 625m^2. Different data sources in different data formats and projections required some transformations and conversions to operate at the specified extent and scale.

3.5.2. Simulation

The results of the different modeling structures are presented below in three parts: (1) Trial 1: demonstrating three different growth patterns, (2) Trial 2: demonstrating temporally constrained fast and slow growth scenarios, and (3) Trial 3: modeled asynchronous urban growth.

3.5.2.1. Trial 1 Simulations

As a means of assessing the performance of the LSP-CA model, a LSP aggregation structure was used as the template for all subsequent pattern simulations. Using the aggregation structure as a starting point, three different LSP input layers were created to generate different urban growth simulations. The CA output maps are presented for Scenario 1A (Figure 3-3) Scenario 1B (Figure 3-4), Scenario 1C (Figure 3-5) and Scenario 1D (Figure 3-6).

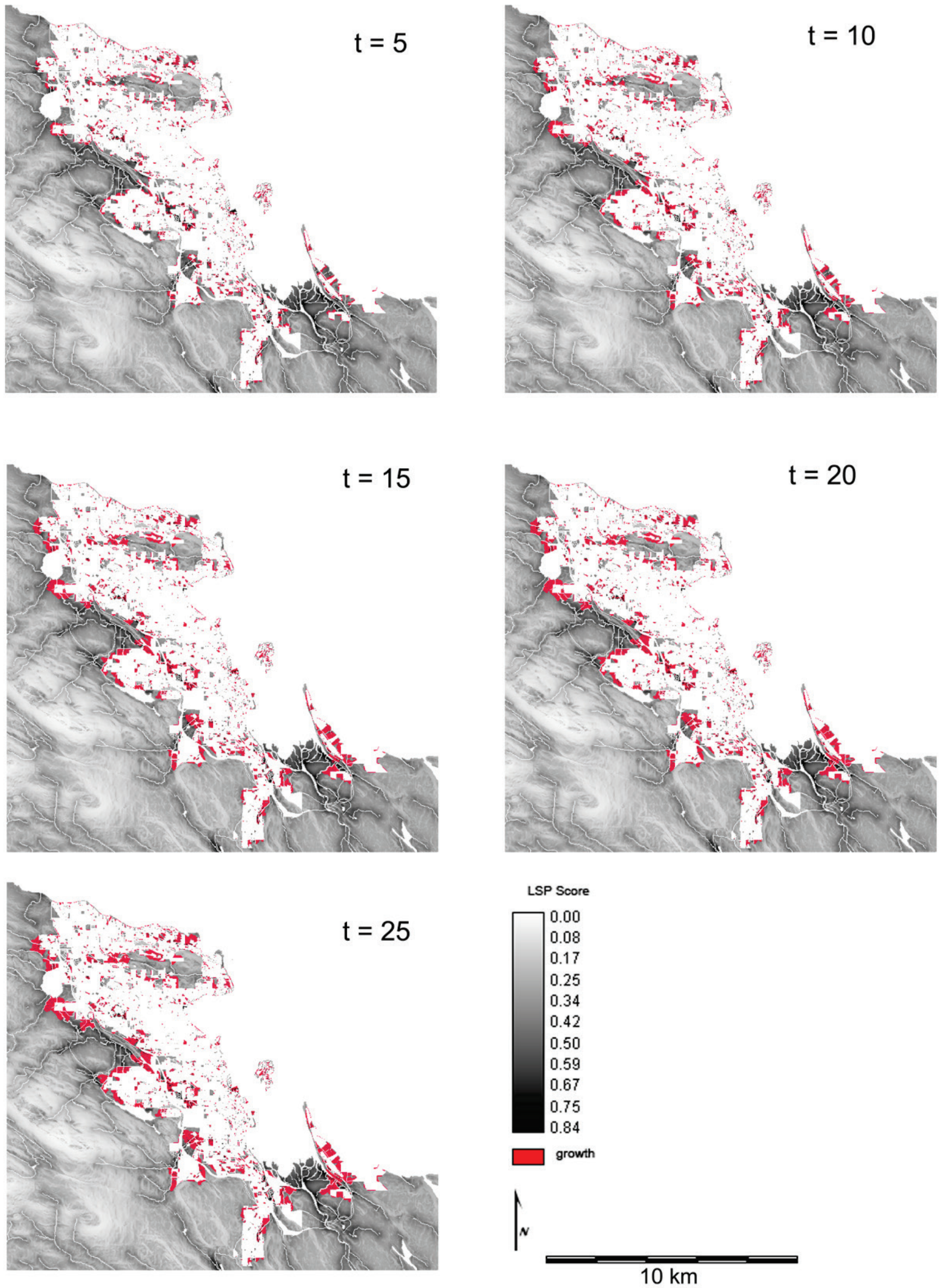

Figure 3-3. Simulation 1A: Transportation oriented growth

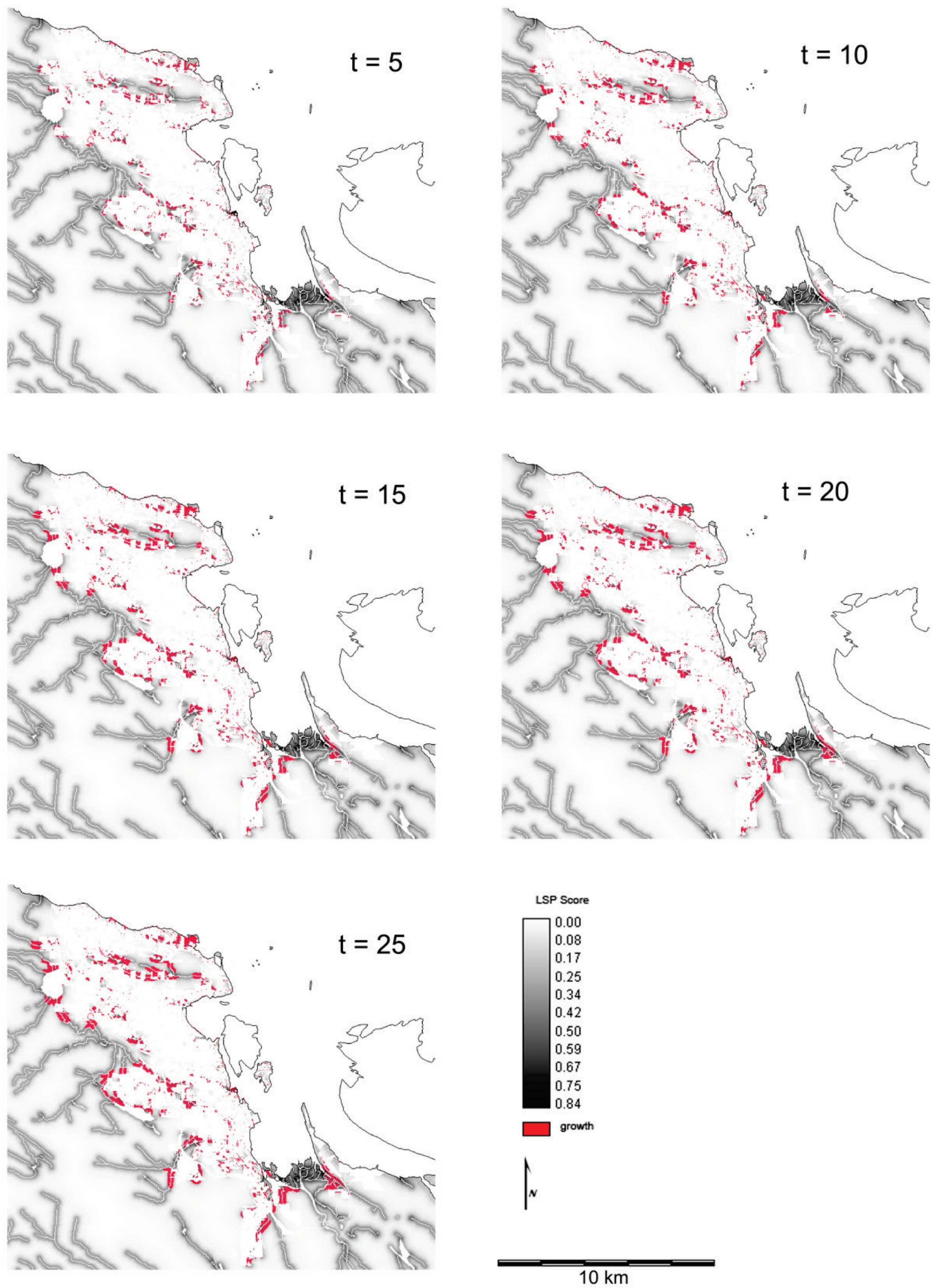

Figure 3-4. Scenario 1B: Growth in environmentally sensitive areas

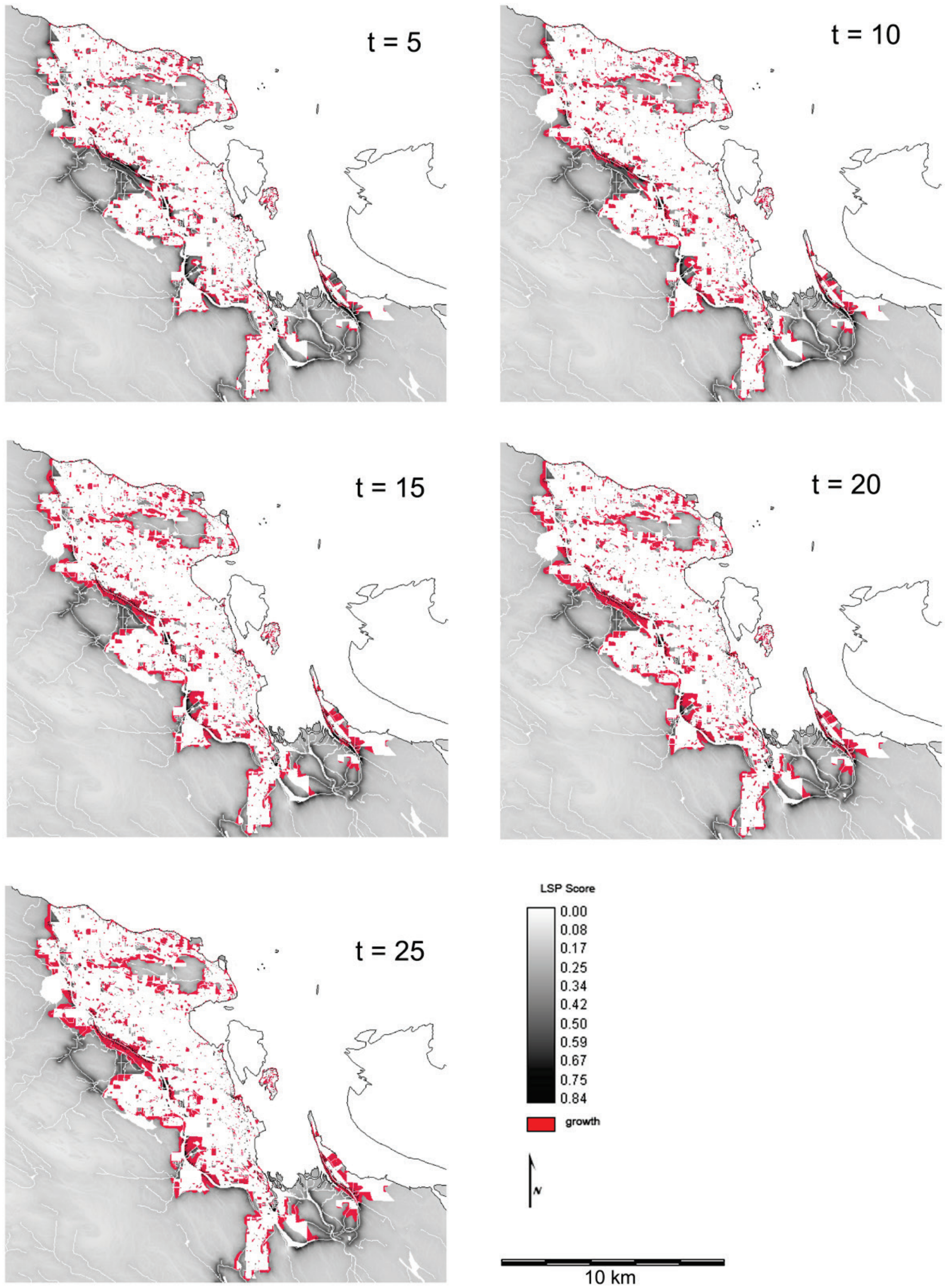

Figure 3-5. Scenario 1C: Compact growth

