DEVELOPMENT OF A FUZZY-CONSTRAINED GIS-BASED CELLULAR AUTOMATA MODEL OF DYNAMIC COMPLEX SYSTEMS: A CASE STUDY OF FOREST INSECT INFESTATIONS

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ABSTRACT

Cellular automata (CA) are suitable for modelling complex geographic and ecological processes such as forest insect infestations; however, problems exist with understanding the complexity of insect-host interactions through geospatial data. The objective of this research was to develop a fuzzy-constrained approach for a GIS-based CA model of forest insect infestations. The methodology was tested with a case study of the mountain pine beetle, *Dendroctonus ponderosae* Hopkins, in the central interior of British Columbia, Canada. Fuzzy sets were used for obtaining information on the susceptibility of trees to attack, while CA was employed for modelling MPB-induced patterns of tree mortality. This research contributes in the advancement of CA models by using fuzzy sets and GIS for addressing uncertainty of dynamic spatial phenomena, and provides a novel approach for modelling MPB outbreaks that is useful to forest management.

This thesis is dedicated to the man who on a cold morning in Greensborough Arena told me that I can accomplish whatever I put my mind towards. Although I didn't make it to the NHL, life seems to be on the right track.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1 – INTRODUCTION

1.1 Introduction

Complexity characterizes various geographic, ecological, economic, political and biological processes where numerous components locally interact to produce emerging patterns. Complex systems theory has materialized in recent decades as a framework for understanding these processes and how emerging patterns are produced. The main element of complex systems is the relationships between the individual components (Manson 2001); as the relationships change so do the emerging patterns.

One of the most prominent mechanisms for understanding complex systems are spatially explicit models. While numerous spatially explicit modelling frameworks have been developed, cellular automata (CA) have surfaced as some of the most diverse and applicable models for complex systems (White and Engelen 1993). These models are developed in order to determine how the relationships between numerous components result in various spatial patterns over time. Simple rules or algorithms explaining the relationships are computationally defined, and the model is performed for a number of iterations, resulting in various patterns. One of the main benefits of CA models is that relationships can be easily altered in a raster-based GIS framework in order to display and visualize the various simulation outcomes. This serves as a utility for spatial decision support systems (SDSS) where interested parties inquire about different potential scenarios.

According to White and Engelen (2000), CA consist of five main components: 1) a grid of cells, 2) cell states, 3) the neighbourhood, 4) transition rules that determine how cells change from one state to another at each time step, and 5) the number of time steps for which the model is run. The grid is composed of a number of cells that are typically identical in size and shape. Cells can take on an infinite number of states that are traditionally represented as discrete. The neighbourhood implies the surrounding area that influences the future of each cell at the next time step. For example, the neighbourhood of cell ij (i.e. located at x_i y_j coordinates) is four cells if only the adjacent cells influence the state of cell ij at the next time step. The transition rules express how the states of each cell in the neighbourhood influences the future state of cell ij from one time step to another. The number of iterations expresses the temporal extent of the model so that each time step represents a specific time frame (e.g. one year).

The origin of CA dates back to the 1950's and John von Neumann's theory of parallel processing units; however the application of CA wasn't popularised until the presentation of John Conway's game *Life* by Gardner (1970). Conway's CA version described a grid of cells that were either active (alive) or non-active (dead), and the possibility of the cell dying, becoming alive or remaining in the same state was subject to a series of local rules. Since then, CA has expanded into numerous fields, from mathematics (Wolfram 1983) to physics (Zhu and Liu 2000), geography (Couclelis 1985, Batty and Xie 1994), biology (Ermentrout and Edelstein-Keshet 1993), ecology (Jeltsch and Wissel 1994) and forestry (Jeltsch and Wissel 1994).

The discrete nature makes CA an attractive method for spatially explicit modelling in both conceptual and practical terms. Conceptually, it is simple to understand a model if space is represented by an array of discrete units that change in distinct time steps. In practical terms, the framework of CA facilitates integration with modelling in a geographic information system (GIS) raster-based environment where a landscape is described as a static grid of square cells. GIS and CA serve as complements with regards to spatio-temporal modelling as the former provides the spatial framework for geographic data while the latter contributes the temporal dimension for describing change. For this reason, numerous studies have coupled CA with raster-based geospatial data in order to model various processes.

The utility of CA with geographic applications was first discussed by Tobler (1979), however it wasn't until the following decades that their potential for real-world systems was realized (Couclelis 1985, Deadman et al. 1993, White and Engelen 1993, Batty and Xie 1994). CA have become increasingly common in geographical applications where neighbourhood effects are present. Coupling CA and GIS has proved successful for numerous land use change models of urban growth where discrete landforms occupy various spaces over time. Neighbourhoods can be conceptualised as the cells of the grid, and growth patterns imbedded in urban dynamic theory can be explained by simple transition rules. For example, a loose-coupled CA-GIS model was developed by Clarke and Gaydos (1999) for modelling urban growth in San Francisco Bay region in California and the Washington/Baltimore corridor in the Eastern United States. Various issues such as calibration and data requirements were discussed as integral components of the modelling process. Batty et al. (2000) presented ways in which existing urban activities spawn locations for new activities through definitions of various decision rules that embed distance, direction, density thresholds, and transition or mutation probabilities into the model's dynamics. The authors also presented numerous hypothetical simulations of urban land use in order to illustrate the diversity of model types that can be handled with CA. In addition, combining CA with or within other types of models has also been tested, such as White and Engelen's (2000) application where CA modelled the demand for urban space based on policy and planning goals defined by a regional-scale model. Furthermore, CA have also been combined with neural networks by Li and Yeh (2002) for modelling land use change in China.

Similar to land use change scenarios, ecological processes can be modelled with CA by representing a landscape as an array of cells that change over time based on the state of cells present in a given area. Discrete cell states are advantageous for modelling ecological processes because state transition can be governed by a probability distribution that is based on the initial state of each cell in the grid. This type of probability transition for stochastic processes is represented with a Markov chain, which can be used for defining species competition paradigms, migration patterns, and resource allocation (Baltzer et al. 1998). The discrete value of a cell can represent the presence or absence of a species, or the number of individuals located in a particular area. Furthermore, cell states can also represent a concept such as the susceptibility of a tree in a forest to insect attack at a particular location.

1.2 Research Problem

Forest insect infestations are complex systems as insects and trees interact at the local micro-level (i.e. the scale of an individual tree) to produce emerging patterns at the global macro-level (i.e. the scale of a landscape). Insects travel through a forest seeking potential host trees to attack for food or even kill in order to reproduce. The insect-host relationship is comprised of numerous components that act simultaneously to drive insect population levels and the damage or mortality of trees. Such is the case with outbreaks of the mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, the most serious pest of the pine forests of western North America (Safranyik 1988). MPB attack susceptible lodgepole pine, *Pinus contorta*, and ponderosa pine, *Pinus ponderosa*, with the intention of causing tree mortality in order to successfully reproduce. MPB outbreaks are governed by different components such as temperature, humidity, susceptible trees, the diversity of forest stands and MPB population levels, all of which interact at the scale of individual trees to produce complex spatial patterns of tree mortality at the landscape scale over time.

CA are ideal for GIS-based modelling of spatial patterns for MPB-induced tree mortality over time. Each tree in a forest can be represented by a single cell, and the state of each cell could be either 1 or 0 representing a susceptible or non-susceptible tree, respectively. Additional states could be introduced to represent the location of trees already attacked by MPB; the more MPB infested trees in the neighbourhood would increase the probability of a susceptible tree becoming attacked, which would be governed by the transition rules. Furthermore, each time step of the CA could represent a single-life cycle of the MPB. Therefore, the rules of the CA would define how attacking insects, susceptible trees and non-susceptible trees interact at the local level to produce global patterns of tree damage and mortality over time. However, while CA appear to be applicable for modelling insect infestations, two main problems exist with representing susceptibility to attack as a discrete state.

The first problem with representing susceptibility as a discrete state resides in the definition of the term 'susceptibility'. It is difficult to use contemporary approaches to this problem such as defining a tree as either susceptible or not susceptible, or deriving the probability of a tree becoming attacked. This is due to the fact that insect disturbances are driven by numerous components of the insect-host relationship that are difficult to understand independently, let alone together. Appreciating this relationship is further complicated by the presence of numerous climatic variables such as temperature, wind, humidity and precipitation, which, coupled with the geographic variation of a species' life cycle, produce varying results and incomplete knowledge on insect behaviour. Therefore, considering a raster-based geospatial data representation of a forest landscape, significant uncertainty is present when attempting to assign a discrete binary or probability value to a cell describing a tree's susceptibility to attack.

This issue is further complicated by a second problem, which is obtaining information for defining cell states in a GIS from remote sensing (RS) images, such as satellite imagery or aerial photography. As forests are continuously changing over space and time, the value given to a cell through classification procedures only represents that location for the moment in time when the data were acquired. Local processes change the appearance of the forest canopy as captured by RS data, thus causing significant difficulty in defining heterogeneous areas such as the borders between forest stands (Lowell and Gold 1995). Therefore, when obtaining information from RS imagery, intermediate zones exist between forest stands of different sizes and different species where a discrete and certain definition of a cell cannot be provided.

From examining these problems, it is clear that a significant barrier exists with defining discrete cell states for modelling the attack of trees in a forest by an insect based on susceptibility. Therefore, a method is required for determining susceptibility of trees based on available knowledge and existing certainty in order to utilize the benefits of coupling GIS and CA for spatio-temporal modelling. This research examines the use of fuzzy set theory for providing such a method. Fuzzy set theory was originally developed by Zadeh (1965), and is often used by geographers in order to deal with incomplete knowledge or vagueness for determining the class of an object (Robinson 1988, Wang et al. 1990, Hall et al. 1992). Traditional crisp set theory states that an object either fully belongs or does not belong to a class of objects, thus membership to a class is represented by either 0 or 1. Conversely, fuzzy sets allow for partial membership to a class of objects based on the available knowledge or expert opinions on the nature of an object, resulting in values from 0 to 1. It is believed that fuzzy sets are ideal for defining the susceptibility of trees to insect attack for use in a spatially explicit CA model. Thus far, the use of fuzzy sets for defining cell states for spatio-temporal modelling has received limited attention (Dragicevic 2004).

1.3 Research Objectives

The main objective of this thesis is the development of a GIS-based methodology coupled with CA theory for modelling complex dynamic process such as insect infestation in order to address the described problems. This will be addressed through two parts:

1. Derive information on forest insect infestation from high-resolution remote sensing images using fuzzy set theory to determine susceptibility to insect attack at the individual tree level.
2. Develop a spatially explicit fuzzy-constrained CA to model MPB-induced mortality patterns in a forest.

The developed concepts were applied to MPB outbreaks because 1) patterns of MPB-induced mortality are applicable to the modelling logic of CA, 2) there exists uncertainty and incomplete knowledge with defining cell states based on susceptibility to MPB attack, 3) current MPB outbreaks are having serious ecological, economic and social consequences, and 4) the availability of high-resolution RS data of forests affected by MPB.

1.4 Study Site

High-resolution images previously collected (Roberts et al. 2003) for two sites were used for developing the susceptibility maps. The sites are located in the central interior of British Columbia: Site 1 centred at 53°38'45"W and 123°26'20"N, and Site 2 centred at 53°29'07"W and 125°06'40"N. The size of each site is approximately 750 m x 750 m in which there is minimal variation in elevation. The forest in these areas is dominated by lodgepole pine, and contains a relatively small composition of white spruce, *Picea glauca*, Douglas fir, *Pseudotsuga menziesii*, and trembling aspen, *Populus tremuloides*. The sites also contain roads and open areas that were previously created for forestry operations and forest management.

1.5 Background

Ecological processes such as insect infestations are traditionally modelled with the use of partial differential equations (PDE), as they are able to incorporate numerous variables into an equation and analyse changes in the system through time (Aassine and El Jai, 2002). However, PDE on their own may fail to produce realistic results when the difference between individual properties and local interactions play a significant role in determining the relationship between populations as well as between species and their surrounding environment. Furthermore, PDE are limited to analysis in a temporal dimension as they are strictly aspatial.

CA can be considered the spatial equivalent to PDE and can provide benefits for ecological modelling (Wang et al. 2003). The first benefit is that CA are a spatial modelling concept that allows for examination of the model throughout space and over time; thus, researchers can visually analyze the process at each time step and allow for complete integration in a GIS environment. Secondly, explicit knowledge of the system is not required for creating a valid ecological model with CA because the necessary information for the modelled process is included in the form of rules rather than mathematical equations. This allows for direct incorporation of knowledge from experts that is not necessarily restricted to hard data. This is particularly useful when attempting to model problems that are extremely complex (Jeltsch et al. 1996). Third, compared to PDE, CA have more flexibility to implement individual property differences and local interactions, and it is suggested that this is especially evident with the use of object-oriented programming (Chen et al. 2002). There have been attempts to model PDE using CA (Keymer et al. 1998) in order to utilize both types of models, however, PDE can be computationally inefficient when approximated on a grid, especially compared with computing CA alone (Darwen and Green 1996). Lastly, CA are a suitable modelling approach for ecological dynamics because it has the ability to incorporate numerous simultaneous interactions at various locations in a landscape leading to results that may be difficult to predict. For these reasons, a CA approach was chosen for modelling MPB-induced tree mortality in a GIS environment. However, the problems regarding uncertainty and incomplete knowledge in defining cell states needed to be addressed.

One approach for dealing with uncertainty and incomplete knowledge in GIS and RS has been the use of fuzzy set theory, which was introduced to the field of geography by Bezdek's (1984) fuzzy c-means algorithm (Robinson 2003). The application of fuzzy set theory has received substantial attention within the realm of GIS and RS research, such as defining characteristics of geographic objects (Burrough 1996, Wang and Hall 1996), defining soil classes (Burrough et al. 1992, Davidson et al. 1994), spatio-temporal and temporal interpolation (Dragicevic and Marceau 1999, 2000), and RS classification (Wang 1990, Foody 1996, Cheng et al. 2001). With regards to applications with forest landscapes, fuzzy sets have been used to appropriately define stand boundaries from digital thematic maps (Lowell and Gold 1995), identifying forest types (Brown 1998) and identifying individual trees (Brandtberg 2002).

1.6 Thesis Overview

This thesis is composed of four chapters. After the Introduction, chapter two explains the development of the initial input for the CA model. The value of a cell state in the input information was based on the certainty that a tree inhabiting the cell was a member of the set of susceptible trees. Membership to a set was determined by a fuzzy membership function that was constructed with the use of expert knowledge and available data. The fuzzy values derived from the process were used to determine the susceptibility of different areas in the forest to attack. The susceptibility data were validated using the frequency of observed attack locations, where the maps were considered valid if areas containing high susceptibility trees were attacked more frequently than areas containing trees of lower susceptibility. While the initial purpose of this section was to develop the input for the CA mdoel, the final product could prove to be useful for forest management to evaluate strategies in the presence of potential MPB infestations.

Chapter three is based on the development and understanding of a CA for modelling patterns of MPB-induced tree mortality. The input for the model is based on fuzzy cell states that represent individual tree susceptibility to attack. The main objective was to explore a method for handling fuzzy cell states in the CA transition rules. The rules for the model explain that trees of high susceptibility require fewer insects present in the landscape than trees of low susceptibility in order for them to become attacked. As MPB population increases, less susceptible trees are attacked. The logic of the model is in accordance with MPB attack behaviour as described by Safranyik et al. (1999a). The model parameters were calibrated by comparing modelled and observed attack locations.

Chapter four is the concluding section of the thesis, and summarizes the results from completed research, discusses the potential and limitations of the employed method, and provides suggestions for future work.

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CHAPTER 2 – INTEGRATING HIGH-RESOLUTION RS, GIS AND FUZZY SET THEORY FOR IDENTIFYING SUSCEPTIBLITY AREAS OF FOREST INSECT INFESTATIONS[1]

2.1 Abstract

The use of fuzzy set theory has become common in remote sensing (RS) and geographic information system (GIS) applications to deal with issues surrounding uncertainty of geospatial datasets. The objective of this study is to develop a model that integrates the concept of fuzzy set theory with RS and GIS in order to produce susceptibility maps of insect infestations in forest landscapes. Fuzzy set theory was applied to information extracted from multiple-year high resolution RS data and integrated in a raster-based GIS in order to create a map indicating the spatial variation of insect susceptibility in a landscape. Variable-specific fuzzy membership functions were developed based on expert knowledge and existing data, and integrated through a semantic import model. The results from a case study on mountain pine beetle (*Dendroctonus ponderosae* Hopkins) illustrate that the model provides a method to successfully estimate areas of varying susceptibility to insect infestation from high-resolution remote sensing images. It was concluded that fuzzy sets are an adequate method for dealing with uncertainty in defining susceptibility variables. The

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[1] The following chapter has been submitted to the *International Journal of Remote Sensing* under the co-authorship of Suzana Dragicevic and Arthur Roberts.

susceptibility maps can be utilized for guiding management decisions based on the spatial aspects of insect-host relationships.

2.2 Introduction

High-resolution remote sensing (RS) images of forest landscapes can provide resource managers with important information regarding insect infestations. Images captured over multiple years can be used to investigate the spatial dynamics of a variety of forest pests, especially those that have significant effects on the forest canopy. While numerous attempts at detecting damage caused by insects have proved successful (Gimbarzevsky et al. 1992, Franklin et al. 2003, Roberts et al. 2003, Skakun et al. 2003, Nelson et al. 2004, Riel et al. 2004), research that utilizes high resolution RS data and the analytical tools of geographical information systems (GIS) for estimating the susceptibility of forests to various insects is not extensive. This is because forests are complex systems that are heterogeneous and continuously changing over space and time. Therefore, it is difficult to capture the dynamic nature of forests in RS images at appropriate spatial and temporal resolutions to be able fully analyze the data in a GIS. Understanding the complexity of forest systems is also limited by the lack of multiple year RS data at an established study site in order to provide information on the nature of insect infestations through time. Furthermore, insect behaviour varies across space and time causing uncertainty in quantitatively describing how specific variables affect susceptibility. Despite existing methods developed in the RS and GIS literature to deal with uncertainty of spatial data (Foody 1996, Cheng 2002) little has been done in relation to the heterogeneous and continuous nature of forest processes (Brown 1988, Lowell 1996).

Uncertainty in Geographical Information Science (GIScience) refers to the degree of inexactness when assigning precise values to both locations and attribute that define geographical data (Robinson 2003). For example, defining boundaries between forest stands in a GIS from RS data may include uncertainty because the exact boundary between two stands cannot be precisely determined, or bias may be introduced when defining the stands as either deciduous, coniferous or mixed (Lowell and Gold 1995) . This explains why the majority of susceptibility mapping to date, that integrates RS and GIS, has focused on processes governed by larger spatial and temporal scales such as landslides (Van Westen 2000, Cevik and Topal 2003, Sarkar and Kanungo 2004), while less research has been performed on short-term dynamic process with greater spatial heterogeneity such as insect infestations (Luther et al. 1997). Uncertainty can also be caused by a lack and insufficiency of relevant data that are necessary to study geographic phenomena. In the absence of sufficient data it is difficult to measure how various elements influence the spatial variation of concepts such as susceptibility. Therefore, there is a need for methods that acknowledge uncertainty in extracting information from RS data for developing susceptibility maps of potential insect disturbance. A method using fuzzy set theory to address this need is proposed in this study.

Fuzzy set theory, developed by Zadeh (1965), has played a role in dealing with uncertainty in RS and GIS since Bezdek (1984) introduced the fuzzy c-means algorithm (Robinson 2003). The use of fuzzy sets and fuzzy logic reasoning was found suitable to address the nature of geographic boundaries and the fact that spatial objects do not always precisely fit into the classes in which they are assigned by traditional RS or GIS procedures. Fuzzy set theory is useful for applications in forestry (Lowell and Gold 1995, Brown 1998, Brandtberg 2002) and in dealing with uncertainty in defining areas of potential insect infestations.

In order to address these issues, the main objective of this study was to develop a model that integrates the concept of fuzzy set theory with RS and GIS in order to define the susceptibility of different areas to insect infestation in forest landscapes. High-resolution data play an important role in this model because forest infestation is often studied at the individual tree level. Higher pixel resolution records more precise detail and information about the site areas than low-resolution. For example, susceptibility to infestation is affected by variables such as the number of host trees in a stand, the locations of trees attacked in the previous year, physical constraints, and biological characteristics of trees, among others, depending on the insect-host relationship as well as the population dynamics of the insect itself. Each of these variables can in some form be measured from high-resolution images in RS and GIS systems. Sensors fixed on satellites and airplanes have the ability to capture images with resolutions higher than 1m; however, few studies such as Bentz and Enderson (2004) have utilized high-resolution images for predicting patterns of tree mortality due to insect infestation.