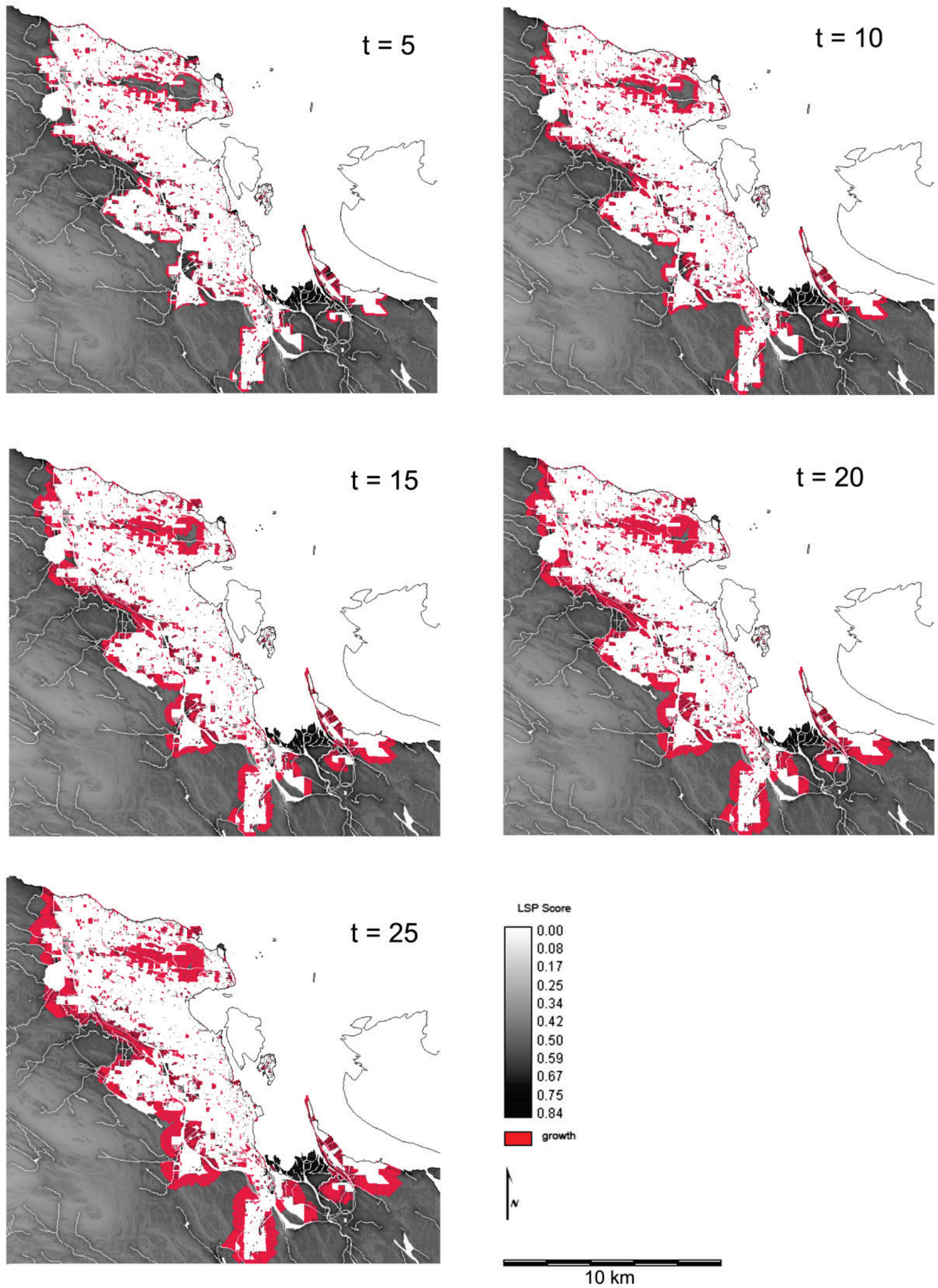

Figure 3-6. Scenario 1D: "Control" simulation using neutral logic

The Map Comparison Kit (MCK) developed by the Research Institute for Knowledge Systems (RIKS) (Hagen and Uljee 2003) was used to compare the scenarios from this first series of trials. The map comparisons are summarized in Table 3-3.

Map Comparison	***1a***	***1b***	***1c***	***2a***	***2b***	***2c***
Simulations compared (Map 1, Map 2)	1D, 1A	1D, 1B	1D,1C	1A, 1B	1A, 1C	1B, 1C
Map 1 unique growth land units (km^2)	18.4	19.9	15.5	5.3	3.3	3.2
Map 2 unique growth land units (km^2)	3.5	2.11	3.7	2.3	6.4	9.1
Overlap (km^2)	5.5	4.0	8.4	3.8	5.7	3.0

Table 3-3. Summary of map comparison procedure

First, scenarios 1A, 1B, and 1C were each compared with scenario 1D (referred to as Map Comparisons 1a, 1b, and 1c in Figure 3-7). 1D mentioned previously served the purpose of a "control" scenario. This was done to test the sensitivity of the CA to LSP aggregation logic parameterization. Then, scenarios 1A, 1B, and 1C were each compared to one another as a means of assessing the ability of the LSP CA to simulate different and non-redundant growth patterns (referred to as Map Comparisons 2a, 2b, and 2c in Figure 3-8).