The proposed model for defining the susceptibility of areas in a forest first extracts information regarding susceptibility from multiple-year high-resolution RS data of a site in order to create a raster GIS database. Fuzzy set theory was used to define how various characteristics of a forest affect susceptibility to insect infestation, and to define the spatial elements of the variables involved in the infestation process. By using fuzzy operators, information from each variable was integrated to produce a final map defining areas represented by level of susceptibility. While modifications will have to be made to the model to fit different forest insects in different geographical locations, the overall framework is applicable to numerous scenarios due to similar life cycle characteristics. In this study, the model was tested with a case study of the mountain pine beetle (*Dendroctonus ponderosae* Hopkins) in the central interior of British Columbia, Canada.

2.3 Background to Fuzzy Set Theory

Fuzzy sets allow for partial membership to one or more classes, thus objects are represented by a value based on a membership continuum between 0 and 1. Conversely, crisp sets either fully contain or do not contain an object, which is reflected in the fact that membership to a class is binary and represented by either 0 or 1 (Zadeh, 1965). The membership function of an element x belonging to a fuzzy set A is represented by $\mu_A : U \rightarrow [0,1]$, where U is the universal set of x. This explains that the function associates a graded membership with each point x in U. The development of the fuzzy membership function is an important component of using fuzzy sets, and is accomplished using expert opinion and available data to define the function.

Traditionally, applications in RS and GIS have operated with crisp sets, where spatial information taken from the real world is represented as discrete objects in space with a discrete definition. Fuzzy sets are employed to handle problems with accuracy and precision as well as a lack of sufficient data when defining objects and their attributes. These problems create difficulties when attempting to represent spatial entities as discrete objects in a computer. As a result, the idea of fuzzy objects and fuzzy attributes was developed so that entities could be described as belonging to a particular class. The application of fuzzy set theory has received substantial attention within the realm of

GIScience. Specifically, the concepts of fuzzy sets have been employed for defining the spatial and attribute characteristics of geographic objects (Burrough 1996, Wang and Hall 1996), soil classes (Burrough et al. 1992, Davidson et al. 1994), temporal interpolation (Dragicevic and Marceau 2000), and enhancing classification of remote sensing images (Wang 1990, Zhang and Foody 1998, Brandtberg 2002, Lucieer and Kraak 2004). With regards to applications with forest landscapes, fuzzy sets have been used to deal with issues surrounding digitizing objects from thematic maps (Lowell and Gold 1995), identifying forest types (Brown 1998) and identifying individual trees (Brandtberg 2002). The challenge still exists to use fuzzy sets for developing a realistic representation of susceptibility to various spatial phenomena.

The need for fuzzy sets in developing susceptibility maps can be better understood by considering an application with the mountain pine beetle (MPB) as an example of forest infestation. A review of this insect's life cycle suggests that a large pine tree within a pure stand of pine trees close to a previous attack, and distanced from large constraints, is more likely to be susceptible than the opposite for each given variable. However, a problem arises when attempting to define how the terms *large*, *all*, *close* and *distanced* affect susceptibility due to the issues regarding representation of reality from RS images in a GIS. With fuzzy sets and fuzzy logic reasoning, membership functions can be developed to explain how these variables affect susceptibility based on existing knowledge. Instead of defining each location in space as either, for example, a large tree or not a large tree, close to a previous attack or not close, etc., each location receives a membership based on the degree to which they represent such variables. As a result of combining these variables, the value representing susceptibility is continuous between 0 and 1 instead of defined as either susceptible or non-susceptible.

2.4 Methodology

This section is divided into two parts. The first presents the model framework for integrating fuzzy sets with multiple-year high-resolution RS data and GIS operations in order to produce susceptibility maps of insect infestation in forest landscapes. The second part is a case study applying the model to MPB infestations.

2.4.1 Model for Fuzzy Susceptibility Mapping

The procedure that defines the model for developing susceptibility maps is illustrated in figure 2.1 where grey boxes indicate processes and the white boxes represent the inputs and outputs of the processes. The first step includes identification of the variables responsible for susceptibility to insect infestation that can be measured from RS images. In the second step, the initial-year image is interpreted in order to integrate these variables in a raster-based GIS. This can be accomplished by either combining image interpretation techniques with ground truth data or by using existing image classifications. This results in multiple layers of information that correspond to different variables.

For the third step, each layer enters a fuzzification process to assign a value that represents both the susceptibility variable and the positional uncertainty of intermediate objects. The susceptibility variables were fuzzified using specifically constructed fuzzy

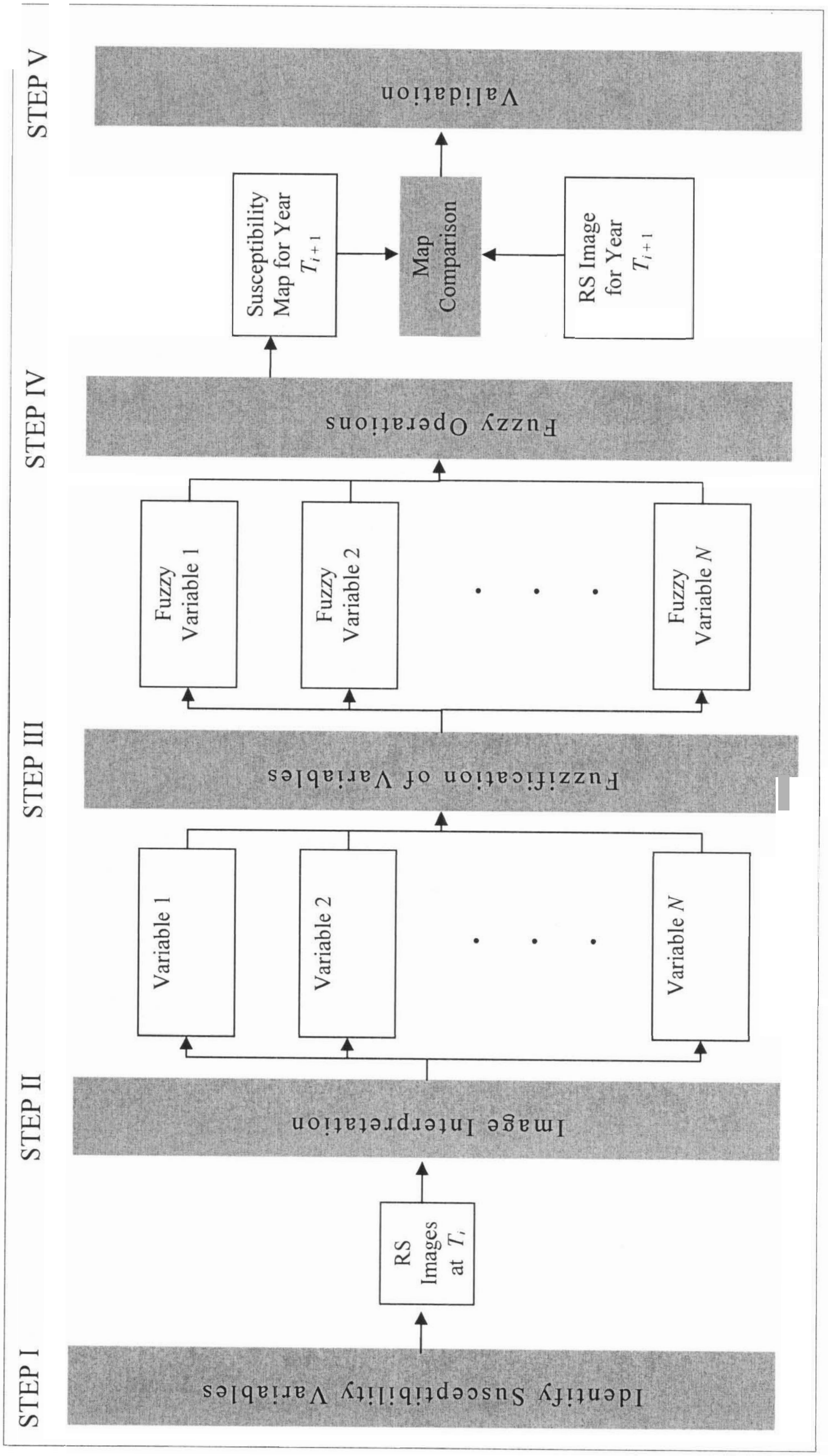

Figure 2-1. Model framework for development and validation of susceptibility maps.

membership functions in order to assign a value to each variable that represents the degree to which they belong to a particular set that has an influence on susceptibility. The fuzzy functions are developed using the semantic import model (Robinson 2003) which uses accumulated expert knowledge of particular insects and the nature of infestations to assign the membership grade. Robinson (2003) provided a discussion on the different types of functions commonly used for geographic phenomena. The output from this stage is layers with information corresponding to each fuzzy variable.

With regards to positional uncertainty, forest stands are considered intermediate objects because the boundary between two different stands cannot be precisely determined. Therefore, the fuzzy area between stands can be defined based on its degree of belonging to either adjacent stand. A fuzzy membership function for belonging to a stand is developed by assigning those cells that are definitely in the stand a value of 1 for full membership, and those cells that are definitely in the adjacent stand a value of 0 to represent non-membership. Each cell in the transition zone receives a value based on its distance to a stand and the susceptibility of that stand to attack, which is given by the equation

$$\mu(Su)\varepsilon TZ = \mathrm{MAX}\left[\mu(Su_{\mathrm{stand}i})\left(\frac{1}{\mu(D_{\mathrm{stand}i})}\right), \mu(Su_{\mathrm{stand}j})\left(\frac{1}{\mu(D_{\mathrm{stand}j})}\right)\right], \tag{2.1}$$

where $\mu(Su)\varepsilon TZ$ is the fuzzy membership of susceptibility of a cell in transition zone TZ, $\mu(Su_{\mathrm{stand}})$ is the fuzzy value for susceptibility of the stand, and $\mu(D_{\mathrm{stand}})$ is the inverse distance D to the nearest cell in that stand. Stands i and j are the two stands joined by the transition area. The equation states that susceptibility of a cell in a transition zone obtains a value based on the product of $\mu(Su)$ of the adjacent stand and the inverse distance to the nearest cell in that stand. Each cell in the transition zone will have two values because it is a member of two stands; the maximum value is obtained in order to represent the higher level of susceptibility. This stage completes the development of the susceptibility map.

The fourth step includes the use of fuzzy operators in order to combine all fuzzy variables into one layer to represent the overall susceptibility in the landscape. The operator computationally obtains one value from the raster layers for each cell location for the output layer. GIS applications traditionally rely upon minimum or maximum operators; however, while their use remains valid for a variety of applications, minimum and maximum for combining susceptibility variables will reflect the worst and best case scenarios, respectively. This can limit the ability to detect the influence of the values from each layer, and can also create problems when calibrating values or performing a sensitivity analysis, because changes in values that are not the minimum or maximum remain unnoticed. A simple solution to this problem is to obtain the algebraic product (i.e. multiplicative operator) of each cell location from the raster layers (Robinson, 2003). This ensures that the susceptibility of each cell takes into account all the variables used in the operation. Therefore, if any membership value has a value of 0, the final value for a cell will be represented by 0, and only when all membership values are 1 will a cell be represented with a value of 1. The result from this step is a single raster layer containing the susceptibility of each cell $\mu(Su)$ to insect infestation based upon the defined variables.

The fifth and final step of the susceptibility model represents the model validation procedure and can be performed if the RS data for consecutive years are available. The validation procedure can by comparing the observed locations of attack at T_{i+1} with the susceptibility map of T_{i+1} in order to determine if higher susceptibility areas experienced a higher frequency of MPB attack than lower susceptibility areas. A statistical test such as a *large-sample test comparing two population proportions* (McClave and Sincich 2000) can be used to determine if a significantly higher proportion of attack occurred in areas of higher susceptibility than lower susceptibility.

2.4.2 Case Study: Mountain Pine Beetle in British Columbia, Canada

MPB is the most serious insect disturbance agent of mature lodgepole pine, *Pinus contorta*, ponderosa pine, *Pinus ponderosa*, in western North America (Safranyik 1988). Trees killed by this insect can be readily detected by high resolution RS imagery as they exhibit a red colour in the year following a mortal attack (Wulder and Dymond 2004). The susceptibility model can be customized for MPB susceptibility as illustrated in figure 2.2.

2.4.2.1 Step I. Identify Susceptibility Variables

The first step is to identify the variables that define the forest's susceptibility to MPB. A life cycle review demonstrates that species diversity within a stand (Amman and Baker 1972, Shore et al. 2000), distance to trees attacked in the previous year (Thomson 1991, Safranyik et al. 1999b), and host tree diameter (Mitchell and Preisler 1991, Moeck and Simmons 1991, Perkins and Roberts 2003) are significant indicators of susceptibility to attack. Exploratory analysis of the data revealed that distance to large deciduous stands also played a role in influencing areas attacked by MPB. These four variables can be used in the model in order to develop maps of forest susceptibility.

2.4.2.2 Step II. Image Interpretation

The high resolution multi-spectral aerial photographs used for this study were collected in 2002 and 2003 at a pixel resolution of 15cm (Roberts et al. 2003). The ground truth data for the aerial photographs were collected in 2001 by the British Columbia Ministry of Forestry (BC MoF), and in 2002 by Simon Fraser University and BC MoF. The sites are located in the central interior of British Columbia: Site 1 centred at 53°38′45″W and 123°26′20″N, and Site 2 centred at 53°29′07″W and 125°06′40″N (Figure 2.3). The size of each site is approximately 750m^2 in which there is minimal variation in elevation. The forest in these areas is dominated by lodgepole pine, and contained a relatively small composition of white spruce, *Picea glauca*, Douglas fir, *Pseudotsuga menziesii*, and trembling aspen, *Populus tremuloides*. The sites also contained roads and open areas that were previously created for forestry operations and forest management.

The images were interpreted to specify the four variables and produce GIS raster-based information for (1) *Attacked Trees* variable - polygons indicating trees attacked by MPB at T_i (2000), T_{i+1} (2001) and T_{i+2} (2002); (2) *Constraints* variable – polygons representing water bodies, open areas and deciduous stands; (3) *Species Diversity* variable - polygons defining stands of deciduous and coniferous trees and individual coniferous trees found in deciduous stands; (4) *Tree Size* variable - polygons defining the density of coniferous areas (i.e. high, medium and low). The values for density in this

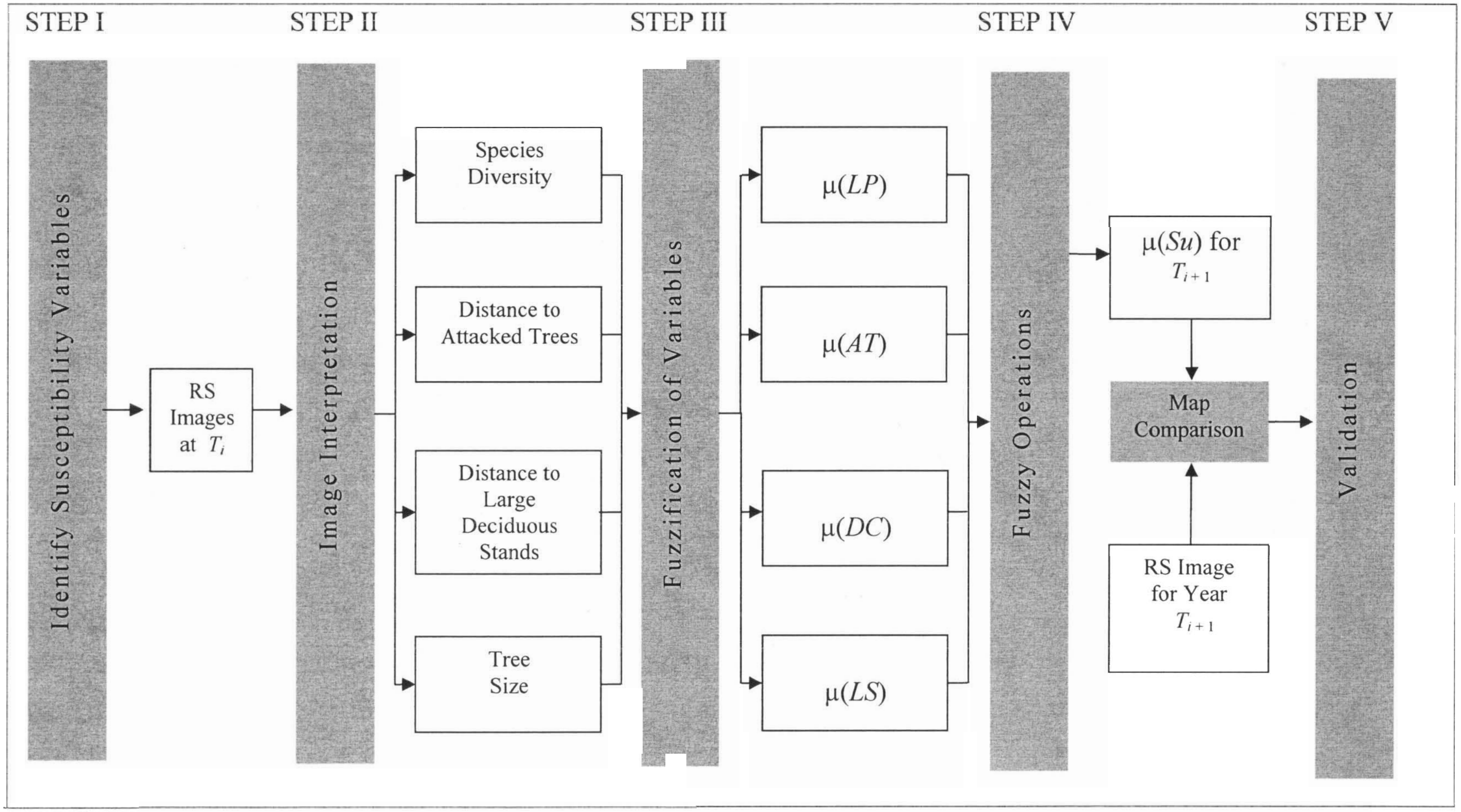

Figure 2-2. Model framework for development and validation of susceptibility maps specific to mountain pine beetle. The model combines the fuzzy variables of species diversity $\mu(LP)$, distance to attack $\mu(AT)$, distance to large deciduous stand $\mu(DC)$, and tree size $\mu(LS)$.

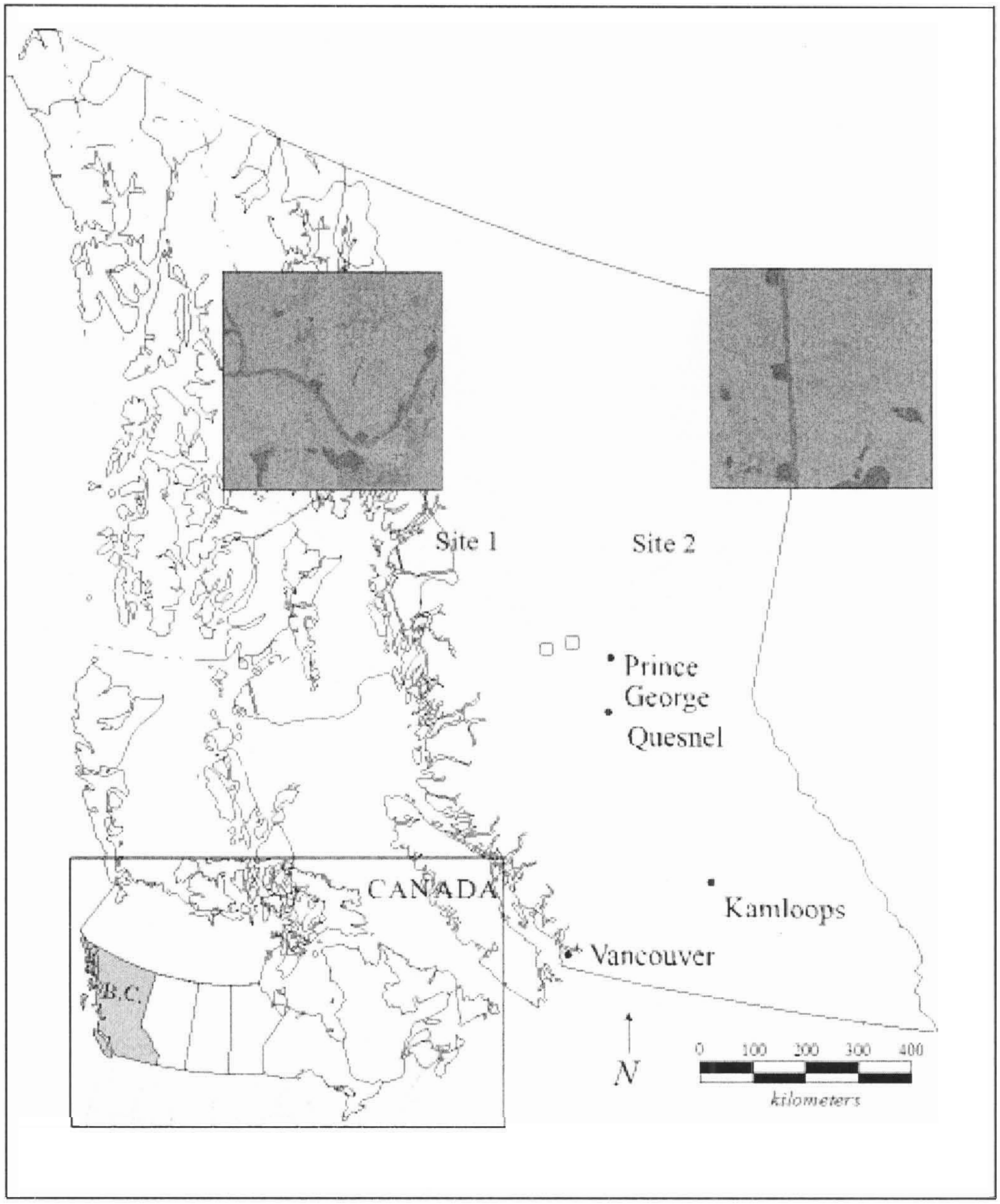

Figure 2-3. Study sites in central interior of British Columbia, Canada.

layer were used to construct information on tree size. After digitizing was completed, each layer was converted to raster files in order to perform cell-based operations.