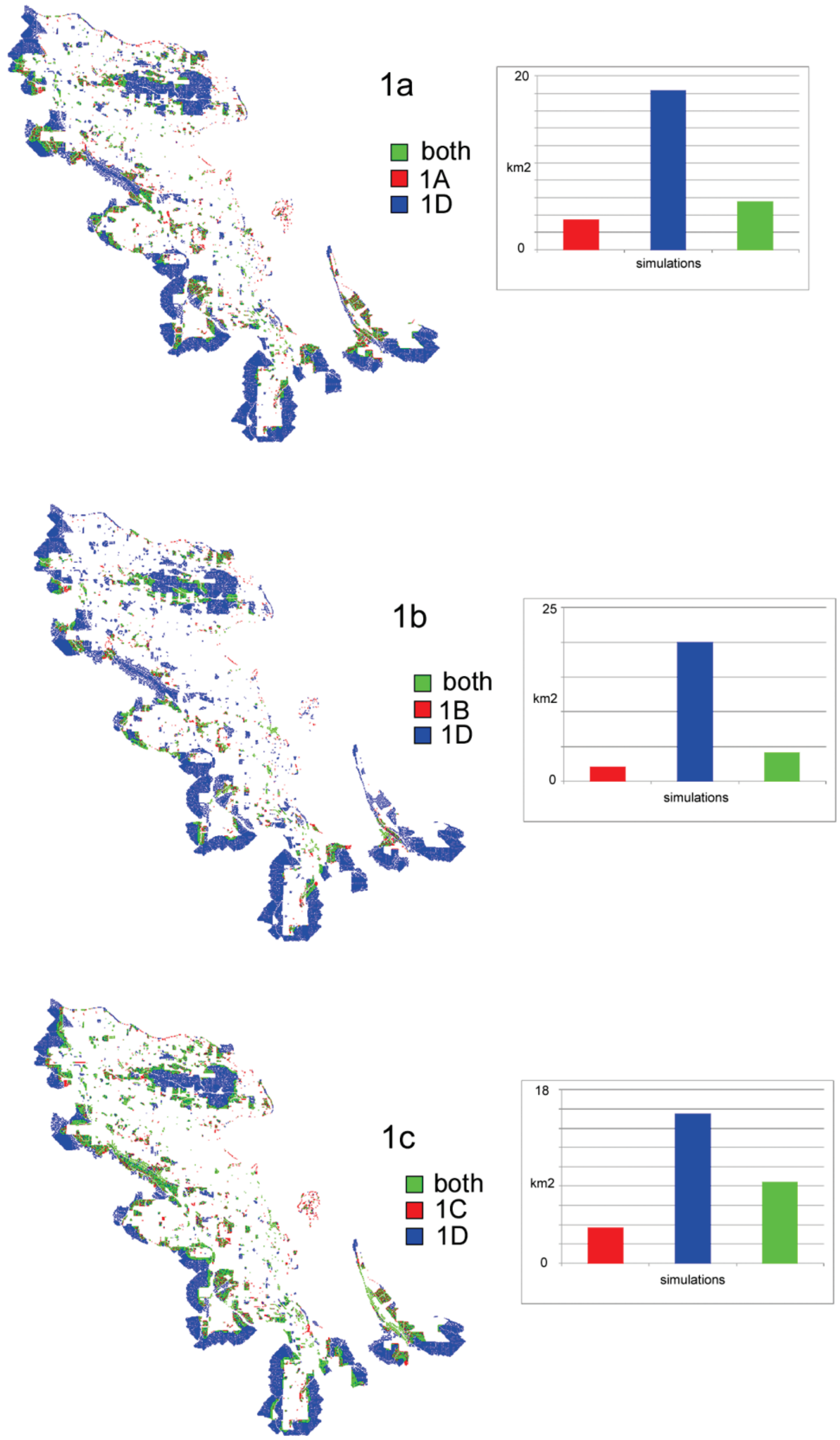

Figure 3-7. Map Comparisons 1a, 1b, and 1c

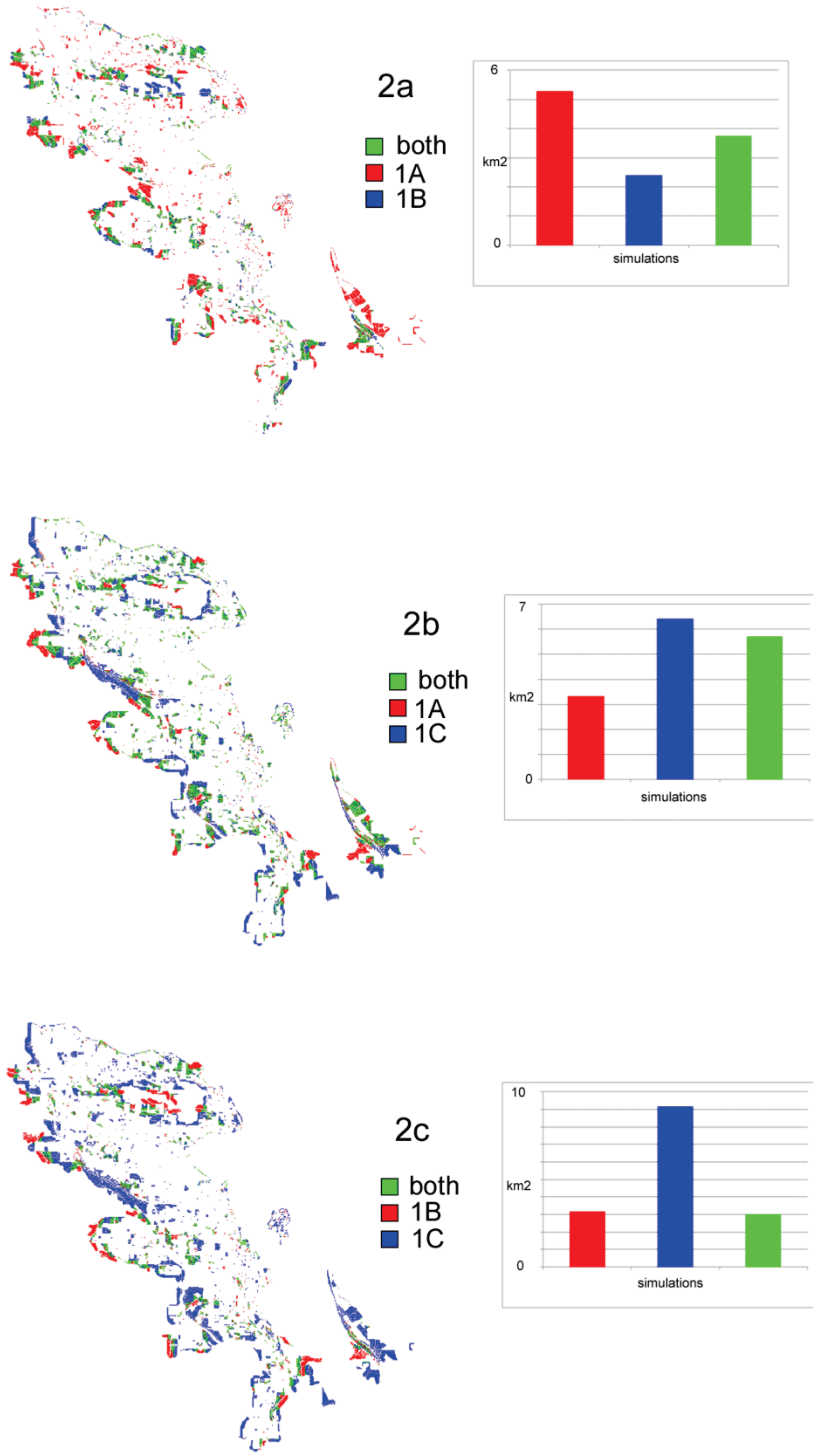

Figure 3-8. Map Comparisons 2a, 2b and 2c

3.5.2.2. Trial 2

For Trial 2 the LSP-CA was operated on the LSP-generated “compact growth” input employed for Scenario 1C, Trial 1. In this trial the LSP-CA was used to create two different growth scenarios, accelerated (2A) and slow (2B) (shown in Figures 3-9 and 3-10). Scenario 2A was set with an annual growth rate of 1.25 km^2 per year, and Scenario 2B was set with a 1 km^2 per year rate.