A resolution of 1m was chosen during the conversion to raster files because the smallest significant tree crowns were estimated to occupy this area. The choice to use this spatial resolution inflicted some bias in the procedure because the original image resolution was significantly higher.

2.4.2.3 Step III. Fuzzification

In this step specific fuzzy membership functions were developed in order to assign a value that represented both the susceptibility variable and the positional uncertainty of the intermediate objects.

The *Species Diversity* variable was used to define the proportion of host trees in a stand. A stand is considered more susceptible if it only contains lodgepole pine. First, all deciduous and coniferous stands were identified and digitized, and an estimation of the proportion of each species in each stand was obtained from the ground truth data. A fuzzy membership function for pure lodgepole pine stand $\mu(LP)$ was then developed using expert knowledge. An increase in the proportion of host trees in a stand leads to a higher membership of $\mu(LP)$, which corresponds to an increase in susceptibility (Amman and Baker 1972, Thomson 1991, Shore and Safranyik 1992). Figure 2.4a illustrates this relationship that is defined by the location of d_1 and d_2 on the x-axis. A shift in d_1 to the right increases the influence of non-host trees to susceptibility. This means that susceptibility does not change as the proportion of lodgepole pine becomes higher until x reaches d_1. Conversely, a shift in d_2 to the left dampens the effect of diversity on susceptibility. The fuzzy membership function is defined by

$$\mu(LP) = \begin{Bmatrix} 0 & \mathit{for}\ x < d_1 \\ \dfrac{x - d_1}{d_2 - d_1} & \mathit{for}\ d_1 \le x \le d_2 \\ 1 & \mathit{for}\ x > d_2 \end{Bmatrix} \tag{2.2}$$

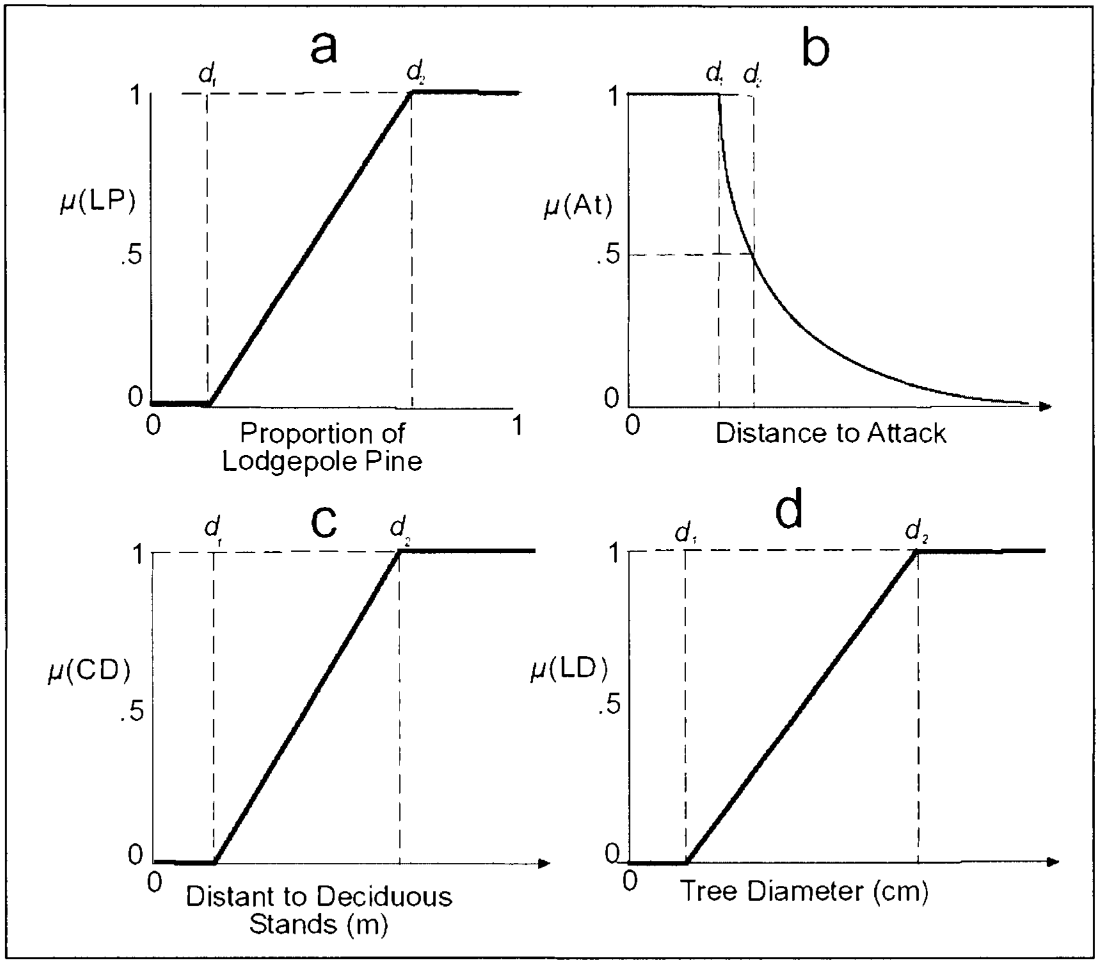

Figure 2-4. Potential fuzzy membership functions for susceptibility *μ(Su)* to mountain pine beetle attack based on (a) species diversity *μ(LP)*, (b) distance to attack *μ(AT)*, (c) distance to large deciduous stands *μ(CD)*, and (d) tree size *μ(LP)*.

The *Attacked Trees* variable was used to build layers representing trees attacked in T_i, T_{i+1} and T_{i+2} (the latter two are used to develop susceptibility maps for subsequent years and for validation). A standard distance function was performed on the layer containing trees attacked in T_i. This provides the distance between each location in space and the nearest attacked tree. Next, a fuzzy membership function was constructed in order to assign each cell a value representing the degree to which it is close to a cell attacked in the previous year $\mu(AT)$. Thomson (1991) explained that MPB first attack trees in a small patch, then move outwards to other areas, then outside the stand. This suggests a negative relationship between susceptibility and distance to attacked trees. This is supported by Shore and Safranyik's (1992) rating system where the likelihood of attack is considered greater the closer a tree is to the nearest infestation. However, the results from some studies suggest that this relationship is not linear (Safranyik et al. 1989), which is potentially due to a constant occurrence of attack within a certain distance from previously attacked trees, followed by a non-linear decrease as distance increases. This type of relationship can be represented using a *j-shaped* function shown in figure 2.4b, which is expressed as

$$\mu(AT) = \left\{ \begin{array}{ll} \dfrac{1}{1 + \left(\dfrac{x - d_2}{d_2 - d_1} \right)^2} & for \;\; x > d_1 \\ 1 & for \;\; x < d_1 \end{array} \right\}, \qquad (2.3)$$

where x is the distance between an infested tree and a susceptible host, d_1 is the location on the x-axis where $\mu(AT)$ begins to deviate from 1, and d_2 indicates the position of the curve where $\mu(AT) = 0.5$. As d_1 shifts to the left, the distance of constant occurrence of attack decreases, and the slope also shifts to the left. A shift of d_2 in either direction changes the nature of the curve.

The *Distance to Constraints* variable was used to obtain information on the impact large deciduous stands on susceptibility. Observations from images for both sites indicated that the attack was relatively low close to the large deciduous stands. This was characterized by positive relationship between increasing infestation and distance. An analytical procedure was performed to determine the distance over which large deciduous stands affect MPB, and the nature of this relationship. This information was then used to build a fuzzy membership function in order to assign a value to each cell representing proximity to large deciduous stands $\mu(CD)$. Figure 2.4c illustrates a linear function that can be explained by

$$\mu(CD) = \left\{ \begin{matrix} 0 & for \ \ x < d_1 \\ \frac{x - d_1}{d_2 - d_1} & for \ \ d_1 \leq x \leq d_2 \\ 1 & for \ \ x > d_2 \end{matrix} \right\}. \tag{2.4}$$

As d_1 moves to the right, the distance over which the beetle does not attack near large deciduous stands increases. As d_2 moves to the left, attack will occur closer to large deciduous stands.

The *Tree Size* variable was used to develop information regarding the overall tree size of a stand. The larger the trees in a stand, the more susceptible that stand will be to attack. The frequency of tree size is generally a function of stand density, which can be visually interpreted from the images. Stands exhibiting high density are younger stands that have yet to experience competitive exclusion, thus there are many trees of relatively small diameter. Conversely, low-density stands contain larger and older trees that have out-competed other trees, which in turn decreased the number of trees. Ground truth data were used to confirm if the visually defined levels of stand density contained different tree size distributions, and individual stands were then digitized and defined accordingly.

Next, a fuzzy membership function was developed that represented membership for the class of large trees $\mu(LT)$. The MPB susceptibility of a tree increases as diameter increases (Shore and Safranyik 1992, Hindmarch and Reid 2001). This was supported by the ground truth data. The value of $\mu(LT)$ is represented by a positive linear fuzzy function (figure 2.4d) which is explained by

$$\mu(LT) = \left\{ \begin{matrix} 0 \quad for \;\; x < d_1 \\ \\ \frac{x - d_1}{d_2 - d_1} \; for \; d_1 \leq x \leq d_2 \\ \\ 1 \quad for \; x > d_2 \end{matrix} \right\}. \tag{2.5}$$

Shifting d_1 to the left increases the size range of trees that are susceptible to attack. Moving d_2 either direction will affect the size of trees that are most susceptible. The degree of membership values for $\mu(LT)$ were then used in equation 2.6 to obtain a single fuzzy value for belonging to a stand with large trees:

$$\mu(LS) = 2[\Sigma(p\mu(LD))], \tag{2.6}$$

where p is the proportion of each tree size in the frequency distribution provided by the ground truth data. The products of p and $\mu(LD)$ are summed in order to represent the susceptibility given by the entire distribution of trees. The sum is multiplied by two in order to exaggerate the difference between stand susceptibility.

The final process in Step III was to transform the discrete boundaries of the forest stands into fuzzy boundaries. Applying equation 2.1 to the fuzzified *Species Diversity* and *Tree Size* layers ensured that all forest stands contained fuzzy boundaries that represented their intermediate nature.

2.4.2.4 Step IV. Fuzzy Operator

The four layers with fuzzy values were then combined using the operator mentioned in section one of methods. The result was a single map for each site showing the estimated degree of susceptibility $\mu(Su)$ of the various site areas in the forests for the T_{i+1}. The fuzzy operator for $\mu(Su)$ is expressed as

$$(Su) = \mu(LP) \times \mu(At) \times \mu(CD) \times \mu(LS). \qquad (2.7)$$

2.4.2.5 Step V. Validation

In order to validate the susceptibility maps for each site, the raster layer containing observed locations of insect attack for the year T_{i+1} was overlaid on the map of susceptibility at T_{i+1} to visually and statistically determine if the maps appropriately estimated areas of susceptibility. The susceptibility values from 0.1 to 1 were classed into *low, medium,* and *high*, susceptibility for the statistical analysis. A *large-sample test comparing two population proportions* (McClave and Sincich 2000) was used to determine if a significantly higher proportion of cells were attacked in areas of higher susceptibility than areas of lower susceptibility. The null and alternate hypotheses are therefore

$$\begin{aligned} &H_o: (p_1 - p_2) = 0 \\ &H_a: (p_1 - p_2) > 0 \end{aligned} \tag{2.8}$$

where p_1 and p_2 are the proportion of a higher susceptibility class and a lower susceptibility class, respectively. For this test, observed attack locations in areas of *high susceptibility* were compared with areas of *medium susceptibility*, areas of *medium susceptibility* were compared with areas of *low susceptibility*, and *low susceptibility* was compared to *zero susceptibility*. The test is described as

$$z = \frac{p_1 - p_2}{\sigma_{(p_1 - p_2)}}, \tag{2.9}$$

where the null hypothesis is rejected if $z > z_\alpha$.

The entire procedure for this case study was repeated with replacing the T_i attack locations raster layer with the T_{i+1} attack locations layer in order to develop a susceptibility map for T_{i+2}.

2.5 Results

2.5.1 Fuzzy Membership Functions

The values for d_1 and d_2 were assigned for each variable based on expert opinion and information from research literature. Figure 2.5 depicts these values for each variable with the respective function. For membership in $\mu(LP)$, $d_1 = 0$ and $d_2 = 1$ were selected to represent a 0.1 increase in susceptibility with every 10% increase in lodgepole pine trees in the stand. Therefore, the influence of the presence of host trees was directly proportional to the number of host trees present.

With regards to membership in $\mu(AT)$, this study used information from a collection of resources to derive a *j-shaped* function where $d_1 = 50$m and $d_2 = 60$m. This function explains that susceptibility due to dispersal behaviour is high over the first 50m, and then decreases non-linearly over the remaining dispersal range.

The values for d_1 and d_2 for $\mu(DC)$ were determined from an analysis of ground truth data. Figure 2.6 reveals that minimal attack occurs close to deciduous stands greater than 300 cells (17.32m^2) in size, and observations of attack increase linearly up to approximately 50m from the these stands. This information suggest that for membership in $\mu(CD)$, $d_1 = 0$ because the attacked cell itself is not susceptible, and $d_2 = 50$m as it is this distance that specifies observations of attack become independent from the distance to large deciduous stands.

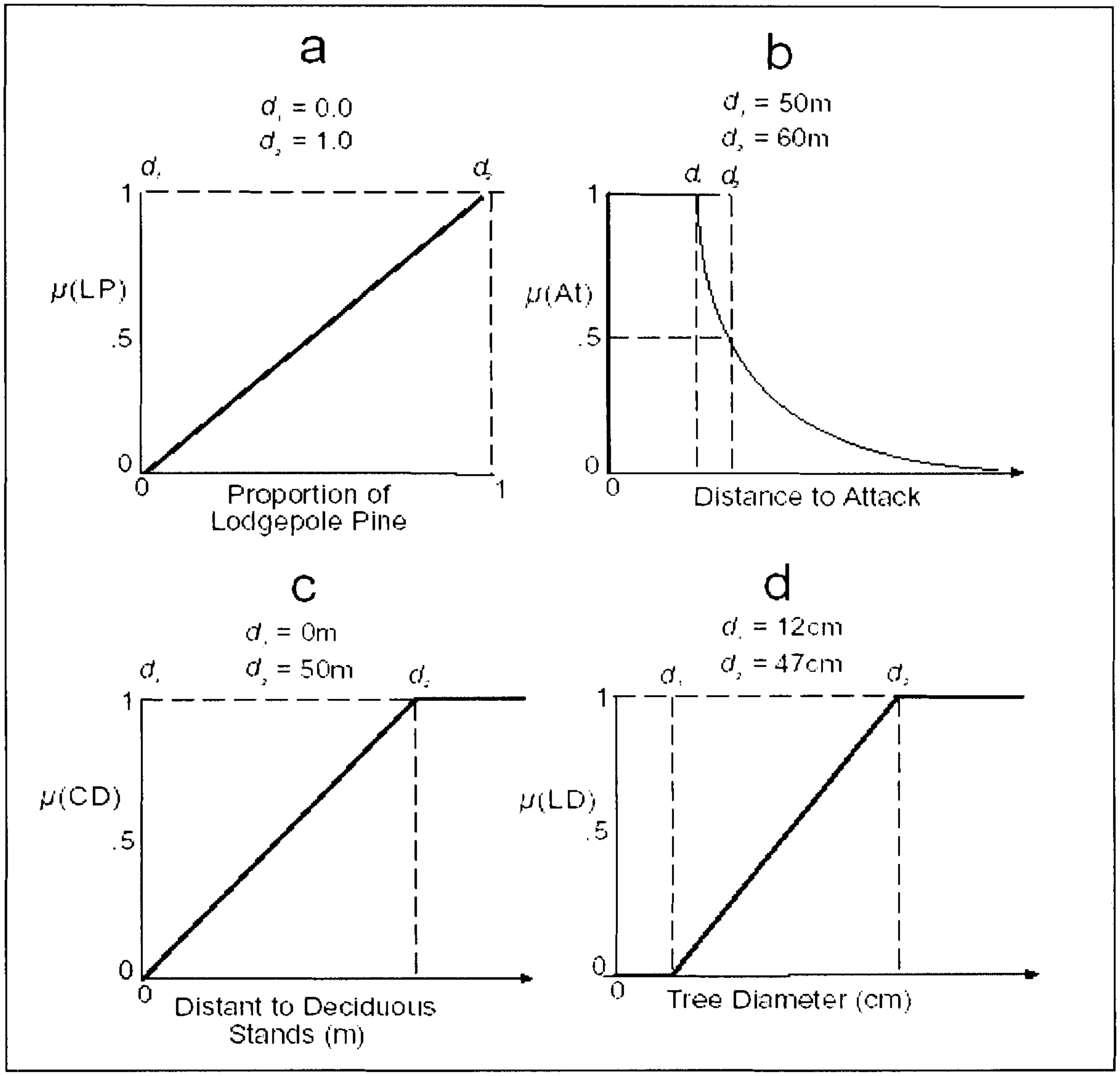

Figure 2-5. Actual fuzzy membership functions for susceptibility μ(Su) to mountain pine beetle attack based on (a) species diversity *μ(LP)*, (b) distance to attack *μ(AT)*, (c) distance to large deciduous stands *μ(CD)*, and (d) tree size *μ(LP)*.

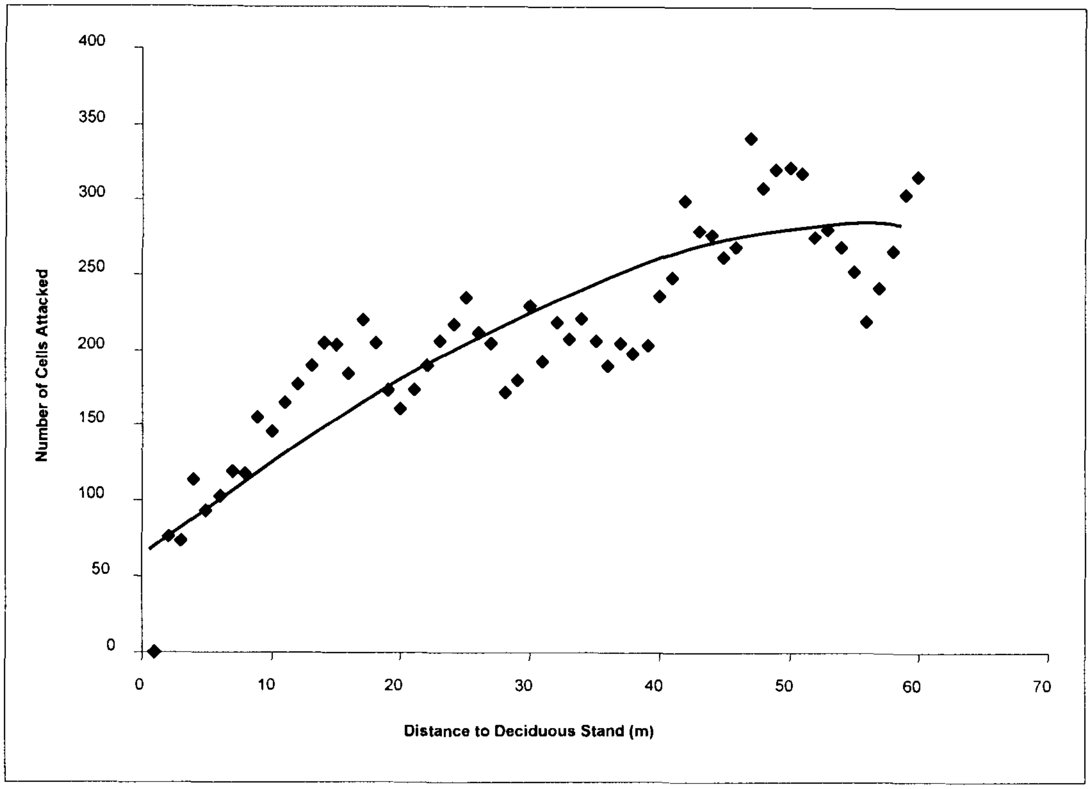

Figure 2-6. Relationship between number of trees attacked and distance to large deciduous stands.