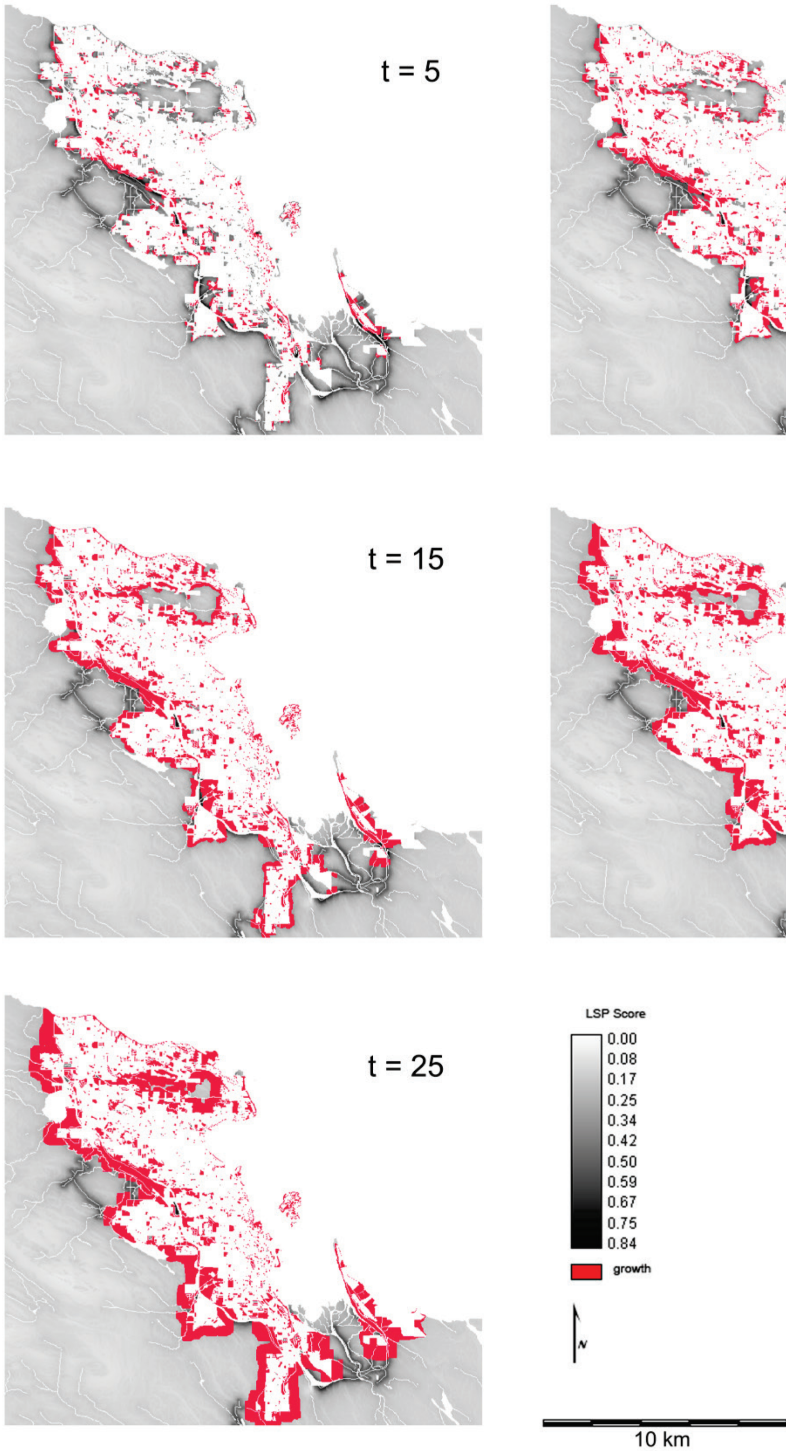

Figure 3-9. Simulation 2A: Accelerated growth

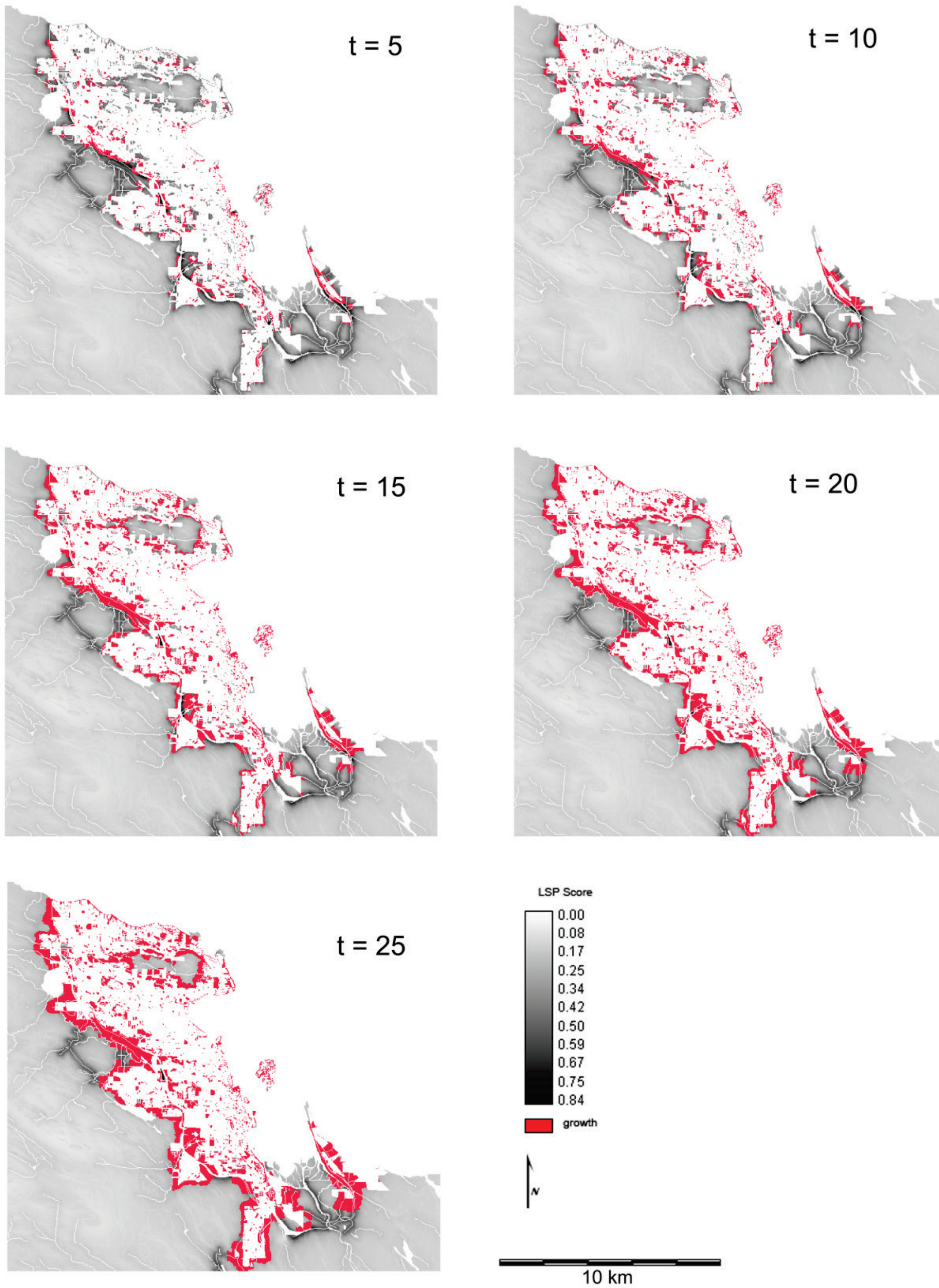

Figure 3-10. Scenario 2B: Slow growth dynamics

3.5.2.3. Trial 3

For the Trial 3, simulation 3A, the model output is shown in Figure 3-11. The growth pattern exhibited demonstrates a higher rate of growth in sub-region C (0.5 km^2 per year), with slower rates of growth in sub-regions A (0.15 km^2 per year) and B (0.3 km^2 per year). This output exhibits an unbalanced, asynchronous growth pattern, compared with the output from the previous structure that relies on a single growth dynamic parameter.

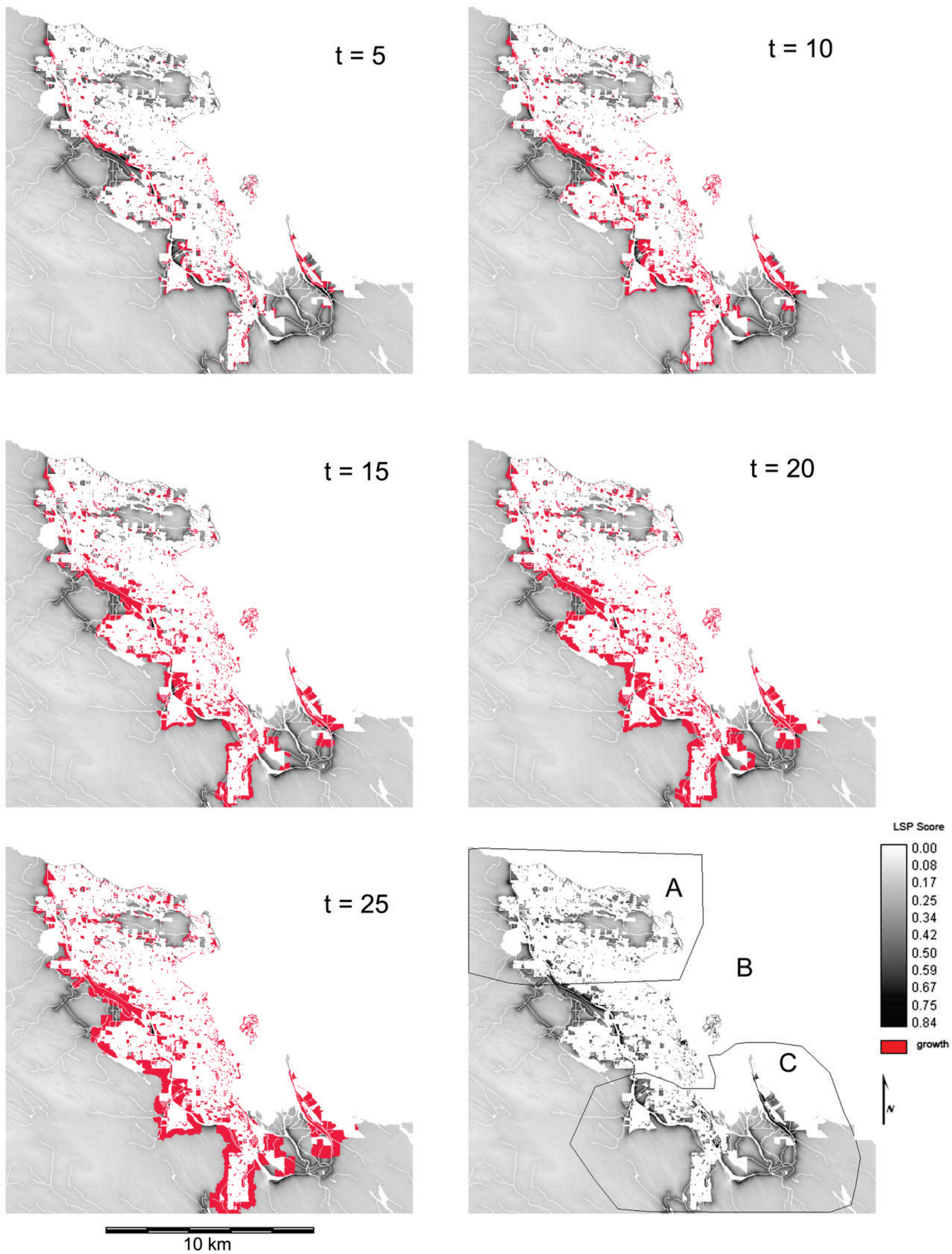

Figure 3-11: Scenario 3A: Asynchronous growth

3.6. Discussion and Conclusion

The development of an urban model using an LSP-CA integrated structure that addresses the limitations of MCE-CA approaches was configured in different ways to model realistic urban growth patterns. Three different modeling trials were designed to satisfy this research objective. The first trial was used to test the responsiveness of the CA to the LSP approach. Responsiveness of the CA was measured through map comparison summarized in Table 3-3. The second trial tested LSP's utility in modeling different rates of growth dynamics. The third trial functioned as an extension of the second in which a simulation was produced representing an asynchronously growing city.