Finally, information regarding membership in $\mu(LS)$ was gathered from the literature and also collected from ground truth data (see Figure 2.7). As previous literature suggests (Amman and Baker 1972, Shore and Safranyik 1992, Preisler and Mitchell 1993, Mata et al. 2003), larger trees were attacked more frequently than smaller trees. Although very large trees were underrepresented in the ground truth data, there did exist an obvious linear increase for those age classes that were sufficiently represented. This suggests a linear fuzzy membership function for $\mu(LS)$. No trees in the ground truth data less than 15cm in diameter at breast height were attacked, d_1 = 14cm. All trees in the ground truth data larger than 46cm in diameter were attacked, therefore d_2 = 47cm.

The results from the GIS overlay procedure produced the fuzzy susceptibility maps for T_{i+1} (2001) and T_{i+2} (2002) are shown in figures 2.8a-b. These maps were then used with the original RS data for model validation.

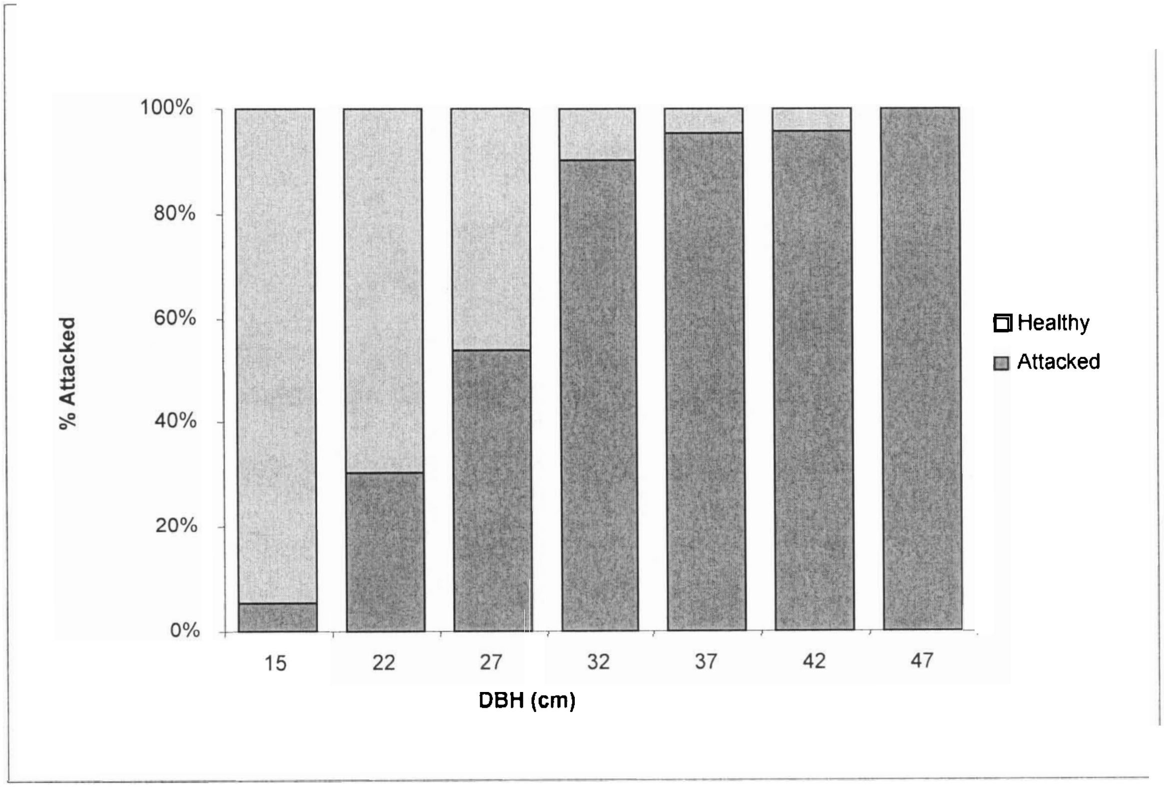

Figure 2-7. Ground truth data for the proportion of trees attacked (heavy and moderate) per age class.

2.5.2 Susceptibility Map Validation

In order to validate the model, the T_{i+1} and T_{i+2} attack layers were overlaid onto the appropriate susceptibility maps for both sites. Figure 2.9a-d provides for a visual comparison between the estimated areas of susceptibility and the observed locations of attack. The locations of attack in the high-resolution RS images are observed in Figure 2.10. Small areas of each site were magnified in order to illustrate the patterns of MPB attack over the two years. The images from 2002 show red trees that were killed by MPB in 2001, and grey trees killed by MPB before 2001. The 2003 images show red trees that were killed by MPB in 2002, and grey trees killed by MPB before 2002. The images illustrate that more attack was observed in areas of higher susceptibility at T_{i+1}, but attack became present in areas of lower susceptibility at T_{i+2}.

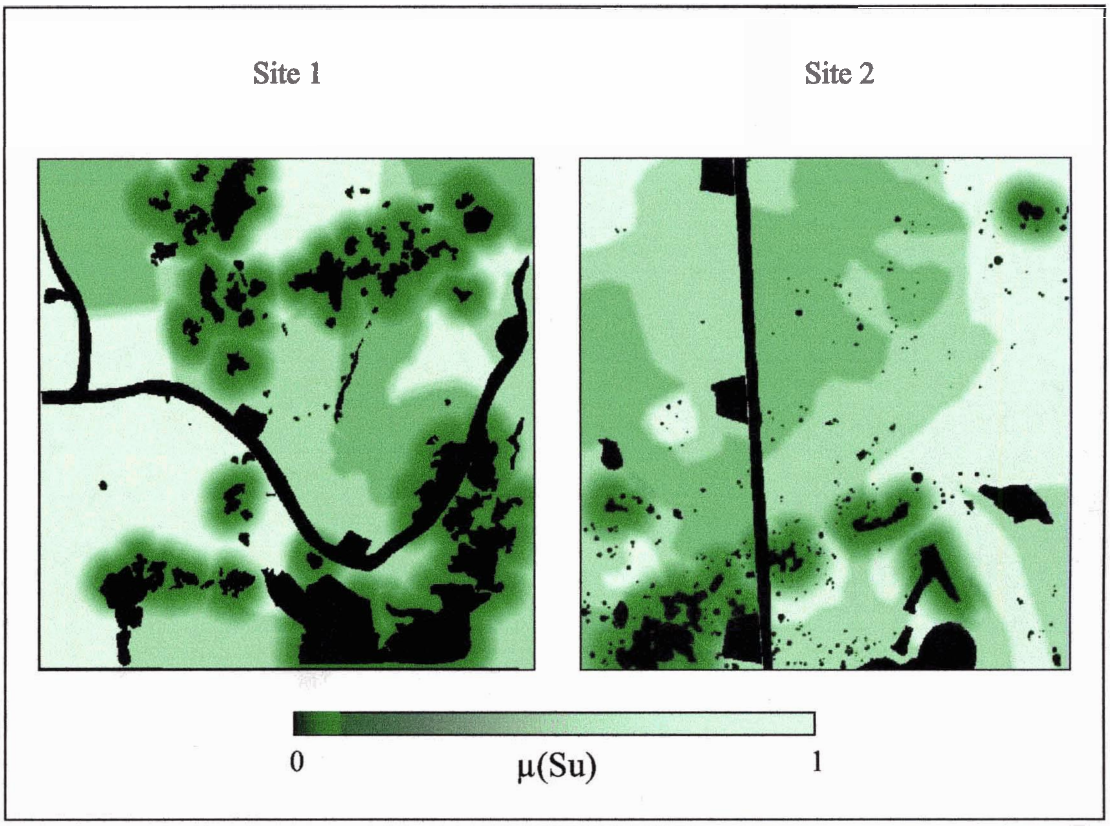

Figure 2-8. Susceptibility μ(Su) maps, resulting from fuzzy operations for Site 1 and Site 2. Dark tones indicate no susceptibility (i.e. roads and clear cuts) and light tones indicate high susceptibility.

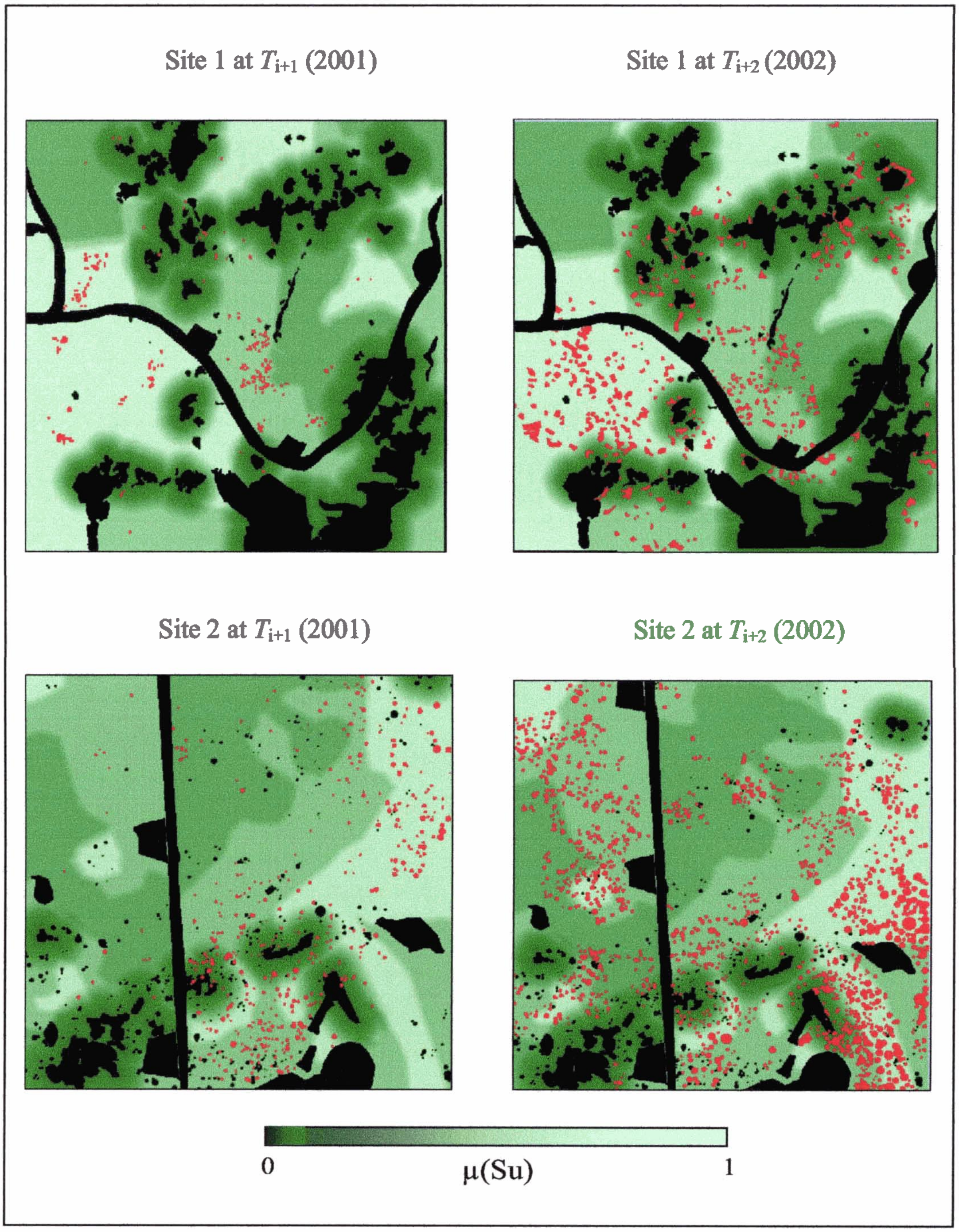

Figure 2-9. Validation of susceptibility maps using observed attack locations from aerial imagery for Site 1 at T_{i+1}, Site 1 at T_{i+2}, Site 2 at T_{i+1}, Site 2 at T_{i+2}. Red cells indicate trees attacked by mountain pine beetle.

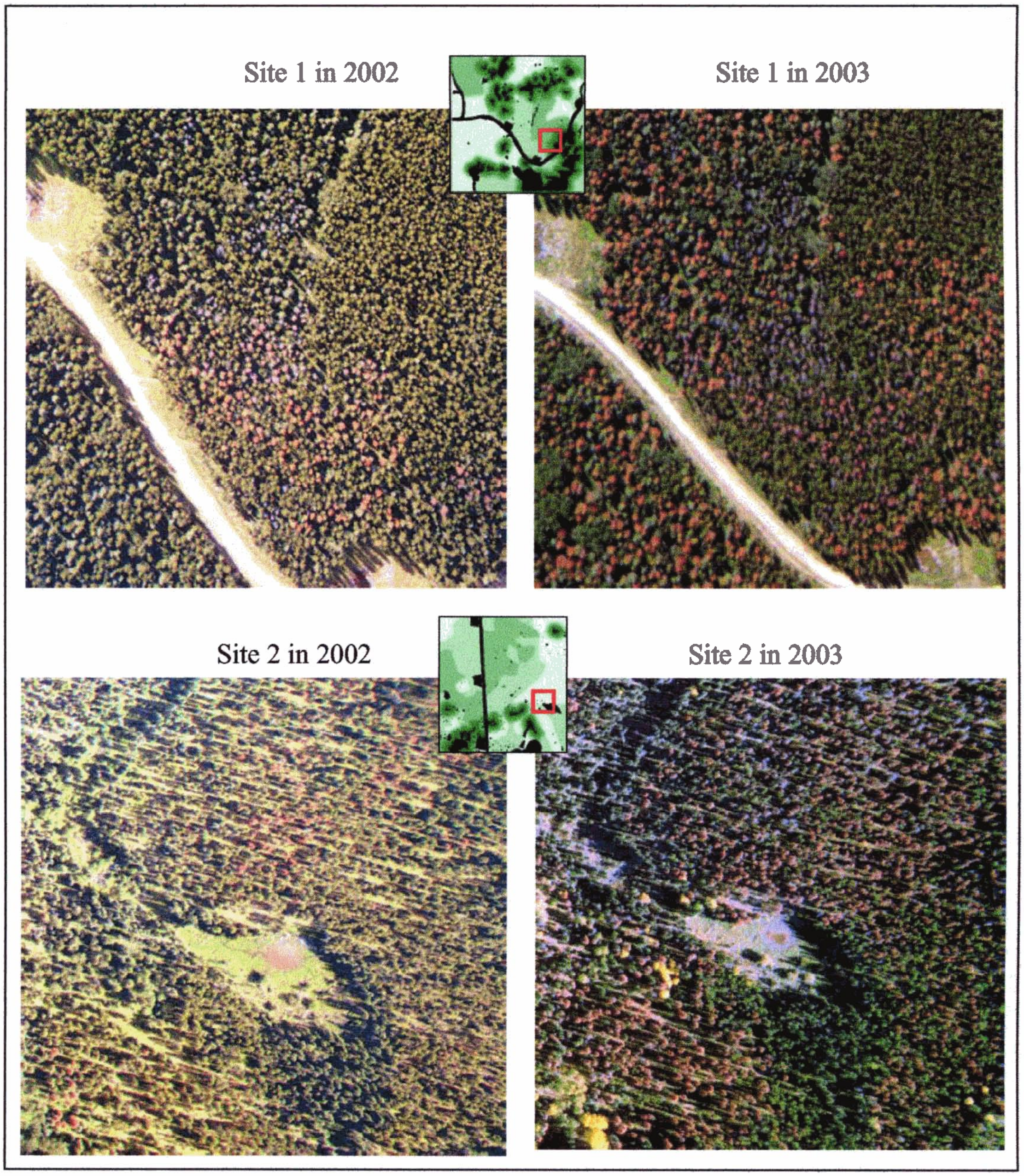

Figure 2-9b. Magnified aerial imagery of Site 1 and Site 2 from 2002 and 2003. For the 2002 imagery, trees attacked in 2001 appear red; trees attacked before 2001 appear grey. For the 2003 imagery, trees attacked in 2002 appear red; trees attacked before 2002 appear dark red or grey. Different stands can be visually distinguished based on tree size; larger trees are more susceptible and therefore are attacked sooner and more frequently.

Next, the proportion of attacked cells in each susceptibility class was tabulated. Figure 2.11a-b shows the proportion of cells attacked in each susceptibility class, which indicated that the high susceptibility class had the highest proportion of attack, and the proportion gradually decreased with a decrease in susceptibility rating. The one exception was for the zero susceptibility class for Site 2 at T_{i+2}.

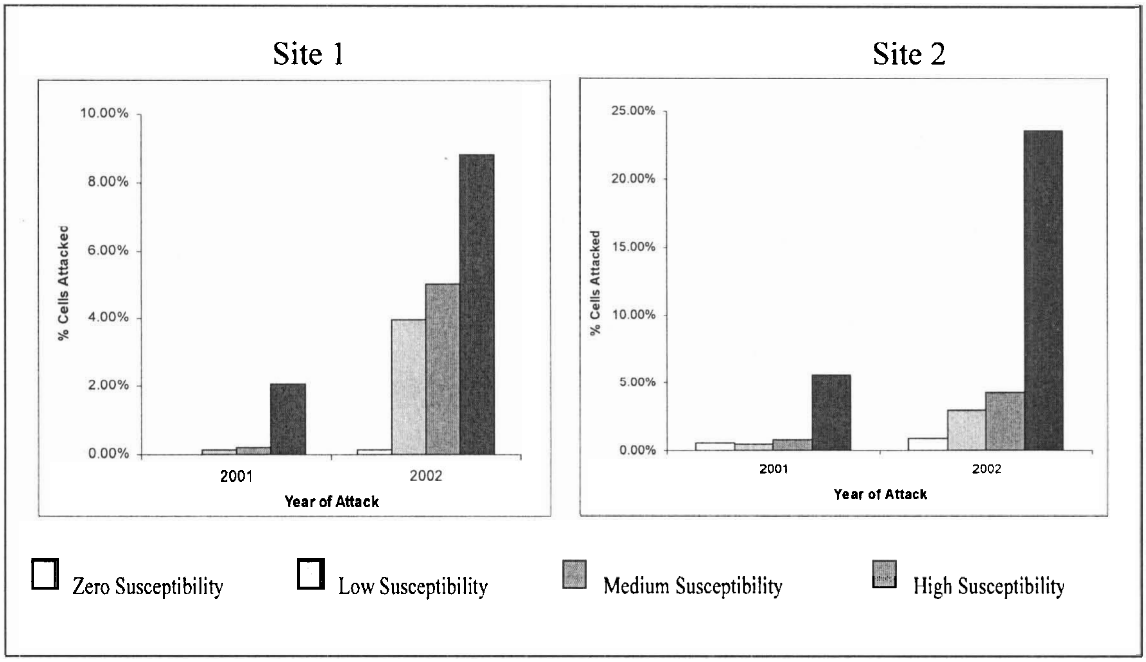

Figure 2-10. Proportion of cells attacked in each susceptibility class at T_{i+1} (2001 attack) and T_{i+2} (2002 attack) for Site 1 and Site 2.

The significance of these observations was statistically evaluated in the test for the hypothesis $(p_1 - p_2)$. The z-scores from the test are presented in Table 2. In order to reject the null hypothesis with 95% confidence, $z > 1.96$. These results indicate that most of the higher susceptibility classes contain a significantly greater proportion of cells that were attacked by MPB than lower susceptibility classes, with the exception of the difference between the medium and low susceptibility classes and low and zero susceptibility classes for Site 2 in T_{i+1}. Therefore, the null hypothesis was rejected for ten of the twelve tests.

Table 2.1. Proportion scores (z) for the *large-sample test comparing two proportions* (McClave and Sincich 2000). The z values indicate the proportional difference of MPB attacked cells in adjacent susceptibility classes. With 95% certainty, higher susceptibility classes experience significantly more attack if $z > 1.96$.

Site 1	T_{i+1} **(2001)**	T_{i+2} **(2002)**
High vs Medium	46.33	31.07
Medium vs Low	4.09	12.76
Low vs Zero	14.13	79.44
Site 2		
High vs Medium	12.77	165.81
Medium vs Low	1.33	15.34
Low vs Zero	-0.23	22.47

2.6 Conclusion

The results indicate that the methods in this study were mostly successful at classifying levels of susceptibility to MPB attack in the two sites. An issue of concern exists, however, with the locations of attack in areas of zero and low susceptibility for Site 2 at T_{i+2}, which were not significantly different from each other. A visual analysis of the original RS images confirms that pine beetle attack did occur in areas estimated as zero susceptibility, which were mostly single or small groups of lodgepole pine trees that were located within large deciduous stands. Due to digitizing errors, these trees were not properly identified. Furthermore, there appeared to be several attacked trees that were located on the perimeter and also within open areas. It should also be noted that the presence of attacked trees in the low susceptibility areas did not come as a surprise because it was expected that trees of lower susceptibility will eventually become attacked once higher susceptible trees are killed (Safranyik et al. 1999a).

The quality of the model stems from the ability to identify the degree of susceptibility of various areas coupled with acknowledging the uncertainty involved in model development. Although some may argue that probability theory could have been used to produce values from 0 to 1, fuzzy set theory was considered necessary in order to deal with the level of available data and available information for defining susceptibility. The spatial and temporal extent of the data was a main contributing factor in limiting the knowledge of MPB attack behaviour. With regards to the spatial extent, small study sites make it difficult to determine if there were attacked cells adjacent to the site boundary that could play an important factor in determining susceptibility. Furthermore, a limited spatial extent made the presence of clear-cut patches more significant. Clear-cuts occurred in some areas between the two years when the images were collected which removed important data components.

The fact that high resolution RS data on MPB infestations exists for a limited temporal frame limits the ability to monitor and study insect infestations over time. Long-term projections of susceptibility can be restricted by lack of information regarding insect locations for each year. The success of the model proposed in this study was partly due to knowing the locations of insects from the ground truth data in the year previous to when susceptibility was estimated. Susceptibility maps can, however, play a significant role in long-term forecasting when used as data sources in spatio-temporal models. These models would require greater knowledge of insect population dynamics in order to estimate their infestation behaviour over periods of time. Spatio-temporal models are commonly used in analyzing vegetation dynamics, but their use with datasets based on fuzzy sets has been largely unexplored.

The model explained in this research can be presented to forest management as a spatial decision support system (SDSS) that will allow forest managers to input spatial data of their forest areas in order to determine areas of potential infestation. Once a decision support framework is created, managers could test how different management scenarios affect susceptibility levels, such as sanitization through clear-cutting or selective logging.

The use of fuzzy set theory for GIS and RS applications can play a significant role in forestry research with numerous natural disturbance agents where dynamic complexity creates a situation where empirical results are not always consistent or readily available. For example, it is difficult to produce consistent results on insect dispersal when wind and temperature play a significant role. Such difficult issues can be addressed with the use of fuzzy sets derived from general expert knowledge. Applications for developing susceptibility maps with fuzzy sets can go beyond insect dispersal to include phenomena such as susceptibility to wildfire, wind, diseases and invasive species by having adequate data and information regarding the development of these specific membership functions. Integrating fuzzy set theory with GIS can also act as a decision support tool for forest management as landscapes can be digitally manipulated in order to find optimal practices in light of potential disturbances.

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CHAPTER 3 – A SPATIALLY EXPLICIT FUZZY-CONSTRAINED CELLULAR AUTOMATA MODEL OF FOREST INSECT INFESTATIONS[2]

3.1 Abstract

Geographical and ecological processes are complex systems where individual elements interact to create complex behaviour. These systems can be examined with spatially explicit models such as cellular automata (CA) that explain how interactions at the local level lead to global patterns. Tree mortality patterns caused by forest insects provide a good case for CA as local interactions lead to changes at the landscape level. However, problems exist with defining aspects of insect-host relationships that explain the susceptibility of a tree to insect attack. The main objective of this study is to develop a GIS-based CA model of forest insect infestations that incorporates fuzzy set theory in order to obtain information from high-resolution remote sensing (RS) images. The model is based on tree mortality patterns caused by outbreaks of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, in the central interior of British Columbia, Canada. Fuzzy sets are used in order to quantify the susceptibility of trees to MPB attack and to acknowledge the uncertainty inherent in dealing with geospatial data. Fuzzy values provide the input for the CA model where MPB attack behaviour is constrained by the susceptibility level of trees. The results reveal that CA modelling with fuzzy-based

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information can produce realistic patterns of MPB-induced tree mortality. Furthermore, fuzzy-constrained CA modelling can provide useful information for forest management in the presence of insect outbreaks.

3.2 Introduction

Geographical and ecological processes are complex dynamic systems with an inherently spatial nature. The complexity is manifest in the numerous elements that interact locally to produce global patterns that are difficult to predict, while the spatial nature is apparent in the significance of scale, distance and spatial arrangement of the interacting elements. Complex systems theory is suitable for incorporating both the complexity and spatial significance in ecological processes, and can provide results that enhance ecological knowledge for decision support systems. One class of complex system models that has recently gained recognition in ecology is cellular automata (CA) (Cannas et al. 1999, Grist 1999).

CA are dynamic models that are discrete in time, space, and state (Baltzer et al. 1998). CA models typically consist of five main components: 1) a grid of cells, 2) cell states, 3) the neighbourhood, 4) transition rules that determine how cells change from one state to another at each time step, and 5) the number of time steps for which the model is run (White and Engelen 2000). The grid is composed of a number of cells that are typically identical in size and shape. Cells at initial time T_i can take on an infinite number of states that are traditionally represented as discrete. The neighbourhood refers to the cells in a defined area surrounding each individual cell that will have an influence on the state of that cell at the next moment in time (i.e. T_{i+1}). The transition rules express how the state of each cell in the neighbourhood influences the future state of a cell from one time step to another. A CA model can be formulated as

$$s_{xy}^{T_i+1} = f(s_{xy}^{T_i}, N_{xy}^{T_i}), \qquad (3.1)$$

where $s_{xy}^{T_i}$ and $s_{xy}^{T_{i+1}}$ are the states of cell at a location described with x and y coordinates at time T_i and T_{i+1}, respectively; $N_{xy}^{T_i}$ represents the neighbourhood surrounding cell xy; f represents the transition rules that explain how the initial state will change in the next time step. The number of time steps refers to the temporal extent of the model.

The discrete nature of cell states makes CA attractive for spatio-temporal modelling in a geographic information system (GIS) raster-based environment, which describes the world as a static representation based on a discrete array of cells. GIS and CA are complementary with regards to spatio-temporal modelling as the former provides the spatial framework for geographic data while the latter contributes the temporal dimension for describing change. Furthermore, the ability to develop realistic spatial models within a GIS environment has progressed due to the increasing availability of remote sensing (RS) data. In geography, GIS-based CA have proven especially successful in simulations of urban dynamics (White and Engelen 1993, Batty and Xie 1994, Couclelis 1997, Clarke and Gaydos 1998), rural residential settlement patterns (Deadman et al. 1993), and socio-environmental systems (Engelen et al. 1995). CA models have also gained popularity in the field of ecology as discrete cell states can represent the presence of organisms at a given location which can change over time due to competition and resource allocation (Cannas et al. 1999, Grist 1999). Balzter et al. (1998) explain that discrete cell states are advantageous for modelling ecological processes because discrete state transition can be governed by a probability distribution based on the initial state of each cell.

While CA are applicable for modelling numerous ecological scenarios, problems exist when examining complex processes where cell states cannot be readily defined as discrete. A good example is representing a tree in a forest by its susceptibility to attack by an insect, whereby susceptibility is defined by numerous variables of the insect-host relationship. In such cases, two main problems exist with providing a binary definition (i.e. susceptible or not susceptible to attack by an insect).

The first problem concerns the issue of uncertainty in defining susceptibility. It is difficult to use traditional approaches to this problem such as defining a tree as either susceptible or not susceptible, or deriving the probability of a tree becoming attacked. This is due to the fact that insect disturbances are driven by numerous components of the insect-host relationship that are difficult to understand. Appreciating this relationship is further complicated by the presence of numerous climatic variables such as temperature, wind, humidity and precipitation, which, coupled with the geographic variation of a species' life cycle, produce varying results and incomplete knowledge on insect behaviour. Therefore, considering a raster-based representation or a forest landscape, significant uncertainty is present when attempting to assign a discrete binary or probability value to a cell describing a tree's susceptibility to attack. Furthermore, deriving probabilities requires sufficient data that illustrate the types of trees that are most likely to be attacked. However, the often-inappropriate spatial and temporal resolutions of commonly used geospatial data hamper the ability to study and understand the forest infestation process. Thus, it is difficult to determine attack patterns with large-scale images collected over a short or inappropriate time period.

The second problem is the inherent uncertainty in classifying RS data of forest landscapes in a GIS in order to obtain information on the susceptibility of trees in a forest (Lowell and Gold 1995). As forests are continuously changing over space and time, the value given to a cell through classification procedures only represents that location for the moment in time when the data were acquired. Processes such as insect infestations operate at refined spatial and temporal scales. The process itself is difficult to capture by remote sensing imagery due to the continuous change of an individual tree's appearance in the canopy at the local level. This leads to uncertain transition zones between forest stands of different sizes and different species where a discrete definition of a cell cannot be provided

As a solution to these two problems, fuzzy set theory has been suggested in situations where the presence of uncertainty prevents a discrete definition of cell states (Brown 1988, Robinson 1988) . Fuzzy sets, developed by Zadeh (1965), allow for membership to one and/or several sets, thus objects in space are represented by a fuzzy value between 0 and 1. The membership function of an element x belonging to a fuzzy set A (e.g. A = susceptibility of a cell to insect attack) is represented by $\mu(A) : U \rightarrow (0,1)$, where U is the universal set of x. This explains that the function associates a graded membership with each point x in U. Therefore, trees can be represented by 'fuzzy' values from 0 to 1 based on membership its the fuzzy set of susceptible trees. Many applications with fuzzy sets have proven useful in geography for defining soil classes (Burrough 1989), RS classification (Foody 1996), explaining sediment dynamics (Cheng 2002) and temporal interpolation (Dragicevic and Marceau 1999). Fuzzy sets have also been utilized in forestry for distinguishing stand boundaries (Brown 1998), digitising forest types (Lowell and Gold 1995) and identifying individual trees from high-resolution images (Brandtberg 2002).

The objective of this paper was to develop a fuzzy set theory driven methodology for developing a GIS-based CA model of insect-induced tree mortality patterns. The methodology used derived values of tree susceptibility to attack by mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, in the central interior of British Columbia, Canada where MPB commonly attack susceptible lodgepole pine, *Pinus contorta*. Outbreaks of MPB in recent decades have generated interest in understanding the behaviour of the insect and the patterns of tree mortality that it inflicts on a landscape. In particular, studies have examined the use of partial differential equations (Bolstad et al. 1997, Logan et al. 1998, Powell et al. 2000), climate models (Jackson and Murphy 2004), remote sensing techniques (Franklin et al. 2003, Roberts et al. 2003) landscape-scale spatial analysis (Fall et al. 2004, Nelson et al. 2004) and spatio-temporal models (Riel et al. 2004). This study employed the use of a fuzzy-constrained CA model because patterns of MPB-induced mortality are applicable to the modelling logic of CA, and also to incorporating existing uncertainty and incomplete knowledge with a definition of trees' susceptibility to MPB attack.

3.3 Discrete versus Fuzzy CA

The use of discrete cell states for CA modelling has been suitable for a variety of ecological applications where cells represent the presence or absence of organisms in order to model different forms of species competition (Jeltsch et al. 1996, Wilson and Nisbet 1997, Grist 1999). Furthermore, discrete states are easily determined when the initial CA grid is either developed from field data (Matsinos and Troumbis 2002) or from a hypothetical study site (Darwen and Green 1996, Jeltsch et al. 1996, Cannas et al. 1999, Grist 1999). Discrete cell states are considered appropriate in both situations because the information for the initial grid was not obtained from a time-dependant "screenshot" of an ecological landscape.

The notion of relaxing traditional CA characteristics to accommodate non-discrete or continuous components was introduced independently in the 1970's through various computer applications and remained strictly theoretical (Wolfram 2002). More recently, non-discrete cell states were used in the field of physics (Cattaneo et al. 1997) where the limitations of traditional CA were examined in order to develop 'continuous-states' that produce chaotic properties. Following this, Zhu and Liu (2000) used a continuous state CA for simulating crystalline etching whereby the authors found improved results over conventional CA methods.

Parallel to the use of non-discrete cell states in these fields was the development of CA models using fuzzy sets and fuzzy logic for defining transition rules in biological and land use applications. Ito and Gunji (1997) provided an explanation of using fuzzy logic for describing the intrinsic ambiguities in non-linear biological systems with CA as the model framework. A CA wildfire model was developed by Mraz et al. (1999) using fuzzy logic in order to drive the decision process for determining cells to be burned by a spreading fire. Furthermore, Wu (1998) and Liu and Phinn (2001) explored the use of fuzzy reasoning for controlling transition rules for modelling urban encroachment on rural land in a GIS environment. These studies illustrate the utility of using fuzzy approaches for acknowledging uncertainties in developing CA models. Coupled with the notion of non-discrete cell states, these studies demonstrate that the traditional discrete definition of CA components can be altered in order to provide realistic results.

3.4 Methods

The fuzzy-constrained CA for MPB-induced tree mortality patterns was conducted using high-resolution RS images collected in 2002 and 2003 at a spatial (pixel) resolution of 15 cm from two forest sites in the central interior in British Columbia. Site 1 is centred at 53°38′45″W and 123°26′20″N, and Site 2 centred at 53°29′07″W and 125°06′40″N. Each site is approximately 750 m x 750 m, in which there exists minimal variation in elevation. The forests are dominated by lodgepole pine, and contained relatively small proportions of white spruce, *Picea glauca*, Douglas fir, *Pseudotsuga menziesii*, and trembling aspen, *Populus tremuloides*. Roads and open areas without trees are also present in the sites that were previously constructed for forestry operations.

The methodology for this study was composed of two main parts (Figure 3.1). Part I consisted of the development of the Susceptibility Model, and the static output was combined with a map of observed MPB attack as input for the CA model. Part II was the development and calibration of the dynamic CA for modelling patterns of MPB-induced tree mortality.

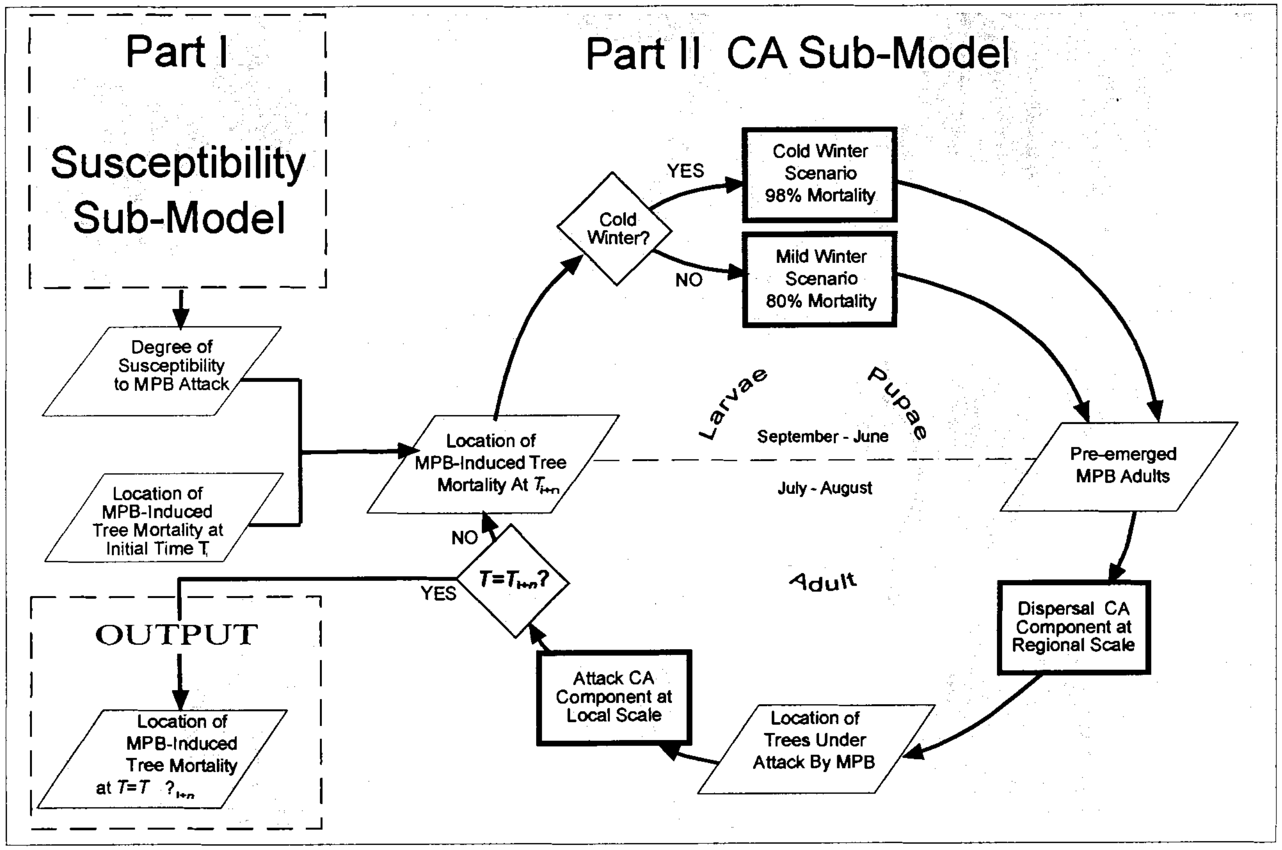


Figure 3-1. Schematic diagram for the fuzzy-constrained GIS-based cellular automata model of forest insect infestation. Part I indicates Susceptible Model and Part II indicates CA Model.

3.4.1 Part I - Susceptibility Model

The first objective of the Susceptibility Model was to identify the locations of trees killed by MPB in 2000, 2001 and 2002. Trees attacked in the year previous to when the images were collected exhibit an observable red colour; trees attacked before the previous year exhibit a grey colour. The locations of MPB-induced tree mortality that occurred in 2000 and 2001 were obtained from the 2002 imagery, while tree mortality in 2002 was identified from the 2003 imagery. A 1 m cell resolution was selected to represent the information that was aggregated from the high-resolution RS images to fit the scale of the size of the average interpreted tree crown surface.

The second objective of the susceptibility model was to develop a fuzzy set-based representation of each site based on the susceptibility of each tree to MPB attack. The 2002 imagery was used to distinguish the difference between those cells that contain living lodgepole pine trees and those cells that do not. Cells not containing living lodgepole pine trees were assigned a value of 0 to represent a constant zero susceptibility to MPB attack. All cells containing living lodgepole pine were assigned four separate values indicating susceptibility to MPB attack. The four variables were: 1) the proportion of lodgepole pine trees in the stand in which the tree is located, 2) the distance to the nearest large deciduous stand, 3) the distance to the nearest tree attacked in the previous year (i.e. the year 2000), and 4) the size of the tree. The justification for using these variables is provided below. The four values for each cell were transformed into a fuzzy membership value between 0 and 1 using a semantic import model based on expert knowledge. The semantic export model uses expert knowledge in order to construct fuzzy membership functions that determines the fuzzy value that corresponds to each value for a specific variable (Robinson 1988). The first value of susceptibility was the proportion of lodgepole pine trees in a stand. A greater proportion of lodgepole pine trees would increase the susceptibility of trees in the stand (Amman and Baker 1972, Thomson 1991). Stands were identified as having a low, medium or high proportion of lodgepole pine. The ground truth data provided an estimated proportion of lodgepole pine associated with the different levels. Each cell was assigned a value based on the estimated proportion of lodgepole pine in the stand in which the cell is located. Membership to as stand of *Pure Lodgepole Pine* μ (*LP*) was represented by a linear function where a 0.1 increase in susceptibility coincided with a 10% increase in lodgepole pine trees in the stand (Figure 3.2a). Therefore, the influence of the presence of host trees was directly proportional to the number of host trees present. The equation for the membership function for μ (*LP*) is thus described with

$$\mu(LP) = \left\{ \begin{array}{ll} 0 & for \;\; x < d_1 \\ \dfrac{x - d_1}{d_2 - d_1} & for \;\; d_1 \leq x \leq d_2 \\ 1 & for \;\; x > d_2 \end{array} \right\}, \qquad (3.2)$$

where, for a positive linear membership function, d_1 represents the location on the x-axis where the function begins to diverge from 0, and d_2 represents the location on the x-axis where the function begins to diverge from 1.