The systematic map comparisons of simulations 1A, 1B, and 1C with "control" simulation 1D demonstrated the effect of parameterization of the LSP logic aggregators. The map comparisons 1a, 1b and 1c (Figure 3-7) indicate that the adjustable strength of logical requirements modeled in the LSP aggregation structure result in a more selective CA. Simulation 1D exhibits growth that outpaces all scenarios. This is expected because the aggregators used for simulation 1D were set to Average (neither AND, nor OR). Increasing the ANDness and reducing the ORness of the LSP Aggregation structure resulted in a more selective and discriminating CA. The results and map comparisons demonstrate the expressive power of flexible logic aggregation that is unavailable in MCE. This feature of the LSP submodel renders scaling functions of the type used by Wu and Webster (1998) for MCE-CA models unnecessary.

The result of Trial 1 also served to demonstrate that LSP can flexibly be manipulated to produce different, non-redundant scenarios. Each simulation was systematically compared and demonstrated significant differences in the locations of predicted growth. The comparison maps 2a, 2b and 2c and associated graphs (Figure 3-8) indicate that the scenarios do not overlap to a large degree. While each simulation is unique, each was created with the same inputs and aggregation structure, albeit parameterized differently. The ability of the LSP-CA to represent different outcomes implies that the significance of the inputs are maintained and that a high level of detail is present in the model

Trial 2 was useful for demonstrating the utility of LSP for modeling annual growth rates. Such a system can be altered to recreate patterns derived from historical datasets. One issue, however is that the rate of growth remains fixed over the iterations, whereas in reality growth may not proceed in such a way. Additionally, the annual growth rate parameter is an essentially "top-down" procedure, detracting somewhat from the "bottom-up" qualities that characterize CA and complex systems in general.

Urban systems, however, are not completely self-contained and an approach that merges the effect of global variables such as planning policy with the local neighbourhood function serve to produce a realistic profile of urban growth. The Trial 3 simulation functioned as a good compromise between a theoretically strict CA and an operational policy tool. By setting different dynamic rates among sub-regions, the system operates with a more realistic interplay between local and global effects.

The LSP-CA performed well, however, the model may benefit from additional development. This includes more realistic input variables generated from policy documents or interviews with planning professionals to enhance the LSP model. The choice of CA parameters also deserves attention. The simulation scenario maps indicated areas that experienced a rapid initial growth and cessation at a midway the duration of 25 years. This behaviour is present in all simulations yet most easily observable in Figures 3-3 and 3-5. These results stem directly from the choice of the 3x3 neighbourhood function. The size of the neighbourhood does not permit growth beyond physical barriers such as streams or roads represented as unsuitable (0%) contained in the LSP input layer. The limitations of Moore neighbourhoods are representative of the issues faced in adapting a rigid classical CA to the complexity of geographic reality.

The integration of the Logic Scoring of Preference approach and cellular automata techniques was proven to constitute a flexible structure for the exploratory simulation of realistic spatial and temporal urban growth. Geospatial data of the City of Nanaimo, BC, Canada was used as a case study for developing different simulations. This research demonstrated that CA is sensitive to LSP analysis and choice of criteria. LSP is a flexible front-end for a CA and represents a tool that can be used to leverage the detail and richness of numerous geospatial data inputs. The findings suggest that LSP is well suited for high detail, data-rich modeling applications. LSP is a powerful tool for modeling a level of selectivity necessary to represent decision logic seen in real-world decision-making. The LSP method could potentially be used as a sophisticated analytical structure for spatio-temporal SDSS methodologies for modeling growth under the constraints of real world planning and policy controls. LSP enables the inclusion of unlimited inputs and allows the expression of continuous logic; two significant features that are unavailable with MCE. The LSP approach and structure has been shown to have advantages over the more established MCE suitability analysis approach, generally, and for the purposes of calibrating urban models in a complex systems theoretical framework.

3.7. Acknowledgements

The Natural Sciences and Engineering Research Council (NSERC) of Canada provided full support under a Discovery Grant awarded to Dr. Suzana Dragićević. The authors are thankful to the City of Nanaimo, and Jodi Wilson, of the Nanaimo Engineering Department for providing the datasets used in this study.

3.8. References

Allen, W., L. III et al., 2011. Identifying and selecting strategic mitigation opportunities; criteria design and project evaluation using Logic Scoring of Preference and optimization. Journal of Conservation Planning, 7, pp.61–68.

Almeida, C.M. et al., 2008. Using neural networks and cellular automata for modeling intra-urban land-use dynamics. *International Journal of Geographical Information Science*, 22(9), pp.943–963.

Bailey, K. & Grossardt, T., 2010. Toward Structured Public Involvement: Justice, Geography and Collaborative Geospatial/Geovisual Decision Support Systems. *Annals of the Association of American Geographers*, 100(1), pp.57–86.

Batty, M., 1997. Cellular Automata and Urban Form: A Primer. *Journal of the American Planning Association*, 63(2), pp.266–274.

Batty, M., 2005. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*, Cambridge, Mass: MIT Press.

Batty, M. & Xie, Y., 1996. Preliminary evidence for a theory of the fractal city. *Environment and Planning A*, 28(10), pp.1745 – 1762.

Batty, M. & Xie, Y., 1994. From cells to cities. *Environment & Planning B: Planning & Design*, 21(Celebration Issue), pp.531–548.

Batty, M., Xie, Y. & Sun, Z., 1999. modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems*, 23(3), pp.205–233.

Boroushaki, S. & Malczewski, J., 2010. Using the fuzzy majority approach for GIS-based multicriteria group decision-making. *Computers & Geosciences*, 36(3), pp.302–312.

Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. *International Journal of Geographical Information Systems*, 5(3), p.321.

Chapin, S., and Weiss, S., 1968. A Probabilistic Model for Residential Growth. Transportation Research 2:375-90.

City of Nanaimo 2008. planNanaimo. Official Community Plan, Nanaimo, BC.

Clarke, K. C., Hoppen, S. & Gaydos, L.J., 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design*, 24(2), pp.247 – 261.

Clarke, K. C. & Gaydos, L.J., 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, 12(7), pp.699–714.

Comber, A. et al., 2010. Different methods, different wilds: Evaluating alternative mappings of wildness using fuzzy MCE and Dempster-Shafer MCE. *Computers, Environment and Urban Systems*, 34(2), pp.142–152.

Couclelis, H., 1985. Cellular worlds: a framework for modeling micro - macro dynamics. *Environment and Planning A*, 17(5), pp.585 – 596.

Dujmović, J.J., 1996. A Method For Evaluation And Selection Of Complex Hardware And Software Systems. In *CMG 96 Proceedings*. pp. 368–378.

Dujmović, J.J., 2007. Continuous Preference Logic for System Evaluation. *Fuzzy Systems, IEEE Transactions on*, 15(6), pp.1082 –1099.

Dujmović, J.J. & De Tré, G., 2011. Multicriteria methods and logic aggregation in suitability maps. *International Journal of Intelligent Systems*, 26(10), pp.971–1001.

Dujmović, J.J. & Larsen, H.L., 2007. Generalized conjunction/disjunction. *International Journal of Approximate Reasoning*, 46(3), pp.423–446.

Dujmović, J.J. & Nagashima, H., 2006. LSP method and its use for evaluation of Java IDEs. *International Journal of Approximate Reasoning*, 41(1), pp.3–22.

Dujmović, J.J. & Scheer, D., 2010. Logic aggregation of suitability maps. In *2010 IEEE International Conference on Fuzzy Systems (FUZZ)*. 2010 IEEE International Conference on Fuzzy Systems (FUZZ). IEEE, pp. 1–8.

Dujmović, J.J., De Tré, G. & Dragićević, S., 2009. Comparison of Multicriteria Methods for Land-use Suitability Assessment. *IFSA World Congress 8 EVSFLAT Conference, Lisbon, Portugal*.

Dujmović, J.J., De Tré, G. & Weghe, N., 2009. LSP suitability maps. *Soft Computing*, 14(5), pp.421–434.

Dujmović, J.J., De Tré, G. & Weghe, N., 2008. Suitability Maps Based on the LSP Method. In V. Torra & Y. Narukawa, eds. *modeling Decisions for Artificial Intelligence*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 15–25.

Eastman, J.R. et al., 1995. Raster Procedures for Multi-Criteria/Multi-Objective Decisions. *Photogrammetric Engineering and Remote Sensing (PE&RS)*, 61(5), pp.539–547.

Gardner, M., 1970. Mathematical Games: The fantastic combinations of John Conway's new solitaire game "life." *Scientific American*, (223), pp.120 –123.

GeoBase, 2012. Canadian Digital Elevation Data [computer file]. 2000-2009. Ottawa, ON: Ministry of Natural Resources. Available FTP: ftp://ftp2.cits.rncan.gc.ca/pub/GeoBase/official/cded/ [Accessed August 3, 2012]

Goodchild, M.F., & Haining, R.P., 2004. GIS and spatial data analysis: Converging perspectives. *Papers in Regional Science*, 83, pp.363–385.

Hagen, A. & Uljee, I., 2003. MAP COMPARISON KIT. User manual, RIKS report, July 2003. Available from: http://www.rivm.nl/milieu/modellen or http://www.riks.nl/MCK/

Jankowski, P., 1995. Integrating geographical information systems and multiple criteria decision-making methods. *International Journal of Geographical Information Science*, 9(3), pp.251–273.

Jiang, H. & Eastman, J.R., 2000. Application of fuzzy measures in multi-criteria evaluation in GIS. *International Journal of Geographical Information Science*, 14(2), pp.173–184.

Laaribi, A., Chevallier, J.J. & Martel, J.M., 1996. A spatial decision aid: A multicriterion evaluation approach. *Computers, Environment and Urban Systems*, 20(6), pp.351–366.

Lathrop, G. T., and Hamburg, J. 1965. An Opportunity-Accessibility Model for Allocating Regional Growth. *Journal of the American Institute of Planners* 31:95-103.

Li, X. & Yeh, A.G., 2001. Calibration of cellular automata by using neural networks for the simulation of complex urban systems. *Environment and Planning A*, 33(8), pp.1445–1462.

Li, X. et al., 2011. Coupling Simulation and Optimization to Solve Planning Problems in a Fast-Developing Area. *Annals of the Association of American Geographers*, 101, pp.1032–1048.

Liu, X. et al., 2007. Discovery of transition rules for geographical cellular automata by using ant colony optimization. *Science in China, Series D: Earth Sciences*, 50(10), pp.1578–1588.

Malczewski, J., 1999. *GIS and Multicriteria Decision Analysis*, New York: John Wiley.

Malczewski, J., 2002. Fuzzy Screening for Land Suitability Analysis. *Geographical & Environmental Modeling*, 6(1), pp.27–39.

Manson, S.M., 2001. Simplifying complexity: a review of complexity theory. *Geoforum*, 32(3), pp.405–414.

O'Sullivan, D., 2009. Complexity Theory, Nonlinear Dynamic Spatial Systems. In *International Encyclopedia of Human Geography*. Oxford: Elsevier, pp. 239–244.

Santé, I. et al., 2010. Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, 96(2), pp.108–122.

Soni, D., Shrivastava, N. & Kumar, M., 2010. A Methodology for Empirical Quality Assessment of Object-Oriented Design. *arXiv:1003.1456*. Available at: http://arxiv.org/abs/1003.1456 [Accessed June 18, 2012].

Stanilov, K. & Batty, M., 2011. Exploring the Historical Determinants of Urban Growth Patterns through Cellular Automata. *Transactions in GIS*, 15(3), pp.253–271.

Statistics Canada, 2012a. Focus on Geography Series, 2011 Census - Census subdivision of Nanaimo, CY (British Columbia). Available at: http://www12.statcan.gc.ca/census-recensement/2011/as-sa/fogs-spg/Facts-csd eng.cfm?Lang=Eng&TAB=0&GK=CSD&GC=5921007 [Accessed June 21, 2012].

Statistics Canada, 2012b. 2011Geographic Boundary File Available at: http://www12.statcan.gc.ca/census-recensement/2011/geo/bound-limit/bound-limit-2011-eng.cfm [Accessed August 3, 2012]

Statistics Canada, 2012c. 2011 Geographic Attribute File. Available at: http://www12.statcan.gc.ca/census-recensement/2011/geo/ref/att-eng.cfm [Accessed August 3, 2012]

Statistics Canada, 2012d. 2011 Road Network File Available at: http://www5.statcan.gc.ca/bsloc/olc-cel?lang=eng&catno=92-500-X [Accessed August 3, 2012]

Stevens, D. & Dragićević, S., 2007. A GIS-based irregular cellular automata model of land-use change. *Environment and Planning B: Planning and Design*, 34(4), pp.708–724.

Tobler, W. 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* 26:234-40.

Toffoli, T., & Margolus N., 1987. *Cellular Automata Machines*. Cambridge, MA: MIT Press. ix, 259 p.

Torrens, P.M., 2000. How cellular models of urban systems work. CASA Working Papers. Centre for Advanced Spatial Analysis. University College, London

Torrens, P.M. & Benenson, I., 2005. Geographic Automata Systems. *International Journal of Geographical Information Science*, 19(4), pp.385–412.

De Tré, G., Dujmović, J. J. & Van De Weghe, N., 2009. Supporting spatial decision making by means of suitability maps.

Ward, D.P., Murray, A.T. & Phinn, S.R., 2003. Integrating spatial optimization and cellular automata for evaluating urban change. *The Annals of Regional Science*, 37(1), pp.131–148.

White, R. & Engelen, G., 1993. Cellular automata and fractal urban form: a cellular modeling approach to the evolution of urban land-use patterns. *Environment & Planning A*, 25(8), pp.1175–1199.

White, R. & Engelen, G., 1994. Urban systems dynamics and cellular automata: fractal structures between order and chaos. *Chaos, Solitons & Fractals*, 4(4), pp.563–583.

White, R. & Engelen, G., 1994. Cellular dynamics and GIS: modeling spatial complexity. *Geographical Systems*, 1(3), pp.237–253.

White, R. & Engelen, G., 2000. High-resolution integrated modeling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, 24(5), pp.383–400

White, R., 2000. High-resolution integrated modeling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, 24(5), pp.383–400.

Wood, L. & Dragićević, S., 2007. GIS-Based Multicriteria Evaluation and Fuzzy Sets to Identify Priority Sites for Marine Protection. *Biodiversity and Conservation*, 16(9), pp.2539–2558

Yeh, A.G.-O. & Li, Xia, 2003. Simulation of development alternatives using neural networks, cellular automata, and GIS for urban planning. *Photogrammetric Engineering and Remote Sensing*, 69(9), pp.1043–1052.