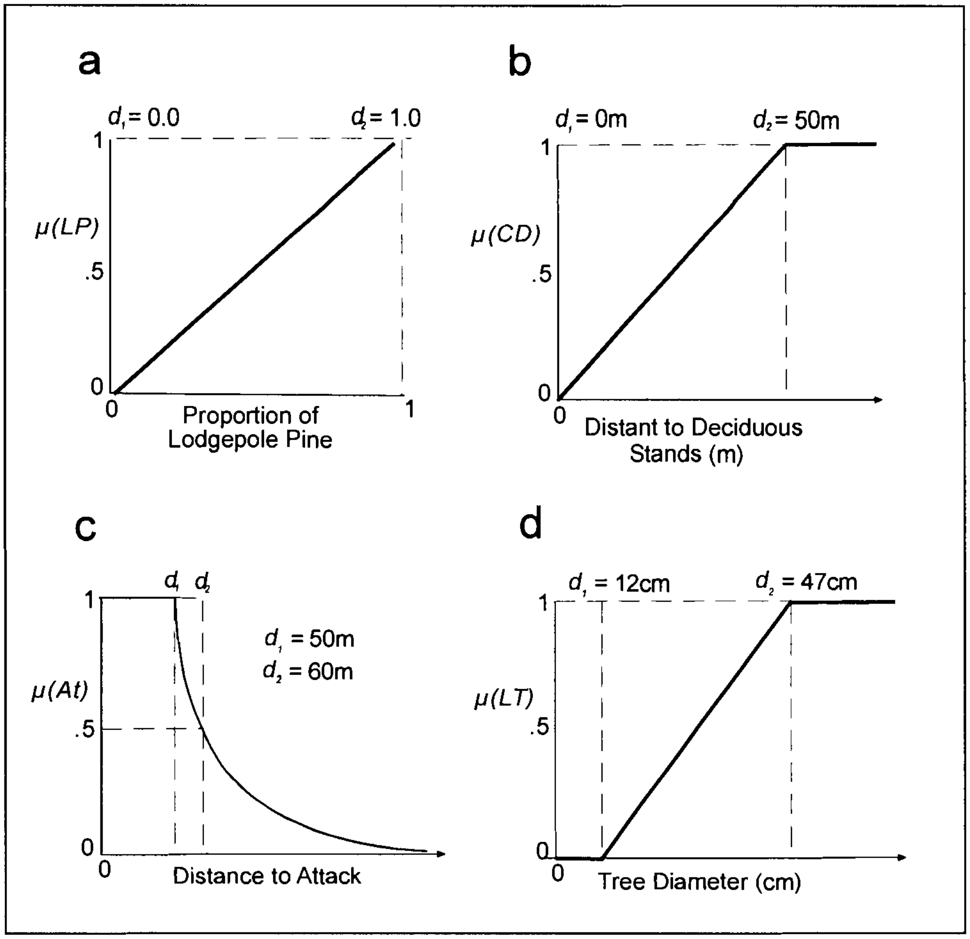


Figure 3-2. Fuzzy membership functions for susceptibility $\mu(Su)$ **to mountain pine beetle attack based on (a) species diversity** $\mu(LP)$**, (b) distance to attack** $\mu(AT)$**, (c) distance to large deciduous stands** $\mu(CD)$**, and (d) tree size** $\mu(LP)$**.**

The second value of susceptibility was the distance of the cell to the nearest large deciduous stand (Figure 3.2b). Image analysis of both sites indicated that the frequency of MPB attack was relatively low close to large deciduous stands that were greater than 17.32m^2. An analysis of the ground truth data revealed that the frequency of attack was minimal close to large deciduous stands and increased linearly to a distance of 50 m. Therefore, the degree to belonging to the set of lodgepole pine trees *Close to a Large Deciduous Stand* $\mu(CD)$ was defined by a linear membership function as explained by

$$\mu(CD) = \begin{cases} 0 & for \quad x < d_1 \\ \dfrac{x - d_1}{d_2 - d_1} & for \quad d_1 \leq x \leq d_2 \\ 1 & for \quad x > d_2 \end{cases}. \tag{3.3}$$

The third susceptibility value was the distance between the cell and the nearest tree that was attacked in the previous year. Studies suggest that lodgepole pine experience a higher frequency of attack the closer they are to infested trees (Thomson 1991), therefore a shorter distance to an attacked tree would result in a higher susceptibility. This value was obtained by calculating the distance from each susceptible tree to the nearest tree attacked in 2000. However, the relationship between frequency of attack and trees previously attacked is not necessarily linear (Safranyik et al. 1989), which is potentially due to a constant occurrence of attack within a certain distance from previously attacked trees, followed by a non-linear decrease as distance increases. Therefore, the degree to belonging to the set of trees *Close to a Previously Attacked Tree* $\mu(AT)$ was defined by a *j-shaped* function (Figure 3.2c). This function explains that susceptibility due to dispersal behaviour is high over the first 50m, and then decreases non-linearly over the remaining dispersal range. The membership to $\mu(AT)$ is given by the equation

$$\mu(AT) = \begin{cases} \dfrac{1}{1 + \left(\dfrac{x - d_2}{d_2 - d_1} \right)^2} & for \quad x > d_1 \\ 1 & for \quad x < d_1 \end{cases}, \tag{3.4}$$

where d_1 is the location on the x-axis where the membership function begins to diverge from 1, and d_2 is the point where the function crosses the fuzzy value of 0.5.

The fourth value of susceptibility was an estimate of the size of the tree, as larger diameter trees are more susceptible as they are older and less able to resist mass attack by MPB (Shore and Safranyik 1992, Hindmarch and Reid 2001). Tree size was estimated based on a visual interpretation of the density of trees in a stand. Stands exhibiting a relatively high density of trees were considered younger stands that have yet to experience competitive exclusion, thus there are many trees of relatively small diameter. Low-density stands contain larger and older trees that have managed to out-compete other trees, which decrease the density of trees in a stand. Stands containing lodgepole pine were digitised based on low, medium and high tree density. The ground truth data provided a sample of tree sizes located in the stands of different density levels. The tree size of a tree was based on an estimate of the overall frequency distribution of tree sizes in a stand given the density of that stand. The ground truth data then provided information regarding the frequency of tree sizes that were attacked by MPB. This information was used to develop the fuzzy membership function to define the degree of belonging to the set of *Large Trees* μ (*LT*). This information coupled with knowledge from the literature suggested a linear fuzzy membership function for μ (*LT*) (Figure 3.2d), which is explained by

$$\mu(LT) = \begin{Bmatrix} 0 \quad for \quad x < d_1 \\ \\ \dfrac{x - d_1}{d_2 - d_1} \; for \; d_1 \le x \le d_2 \\ \\ 1 \quad for \; x > d_2 \end{Bmatrix}. \tag{3.5}$$

The uncertainty in defining the boundaries between stands of different tree sizes and different species was introduced in the functions of $\mu(LT)$ and $\mu(LP)$. Fuzzy boundaries were developed to acknowledge the area between stands where difficulty arises when defining the state of the cell. In order to accomplish this, the $\mu(LT)$ and $\mu(LP)$ values of a cell in the fuzzy zone (represented by $\mu_{FZ}(LT)$ and $\mu_{FZ}(LP)$ was a function of the inverse distance to the nearest cell in an adjacent stand and the $\mu(LT)$ or $\mu(LP)$ value of that cell. This is explained for $\mu(LT)$ by the equation

$$\mu_{FZ}(LT) = \text{MAX}\left[\mu(LT_i)\left(\frac{1}{D}\right), \mu(LT_j)\left(\frac{1}{D}\right)\right], \tag{3.6}$$

where $\mu(LT_i)$ and $\mu(LT_j)$ are the values of the nearest cell in adjacent stands i and j, respectively, and D is the distance to the nearest cell the adjacent stands. Each cell in the fuzzy zone will have two values as it is a member of two stands; therefore, the maximum value is obtained in order to represent the higher level of susceptibility. At the completion of this procedure, each cell in the dataset contained either a $\mu(LT)$ value or a $\mu_{FZ}(LT)$ value to represent membership to the set of large trees depending on if the cell was located in the fuzzy zone. Similarly, the value of a cell in the transition zone between stands of different species was defined by

$$\mu_{FZ}(LP) = \text{MAX}\left[\mu(LP_i)\left(\frac{1}{D}\right)\right],\left[\mu(LP_j)\left(\frac{1}{D}\right)\right]. \tag{3.7}$$

Therefore, a cell contained either a $\mu(LT)$ value or a $\mu_{FZ}(LT)$ values to represent membership to the set of pure lodgepole pine stands.

The four variables for each cell were combined using an algebraic operator which resulted in a single value representing the susceptibility $\mu(Su)$ of a tree. The operator is defined as

$$\mu(Su) = \left[\mu(LP), \mu_{FZ}(LP)\right] \times \mu(CD) \times \mu(AT) \times \left[\mu(LT), \mu_{FZ}(LT)\right]. \tag{3.8}$$

The final output of the Susceptibility Model was a map for each site indicating the susceptibility values $\mu(Su)$ of each tree to MPB attack. The locations of trees killed by MPB in the year 2000 were integrated into the susceptibility maps in order to be used as the initial input for the fuzzy-constrained CA model at time T_i as presented in Figure 3.1 (Part I).

3.4.2 Part II - Cellular Automata Model

The intention of the model is to emulate tree mortality pattern based on the premise provided by Safranyik et al. (1999a) that highly susceptible trees are attacked sooner and more frequently than less susceptible trees. Figure 3.1, Part II illustrates the three main components of the CA model: *MPB winter mortality*, the *MPB Dispersal CA sub-model*, and the *MPB Attack CA sub-model*. One complete cycle of the CA model simulation is at the temporal scale of one year, which is the lifespan of MPB in the British Columbia interior. A complete cycle is referred to as a time step; the number of time steps can be specified before running the model. Each component is explained in detail below.

3.4.2.1 Modelling MPB Winter Mortality

The input dataset for the fuzzy-constrained CA enters the model in the fall when tree mortality from MPB attack of that year has been intiated. At this point, female beetles have begun constructing vertical egg galleries in the phloem of the attacked tree, and eggs are laid and hatched within a couple of weeks. The various growth stages of MPB development (i.e. the larvae and pupae stages) take place over the winter months as the beetles feed on the phloem of the tree (Safranyik 1988). During the winter months, the larvae and pupae are vulnerable to declining temperatures that can cause large-scale mortality. Acute cold temperature events (i.e. -30 C°) in late autumn (i.e. October to mid-November) or early spring (i.e. March) have the most significant effect on MPB survival because during these times the insects are at a particular stage when they are not cold-tolerant (Bentz et al. 2001, Jenkins et al. 2001). Such events can lead to MPB mortality of approximately 98% or higher (Safranyik 2004). Conversely, severe cold temperatures occurring for several days between mid-November and February may not have a significant impact on MPB mortality as it is during this period that the insects are most cold-tolerant (Carroll and Safranyik 2004). In the absence of severe cold events during late autumn or early spring, winter mortality can decrease to 80% which can lead to landscape-scale outbreaks of MPB (Safranyik 2004).

A generalized winter temperature component was integrated in the model where either a *Cold Winter Sub-Model* or a *Mild Winter Sub-Model* was selected depending on minimum temperatures reached during late autumn or early spring. Minimum temperatures were examined from data provided by a nearby weather station (Environment Canada 2003) for the years when the RS images were collected. If temperatures reached -30 C° during vulnerable periods, the *Cold Winter Sub-Model* was used to inflict a 98% mortality during that winter. Conversely, if the -30 C° threshold was not reached over the specified time period, then the *Mild Winter Sub-Model* was used to inflict a mortality level of 80%. Winter mortality was performed in each model by eliminating a percentage of random infested trees from the forest. The term 'elimination' means that the MPB in the tree are killed, however the tree remains in the forest and is still considered dead but are no longer infested.

The output from the *MPB Winter Mortality* was a layer representing the location of MPB who had reached adulthood. This layer also contained the degree of susceptibility $\mu(Su)$ values representing the susceptibility of non-attacked lodgepole pine trees to attack in the coming summer. However, the $\mu(Su)$ values required updating at this point because the distance to attacked trees had changed as some of the previously attacked trees no longer contained MPB after the *Winter Mortality Model.* In order to accomplish the updating of susceptibility values $\mu(Su)$, the value for $\mu(AT)$ was recalculated and equation 2.7 was applied. The result was a data layer of susceptible trees and trees containing pre-emerged adult MPB.

3.4.2.2 Modelling MPB Dispersal at Global Scale

Adult MPB usually mature in late July to early August when, weather permitting, they synchronically emerge from host trees. Female beetles emerge first and disperse varying distances in search of a tree to attack. MPB Dispersal was depicted using a *Dispersal CA sub-model* (Figure 3.1, Part II) that operates at the global scale of the entire study site. The constraint of the model was that the initial female MPB could only disperse within the stand or to a nearby stand; however it was considered that female MPB could not disperse outside of the study area nor could other beetles disperse from outside the study area. The maximum distance between stands in the study area was calculated from the RS images to be 250 m. Therefore a large neighbourhood of 500 x 500 cells was used in order to depict the pattern of MPB dispersal behaviour.

The transition rules of the *Dispersal CA sub-model* were governed by a function that described the relationship between the degree of susceptibility $\mu(Su)$ of a tree and the number (calculate in percentage) of trees in the neighbourhood that contained MPB adults (N_{MPB}). Higher values of $\mu(Su)$ required a lower N_{MPB} in order for a successful attack to become initiated, while lower $\mu(Su)$ values required a larger N_{MPB}. This logic is consistent with the explanation that highly susceptible trees require less MPB in order to overcome the tree's defensive mechanisms (Safranyik et al. 1989). Difficulty arose when determining the function that defined the transition rules because the function shape had to consider MPB dispersal and attacking characteristics. Therefore, three functions were tested to determine their suitability for modelling the dispersal of MPB: (1) *linear function*, which is a straight line given by the equation $f(x) = ax + b$; (2) exponential *function*, which, given by the equation $f(x) = e^x$, raises the mathematical constant e to a variable power, and (3) *power function* (otherwise know as an allometric function), which raises a variable number by a fixed power and is represented by the equation $f(x) = x^a$. The shapes of the functions are presented in Figure 3.3. The CA rules state that a successful attack of cell at coordinates *x,y* will be initiated if N_{MPB} of cell *xy* is equal to or greater than the function for a given value of $\mu(Su)$. This is illustrated in Figure 3.3, where a $\mu(Su)$ value of 1.0 only requires that $N_{\mathrm{MPB}} = 2\%$ when using any of the functions. However, as $\mu(Su)$ values decrease, the difference between N_{MPB} for each function increases. For example, for $\mu(Su) = 0.4$, the linear function requires $N_{\mathrm{MPB}} = 50\%$, the exponential function $N_{\mathrm{MPB}} = 25\%$, and the power function $N_{\mathrm{MPB}} = 10\%$. The *Dispersal CA sub-model* was run for one time step, which is the equivalent of the time needed for female MPB to disperse and begin attacking susceptible trees. The output of this *sub-model* was the location of trees under attack by MPB.

3.4.2.3 Modelling Attack at the Local Scale

As the initial attack resumes on a new host, the female beetles begin to release chemical plumes called pheromones into the air that act as an attractant to other beetles (both male and female) that have emerged from their hosts. The goal of attracting other beetles is so that they congregate in mass numbers in order to overcome the host's defensive mechanism (Powell et al. 1998). Once the threshold of beetles is reached on a particular host, the insects begin to release verbenones, a repellent, that directs beetles to search for other hosts in the local vicinity of the tree (Huber and Borden 2001). This typically leads to the growth of local infestations, otherwise known as spot growth (Carroll and Safranyik 2004). Mass attack is usually completed within one to two days, at which point tree mortality begins (Safranyik 1988). Spot growth was modelled using an

Attack CA sub-model that depicts MPB attack behaviour at the local scale (Figure 3.1, Part II).

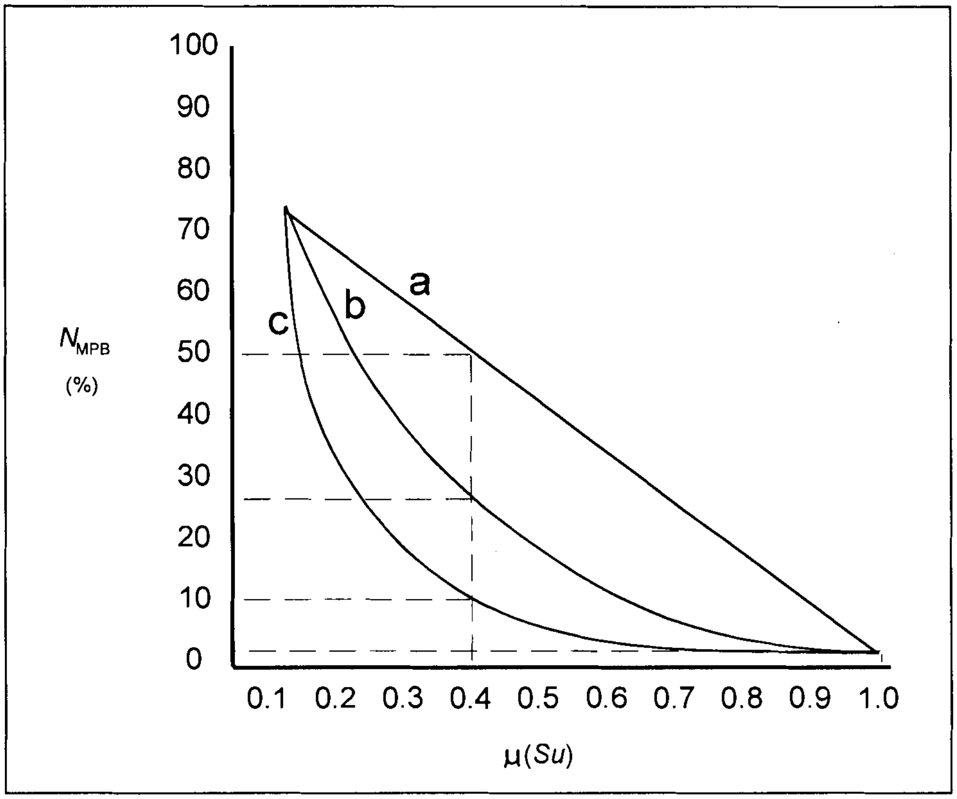


Figure 3-3. Function curves for transition rules a) linear function, b) exponential function, and c) power function. Dotted lines indicate the number of MPB-attacked trees in neighbourhood (N_{MPB}) required in order for a tree with a specific $_{\mu(\text{Su})}$ value to become attacked.

The *Attack CA sub-model* used a small neighbourhood of 25 x 25 cells in order to represent the area over which spot growth was estimated to cover. The transition rules were governed by the same function as the *Dispersal CA sub-model*, however the function for the *Attack CA sub-model* described the relationship between the percentage of trees currently under attack by MPB in the neighbourhood (instead of N_{MPB}) and the susceptibility $\mu(Su)$ value of the cell. The three functions in Figure 3.3 were also tested in order to determine which one best represented local patterns of MPB attack. The number of time steps for the local *Attack CA sub-model* was decided based on heuristic calibration in order to represent the time over which MPB successfully attack and kill their host tree. All trees previously attacked at T_i would become vacant of any beetles, and because they were now dead they could not be attacked in the following time step. The entire CA model was run for T_{i+2} in order to calibrate the model.

3.4.3 Model Calibration

Calibration was performed in order for the model to simulate patterns of MPB-induced tree mortality similar to the patterns that were extracted from the RS images. The first step was to visually determine which of the three functions presented results that were most similar to the observed attacked trees. The second step was to determine the appropriate height of the selected function, which was accomplished in two parts. The first part assessed how the height of the function changed the location of the trees attacked in the simulated results. In order to do this, the average distance between each simulated attacked tree and the nearest actual attacked tree was calculated. The model simulated results more similar to reality as the average distance between simulated and attacked trees decreased. The second part was to determine how the height of the function altered the number of trees attacked per susceptibility level. Susceptibility levels were defined as low susceptibility ($\mu(Su) = 0.01 - 0.35$), medium susceptibility ($\mu(Su) = 0.36 - 0.70$), and high susceptibility ($\mu(Su) = 0.71$ - 1.00). As the function height changed, the number of trees attacked in each susceptibility level changed.

Once the model was calibrated in order to simulate results similar to the MPB-induced tree mortality patterns extracted from the RS images, a five-year simulation was performed in order to determine if the fuzzy-constrained CA approach produced results that are in accordance with MPB attack behaviour. It was expected that highly susceptible trees should be attacked first and more frequently, and less susceptible trees should be attacked once MPB populations increase to a level that allows them to overcome the stronger defensive mechanisms of these less susceptible trees.

3.5 Results

3.5.1 Part I - Susceptibility Model

The Susceptibility Model based on fuzzy sets generated susceptibility maps for Site 1 and Site 2 (Figure 3.4 a and b). The state of each cell in the map for each site was represented by the fuzzy values from 0 to 1. A cell received a value of 0 if it was completely not susceptible to MPB attack. This would include a cell representing a road, open area, deciduous tree, or a non-susceptible lodgepole pine. Cells that represented susceptible lodgepole pine received a value between 0.01 and 1 based on susceptibly value $\mu(Su)$ derived from the semantic import model. For the final stage of the Susceptibility Model, the location of MPB-induced tree mortality that occurred in the year 2000 (i.e. T_i of the model) was integrated into the susceptibility map as shown in Figure 3.4 c and d, and the result was used as the input for Part II of the model.

3.5.2 Part II - Cellular Automata Model

The decision on the appropriate function for the model was carried out by visually comparing the similarity of actual attack locations at T_{i+2} (i.e. year 2002) and the observed simulation results at T_{i+2} using each function (Figure 3.5 a to c). Each function controls the transition rules and results in a variation of simulated attack patterns. The *power function* generated results that were visually the most similar to actual attack locations.

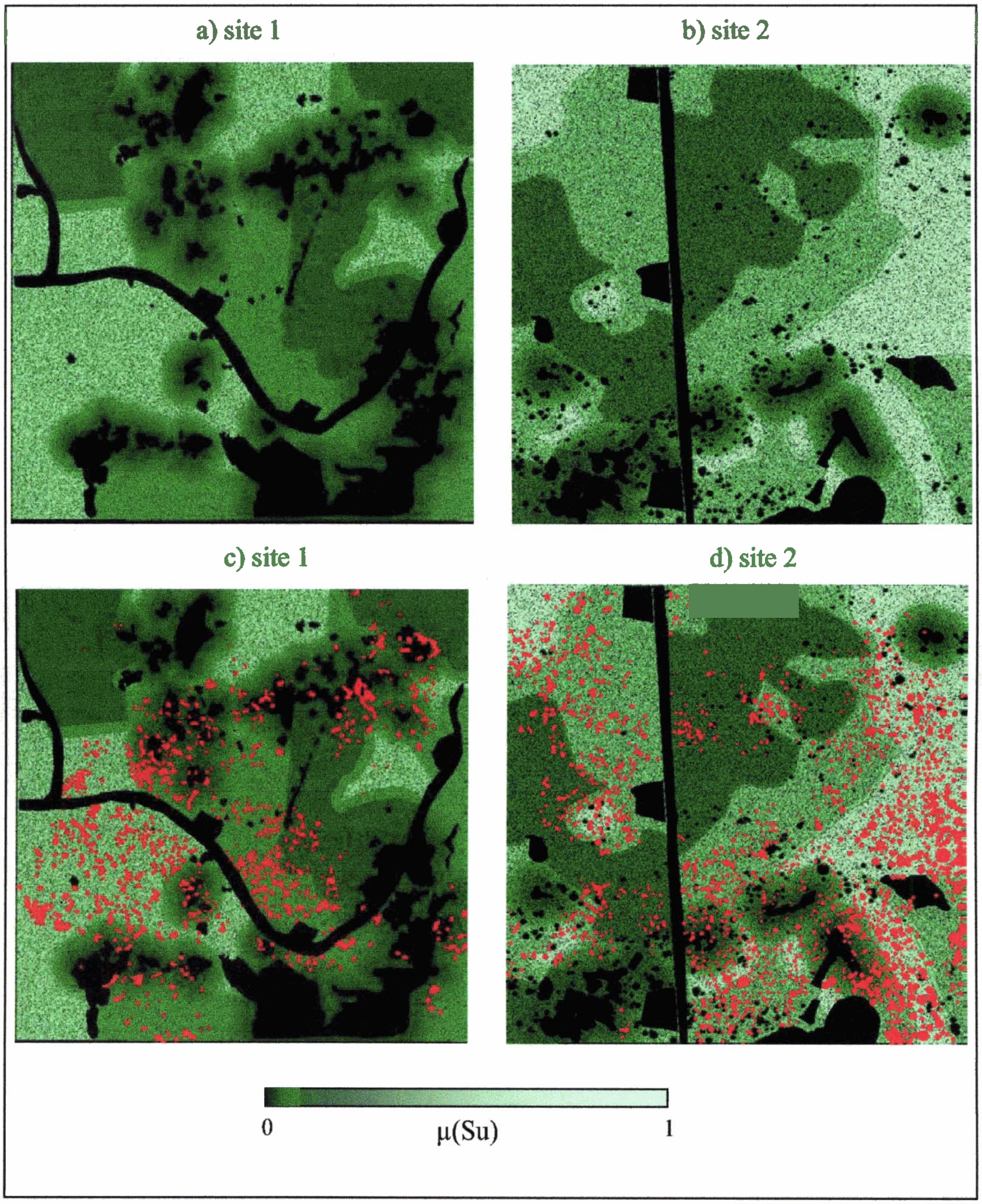


Figure 3-4. Susceptibility μ(Su) maps for a) site 1 and b) site 2, and the location of MPB attacked trees at T_{i+2} for c) site 1 and d) site 2. Dark tones indicate no susceptibility (i.e. roads and clear cuts) and light tones indicate high susceptibility. Red cells indicate attacked trees two years after susceptibility evaluation.

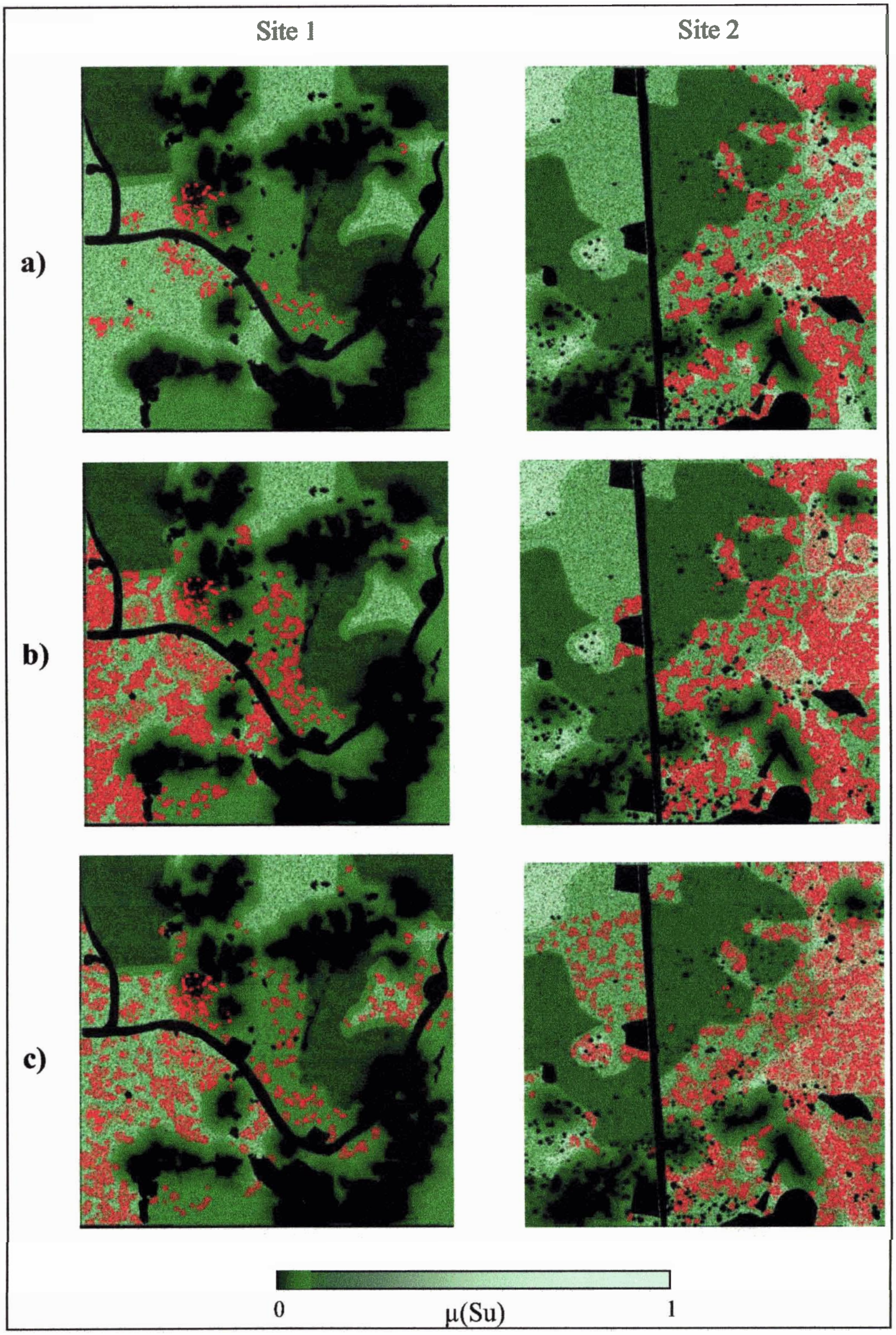


Figure 3-5. CA simulation results after two years (T_{i+2}) for three different functions: a) linear function, b) exponential function, and c) power function.

Further in the calibration procedure the *power function* was tested by altering the value of the exponent *a* in the equation. Figure 3.6 depicts the sensitivity of the function on the decrease of the value of the exponent *a*. For the first part of the calibration of the *power function*, Figure 3.7 a and b illustrates the how a change in the exponent *a* affects the average distance between simulated and actual locations of MPB killed trees. The results indicated that a decrease in the exponent *a* caused the average distance between simulated and actual locations of tree mortality to increase, therefore generating modelling results that were less similar to reality. For the second part of the *power function* calibration, Figure 3.8 depicts how changes in the exponent *a* affects the number of simulated trees killed by MPB for each susceptibility level. The figure shows that as *a* increases, the proportion of the total number of simulated MPB-killed trees belonging to each susceptibility level became increasingly different from the number of actual trees killed per susceptibility level. Therefore, for both parts of the *power function* calibration, an increase in *a* produced simulated results that were increasingly different than the actual patterns of MPB-induced tree mortality as extracted from the RS images.

Figure 3.9 a and b present the five-year simulation of MPB-induced tree mortality patterns using the fuzzy-constrained GIS-based model for site 1 and site 2, respectively, that was performed after model calibration. The simulation was developed using Idrisi Kilimanjaro's Macro Modeller, which provides a framework for GIS-based CA modelling (Eastman 2003a). The model was performed for five time steps in order to represent a time period of five years from 2000-2005.

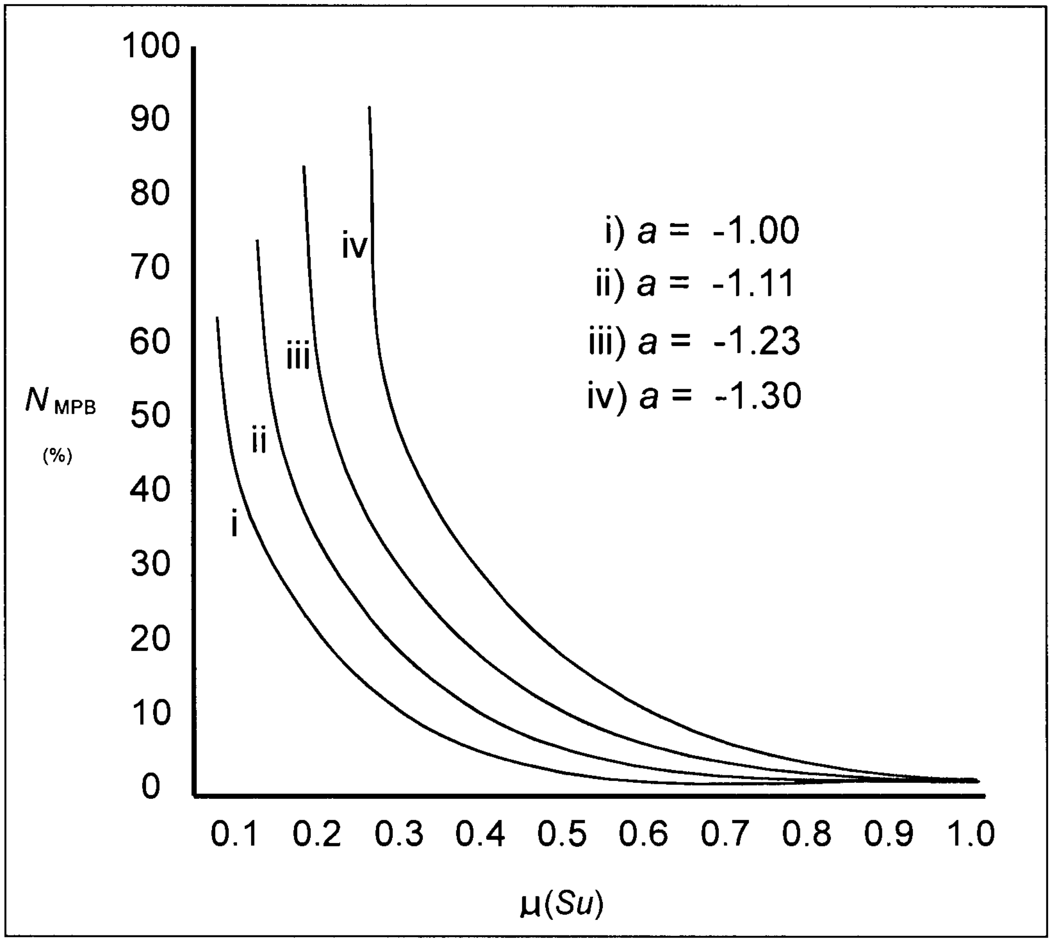
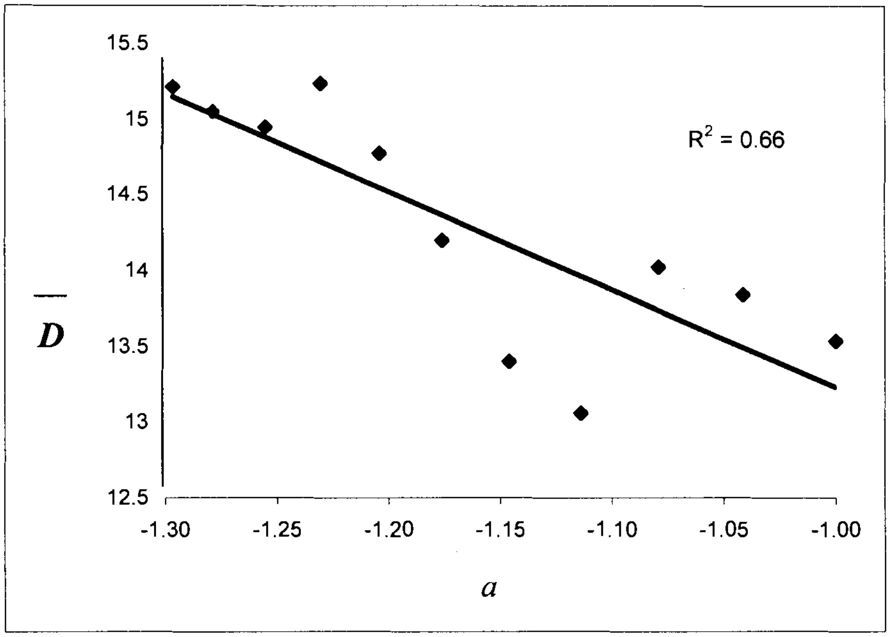


Figure 3-6. The relationship between the shape of the curve of the power function and different values for the exponent value a. The graph shows that as a decreases the curve shifts up.

a) Site 1



b) Site 2

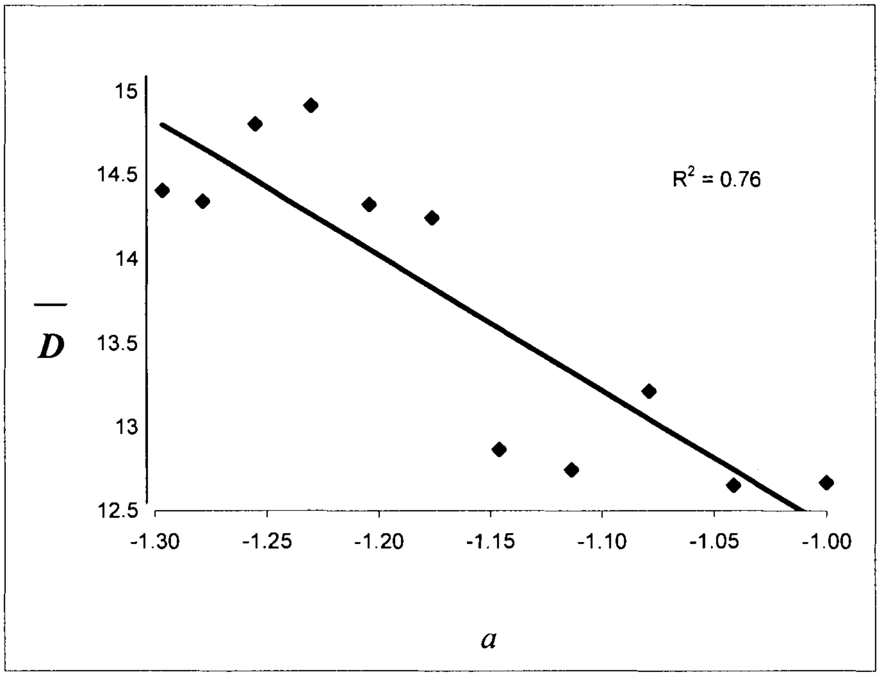


Figure 3-7. Relationship between the value of the power function exponent a and the average distance between simulated and actual locations of MPB-attacked trees for a) site 1 and b) site 2.

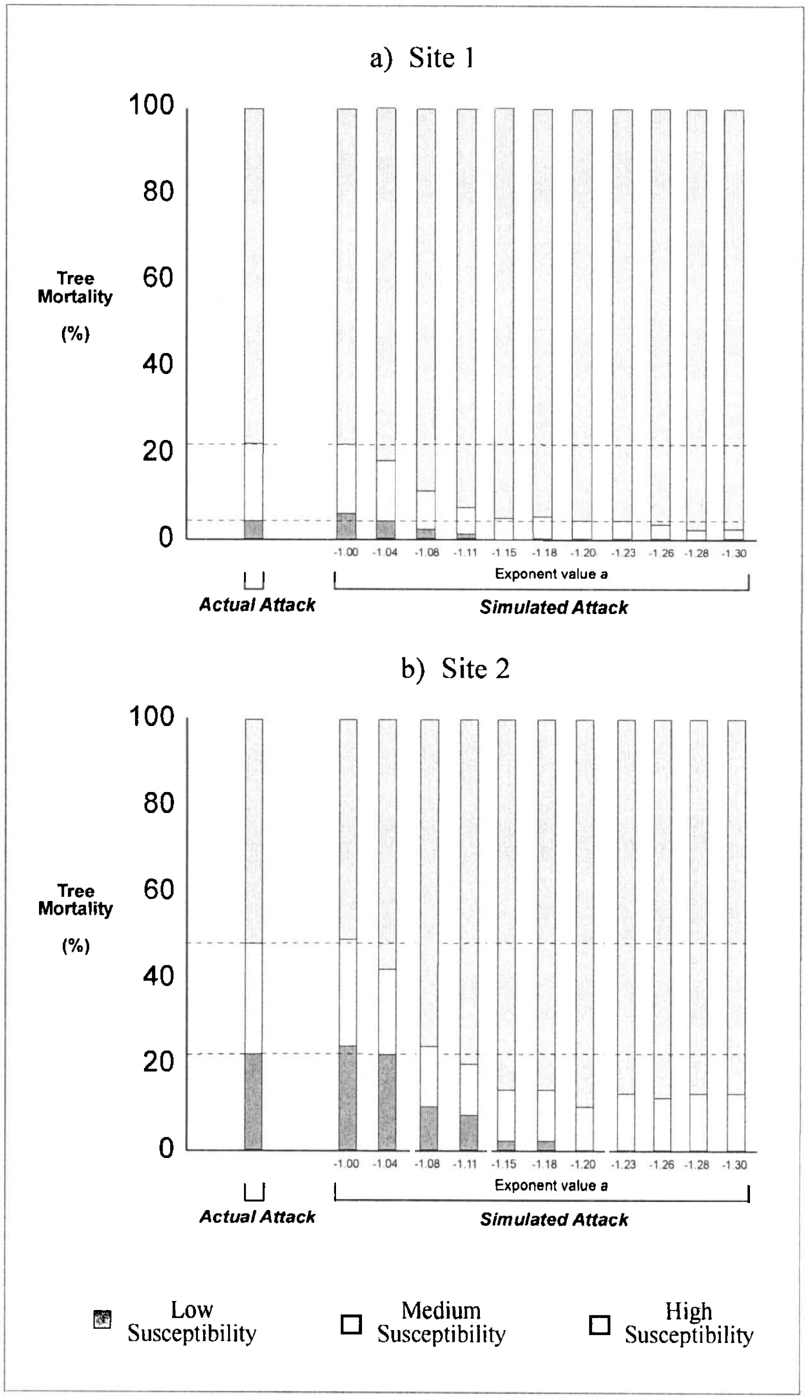


Figure 3-8. Comparison of the proportion of actual (left) and simulated (right) MPB-killed trees in each susceptibility level for different values of the *power function* exponent *a* for a) site 1 and b) site 2.