Yip, M.C.L. & Mendes, E., 2005. Web usability measurement: comparing logic scoring preference to subjective assessment. In *Proceedings of the 5th international conference on Web Engineering*. ICWE'05. Berlin, Heidelberg: Springer-Verlag, pp. 53–62.

Chapter 4: Conclusion

4.1. General Conclusions

The focus of this research was to develop an integrated collection of GIS-based analysis and modeling approaches for the purpose of modeling urban systems employing the Logic Scoring of Preference (LSP) Method and complex systems theory. The research was completed in two stages. The first stage involved the development of a method for land-use suitability analysis using the LSP approach integrated within GIS. Furthermore the comparison of LSP-GIS and commonly used GIS-MCE approaches was done to the purpose of evaluating the usability of both methods in land suitability analysis. The second stage presented a novel LSP-CA modeling approach in which the LSP method is used to develop transition rules for various modeling scenarios of urban growth. Both stages of the research were implemented using the IDRISI GIS software environment (Eastman 2012).

The first stage of the research focused on the integration of LSP and GIS for modeling suitability for residential development. LSP is a method with origins in fuzzy reasoning and soft computing for analyzing software development interfaces, browsers and similar applications. Geographical applications such as raster-based LSP suitability maps have been mostly theorized and the research literature describes only spatial applications on hypothetical datasets. This research demonstrates the first attempt at applying the LSP approach to geospatial datasets of real urban land-use environments. Geospatial data of Bowen Island Municipality was used as a case study. The results are presented as a suitability map with regions defined by logical requirements specified by the LSP method. The results with an integrated GIS-LSP indicate that this approach can be used to structure decision problems using realistic models of human reasoning in a spatial context. Moreover, the test of the LSP approach and its comparison to MCE was performed.Results of this comparison indicate LSP lets users define suitability with preference requirements and employs nonlinear averaging operators that express fuzzy logic such as degrees of ANDness and ORness. It was found that the advantages based in the method aggregation results in a more flexible and sophisticated toolset for defining land-use suitability than the MCE method.

The second stage of the research project develops an integrated LSP and CA modeling approach designed and implemented on geospatial data representation of the City of Nanaimo, BC, Canada, and for the purpose of modeling urban growth. The results include a series of different development scenarios representing 25 years of future urban developments. Results of a map comparison procedure indicate that CA is highly responsive to an LSP input. In addition to producing predictive growth scenarios, the LSP-CA integrated model was modified to simulate (1) different growth dynamics, and (2) asynchronous growth. LSP was shown to be a useful and responsive for land-suitability modeling and for guiding the transition rules of a GIS-based CA capable of producing a range of realistic urban growth scenarios.

4.2. Contributions

The integrated LSP-GIS-CA methods contribute to the fields of geography GIScience and more particularly spatio-temporal modeling. Moreover it provides an effective alternative to the existing methods, such as GIS-MCE, used for land-use site suitability analysis and land-use change modeling. MCE used in the context of land-use suitability, cannot express realistic logic conditions needed for decision-making. MCE-CA models used in land-use change modeling require additional structures such as scaling functions to overcome the limitations of the MCE input and realistically represent development. In Chapter 2 a novel GIS-LSP prototype was developed and compared to a similar GIS-MCE approach. In Chapter 3 LSP was shown to be an effective approach for deriving transition rules for a series of land-use change scenarios. In both stages of the research the key advantages of the integrated LSP-GIS-CA approaches were demonstrated that include no limitations on the number of LSP inputs, and the expression of preference logic. The advantages of the approach, also presented in this study, include the minimization of data loss through nonlinear aggregation and the modeling of suitability scores using fuzzy logic requirements. Additionally the integrated approaches can contribute to fields such as urban planning or natural resource management and related disciplines that employ suitability mapping and GIS for facilitating decision making processes.

4.3. Future Directions

This research was successful at demonstrating that the LSP approach can be integrated in a GIS modeling framework for building land-use suitability maps and for shaping the initial conditions of urban CA models depicting dynamic change. It provides a first step at exploring the potentials for LSP and its use in GIScience and geographical applications. In Chapter 3 the modeling structures were used to simulate different rates of dynamic growth. The LSP-CA prototype has the potential, therefore, to be case study tested in an actual policy or collaborative planning context. Such a study could prove useful for developing suitability preferences and logical requirements.

Further development of a GIS-LSP or LSP-CA could benefit from its use in a spatial decision support system (SDSS). An SDSS could function as a standalone application, or as a methodological approach running parallel to a GIS (Densham 1991). Currently the LSP method is integrated and implemented in IDRISI's modeling environment, and relies on this specific interface design. The system is functional, however, in order to be used collaboratively or with non-experts, the development of an LSP module with a user-friendly and approachable interface is necessary. Dynamic updating of output maps as parameters change would provide users with important feedback on the implications of choosing one type of logic over another (De Tré et al. 2010). In place of LSP oriented terminologies and symbology, a well-designed semantic import interface could serve as the method of defining values and parameters. A user-friendly LSP decision-support structure was developed for Google maps with similar qualities (Dujmović & De Tré 2011) and should be developed as a part the standard modules within the core of the GIS software.

The third chapter also indicated that LSP is useful for models of geographical complex systems. This implies that LSP could be applied to other areas of GIS – CA beyond land-use change and urban growth research domains such as landslides (Lai & Dragićević 2011), spatio-temporal propagation of insect infestations (Bone et al. 2006), forest fire behaviour (Yassemi et al. 2008), or marine area protection (Wood and Dragićević 2007). The successful integration of CA and LSP suggest that the alternative approaches to studying spatio-temporal complexity such as agent based models (ABMs) of urban or biological systems could benefit from the application of the LSP approach. The LSP approach could be useful for developing agent models with sophisticated decision-making parameters employing fuzzy preference logic. As ABMs often have numerous agents with different objectives and goals (Parker et al. 2003); each agent could be designed with its own unique set of preferences specified by LSP methods. Furthermore these preferences could be structured to change dynamically through the processes of agent learning and adaptation under different environmental conditions.

In closing, the research presented in this thesis offers a glimpse of a rich set of possibilities and opportunities awaiting further development of LSP in the contexts of GIS and spatio-temporal modeling.

4.4. References

Bone, C., Dragićević, S. & Roberts, A., 2006. A fuzzy-constrained cellular automata model of forest insect infestations. *Ecological Modeling*, 192(1-2), pp.107–125.

Densham, P., 1991. Spatial Decision Support Systems. In *Geographical Information Systems: principles and applications*. Longman, pp. 403–412.

Dujmović, J. & De Tré, G.D., 2011. Multicriteria methods and logic aggregation in suitability maps. *International Journal of Intelligent Systems*, 26(10), pp.971–1001.

Eastman, J.R.2012. Idrisi Selva Edition. Clark Labs. Worcester, MA.

Lai, T. & Dragićević, S., 2011. Development of an urban landslide cellular automata model: a case study of North Vancouver, Canada. *Earth Science Informatics*, 4(2), pp.69–80.

Parker, D.C. et al., 2003. Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers*, 93(2), pp.314–337.

De Tré, G., Dujmović, J. & Weghe, N., 2010. Supporting Spatial Decision Making by Means of Suitability Maps. In J. Kacprzyk, F. E. Petry, & A. Yazici, eds. *Uncertainty Approaches for Spatial Data Modeling and Processing*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 9–27.

Wood, L. & Dragicević, S., 2007. GIS-Based Multicriteria Evaluation and Fuzzy Sets to Identify Priority Sites for Marine Protection. *Biodiversity and Conservation*, 16(9), pp.2539–2558.

Yassemi, S., Dragićević, S. & Schmidt, M., 2008. Design and implementation of an integrated GIS-based cellular automata model to characterize forest fire behaviour. *Ecological Modeling*, 210(1–2), pp.71–84.