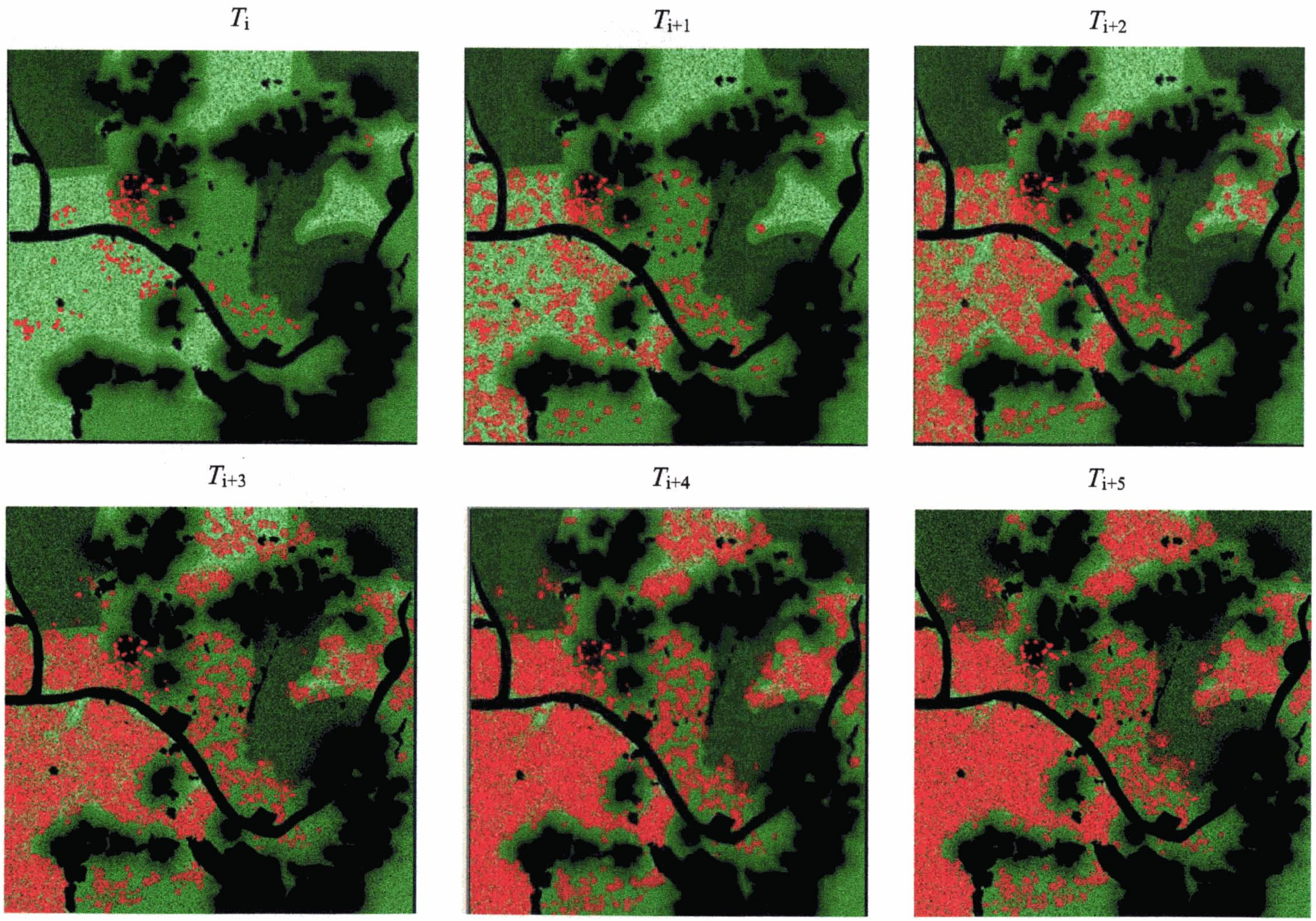


Figure 3-9. a. Five-year simulation output of MPB fuzzy-constrained GIS-based CA model using the power function for site 1.

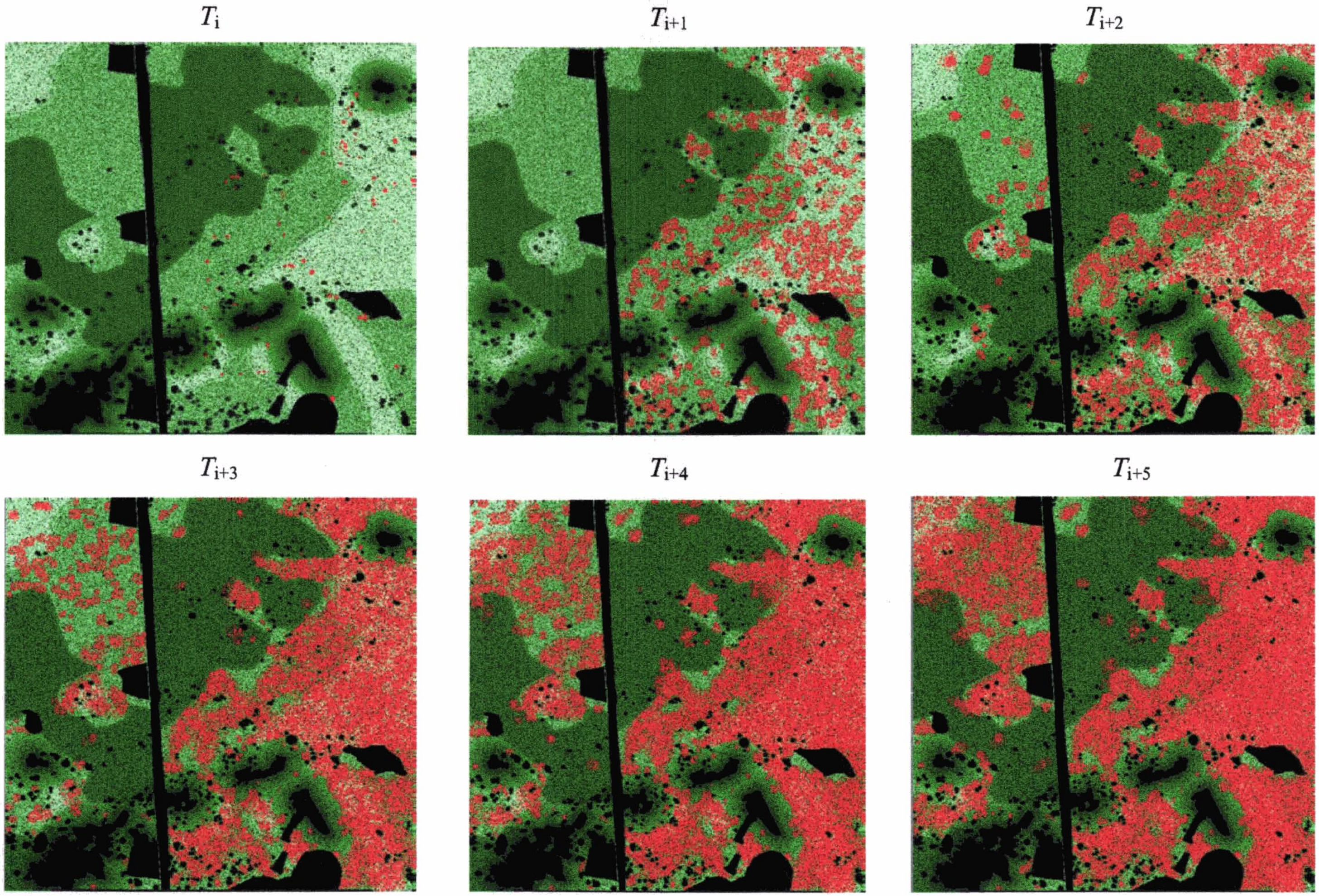


Figure 3-9 b. Five-year simulation output of MPB fuzzy-constrained GIS-based CA model using the power function for site 2.

3.6 Conclusion

This study revealed that MPB-induced mortality patterns can be modelled using the fuzzy-constrained GIS-based CA. The obtained simulation results showed that higher susceptible trees were attacked sooner and more frequently, and less susceptible trees became attacked as MPB population levels increased as the outbreak proceeded through time. Coupling fuzzy sets with CA for developing a complex systems model addressed the problems of defining susceptibility and extracting information from RS imagery of forest landscapes. The first problem was significantly more apparent as the incomplete knowledge concerning MPB attack behaviour prevented the representation of susceptible trees in a discrete manner. The acknowledgement of the second problem also played an important role in the outcome of the model. The fuzzy transition zones that were developed between stands of different tree sizes and different proportions of lodgepole pine allowed for a gradual transition of MPB from areas of higher susceptibility to areas of lower susceptibility. In the absence of these transition zones, MPB dispersal would be confined by unrealistic discrete-state boundaries that would prevent penetration into stands with less susceptibility.

The ability of the CA to appropriately model MPB-induced mortality was also a result of the nature of the function that governed the transition rules. The function allowed for trees of different susceptibility to be attacked at different rates. The importance of this finding is that typical growth curves that explain the number of trees killed per year (Shore and Safranyik 2004a) can be extended to incorporate tree mortality based on susceptibility level. The rules as expressed by the *power function* can be translated into a different growth rate for each susceptibility level. Figure 3.10 a shows the *power function* that was used to explain the relationship between the susceptibility level of a tree and the number of MPB-killed trees required in the neighbourhood in order for the susceptible tree to be killed. This *power function* can be translated into three separate curves as shown in Figure 3.10 b depicting the conceptual rate of trees killed by MPB for each susceptibility level.

The use of the *power function* in the modelling procedure permitted the representation of the non-linearity of complex systems, which was illustrated by the fact that the *power function* and the *exponential function* produced results more similar to reality than the *linear function.* Furthermore, the results obtained form the two calibration procedures clearly indicated that an increase in the exponent a of the *power function* produced results that were more similar to the actual patterns of MPB-induced mortality that was extracted from the RS images. The decreased value of the exponent a required more N_{MPB} in order for a tree to become attacked. As the exponent a drops significantly, there would not be sufficient MPB in the neighbourhood, therefore the low susceptible trees would not become attacked.

This study contributes methods and discussion for addressing the issue of uncertainty in developing a GIS-based CA model of complex systems. While uncertainty has received substantial attention in the fields of GIS and RS, discussion of uncertainty with spatial modelling has been limited to the definition of rules or reasoning that defines the relationship between interacting components in a complex system. Therefore, this research addresses incorporating the uncertainty inherent in geospatial into a CA model. Furthermore, this research has contributed the method of CA for modelling MPB outbreaks. Traditionally, MPB-induced tree mortality has be modelled with partial

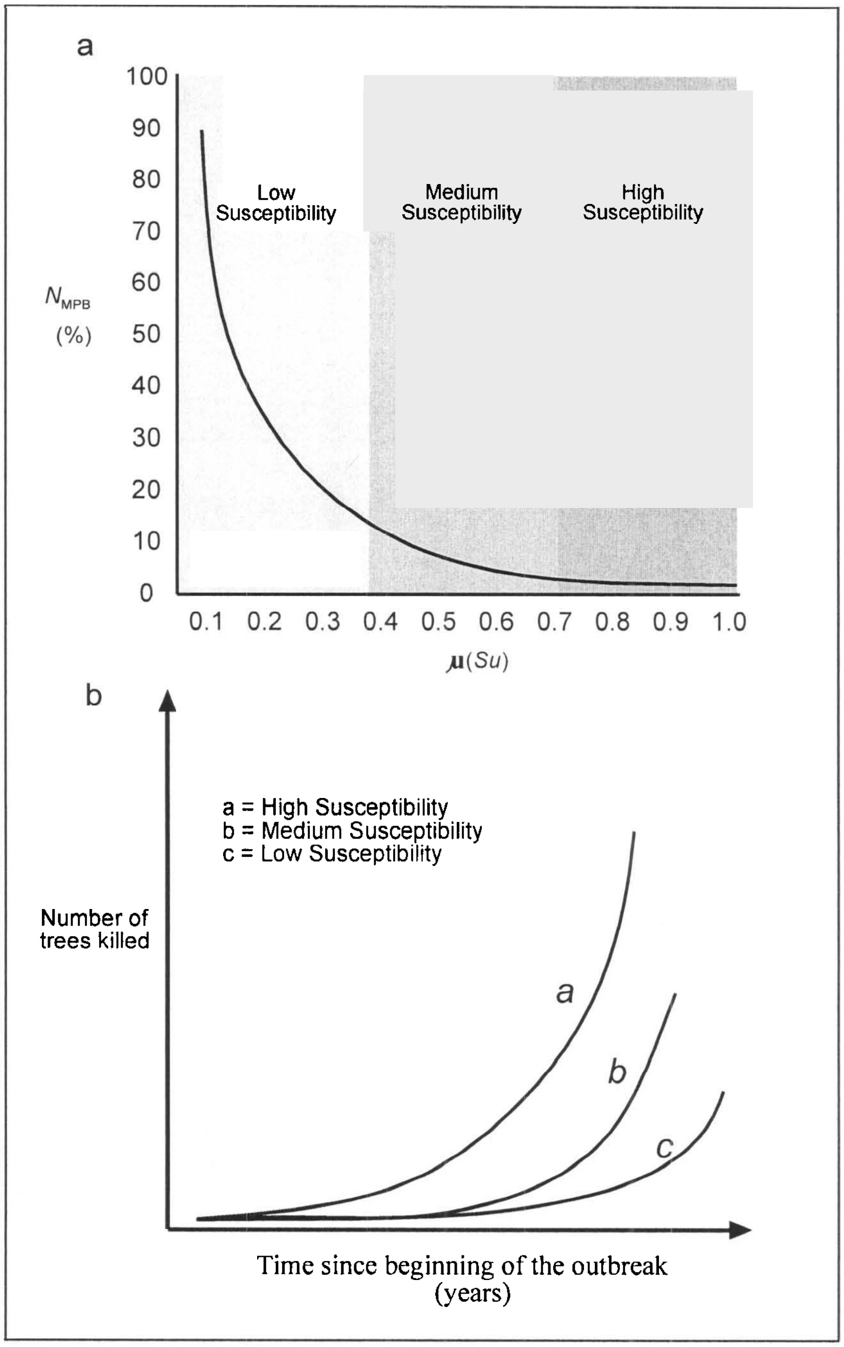


Figure 3-10. Graphical characterization of susceptibility explaining the relationships between a) the power function transition rules and b) conceptual MPB-induced tree mortality curves over time.

differential equations, and only recently have spatial models been employed. The use of CA and fuzzy sets for defining cell states could also be applied to other insect infestation scenarios. For example, it could be useful for modelling applications where insect attack does not inflict mortality on a tree, as the fuzzy value could represent the degree to which the tree is attacked or damaged. The conceptual methods of this study could be extended to other ecological applications of forest disturbances where difficulties persist in defining the variables for cell states that change over time. Furthermore, fuzzy logic reasoning can be useful for defining transition rules, time steps and neighbourhoods when developing CA models that acknowledge the complexities and uncertainties of various phenomena.

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CHAPTER 4 – CONCLUSIONS

4.1 Conclusions

The main focus of this research was to develop a GIS-driven methodology for constructing a spatially explicit fuzzy-constrained CA model for insect infestations. This was successfully accomplished by addressing the two main components of the research.

First, information of the susceptibility levels of trees for forest insect infestation was determined from high-resolution RS images using fuzzy set theory, which was the focus of chapter two. Idrisi Kilimanjaro, a GIS software developed by Clark Labs (Eastman 2003b), was used for implementing the methods of the study. The images were interpreted to determine the variables that represent susceptibility to insect attack. The variables underwent a fuzzification procedure where membership functions derived from expert knowledge transformed discrete values into continuous values indicating a tree's susceptibility to attack. Fuzzy sets were an effective method for handling the uncertainty of defining of cell states as the fuzzification process produced outputs that were able to significantly distinguish between areas of low, medium and high susceptibility. Areas that were estimated as highly susceptible were attacked sooner and more frequently than areas estimated to be of lower susceptibility. This finding, which is in accordance with empirical results from the literature, explains that lower susceptibility areas require higher populations of MPB in order for them to become attacked.

The success of this procedure was mainly due to the use of the semantic import model that facilitated the transfer of expert knowledge from the literature into fuzzy membership functions that define how different variables of the insect-host relationship relate to susceptibility. Another leading contributor to the success of the procedure was the selection of the algebraic operator for combining the different variables of susceptibility. Instead of using a minimum or maximum operator, the study multiplied the values representing all four variables (i.e. tree size, stand diversity, distance to nearest large deciduous stand, and distance to the nearest previously attacked tree) for each cell in order to provide a more detailed representation of susceptibility. While some problems existed regarding digitizing accuracy, the overall framework presented in chapter two was successful at meeting the stated objective.

The second component of the research was to develop a fuzzy-constrained approach for a GIS-based CA to model insect-induced mortality patterns in a forest at the individual tree level (the focus of chapter three). The fuzzy cell-state layers produced in the previous chapters were used as the initial input in the GIS-based CA model that was developed in the Macro Modeller module in Idrisi Kilimanjaro. Macro Modeller provides a graphical user interface for constructing the components of a CA model. The main objective in the development of the model was to determine how fuzzy states can be governed by the transition rules in order to provide realistic results. This was accomplished by testing three different functions that defined the population of MPB required in order to attack trees at a specific level of susceptibility. Inverse functions were selected to represent the notion that less MPB are required to attack trees of higher susceptibility. The *power function* was selected as the best representation of this relationship as it produced results that were most similar to reality. The non-linearity of MPB outbreaks is illustrated by the improvement of the results when using the *power function* compared to the *linear function*. The calibration procedure demonstrated that the model parameters (i.e. the height of the function) can be altered in order to have the results more similar to observed MPB-induced tree mortality patterns. This was a positive finding as it indicated that the results of the model can be controlled by the input parameters that govern the transition rules. Finally, the results from the five-year simulation showed that more susceptible trees were attacked sooner and more frequently than less susceptible trees, which is congruent with MPB outbreak behaviour as explained in the literature. Overall, the fuzzy cell states were successfully implemented in the CA model and the results indicate that the method employed can be useful for understanding the complex nature of MPB outbreaks.

4.2 Contributions

The method and results derived from this research provide a significant contribution to the literature pertaining to GIS-based CA modelling of complex geographic phenomena and the modelling of MPB outbreaks. The main contribution with regards to GIS-based CA modelling was 1) the use of fuzzy set theory for developing information for input into a CA model, and 2) the handling of fuzzy-constrained data by the transition rules. The use of fuzzy sets provided a method to overcome the limitations faced in defining tree susceptibility to insect infestations. This was partially due to the use of datasets that were spatially and temporally limited. The RS data were spatially limited as each study site was 750 m x 750 m, however this made it possible to focus on MPB outbreaks at the individual tree level.

Fuzzy set theory also served as a utility for dealing with a temporally limited dataset. As it is difficult to gain an understanding the complex nature of MPB infestations from data collected over two years, expert knowledge was utilized through fuzzy sets in order to explain the susceptibility of trees to attack. A collection of high-resolution RS images over several years would greatly assist research in defining the patterns of MPB outbreak. However, long-term forest data collection is subject to anthropogenic landscape manipulation such as clear-cutting practices to harvest trees. Such practices interfere with understanding the true nature of MPB-induced tree mortality; therefore, MPB research would benefit from long-term data collection of areas that are void of human influence.

With regards to modelling MPB outbreaks, only recently have spatial techniques been used to understand the morality patterns inflicted by MPB (Fall et al. 2004, Nelson et al. 2004, Shore and Safranyik 2004b), but only a few address the dynamic component of MPB outbreaks (Jackson and Murphy 2004, Riel et al. 2004). However, spatio-temporal studies have yet to focus on MPB outbreaks at the individual tree level. While this research does not fully explore the relationship between the species or age composition of forest stands and MPB attack, it does introduce a suitable method for modelling and understanding MPB-induced tree mortality patterns. The reason why CA have not yet been applied for modelling MPB outbreaks is due to the difficulties with defining cell states at the individual tree level and computational problems with using a large number of cells in the CA iterative modelling process. As the use of fuzzy sets has addressed this issue, CA should be considered in the future due to the parallels between MPB outbreak behaviour and the logic of CA transition rules.

4.3 Future Directions

This research can be extended to model tree mortality patterns at larger scales while still focusing individual tree mortality. This can be accomplished at the landscape level in order to determine how large-scale variables such as average temperatures, elevation, and species composition affects MPB outbreak behaviour. The methods could be extended to model at the regional level in order to determine tree mortality patterns across a province; however both high-resolution RS data for larger areas and the work to conduct the analysis on large datasets are costly. Hypothetical regional datasets could also be used with CA modelling in order to evaluate the consequence of various forestry strategies in the presence of MPB outbreaks over long periods of time (i.e. 20 years). For example, different harvesting practices such as clear-cuts, thinning and variable retention (i.e. retaining certain biological characteristics of the forest) can be compared based on how they affect MPB dispersal and attack behaviour. Alternatively, the ecological consequences of increasing species diversity and uneven-aged stands can be evaluated based on mediating the severity of MPB outbreaks. However, if long-term models of MPB outbreaks are to be successful they will have to consider the fact that the susceptibility of trees will change as time passes. One of the main contributors to a tree's rating of susceptibility is the size of the tree which is an indication of age. As non-attacked stands of host trees age they will become more susceptible to MPB attack. Therefore, a long-term CA model must incorporate a component that is able to alter susceptibility over time.

Although the spatially explicit fuzzy-constrained CA model was developed specifically for emulating patterns of MPB-induced tree mortality, the conceptual framework can be applied to other insect infestation scenarios. For example, fuzzy sets can be used for defining the degree of insect-induced damage in situations where insects do not kill the tree that they are attacking. Cell values of 0 to 1 could represent the degree of damage that would allow forest management to make decisions for prioritizing areas that require attention. The methods can also be manipulated in order in order to be used for modelling land use change. Fuzzy sets could be employed when the motivations of different interest groups conflict and cause uncertainty in the future state of land parcels. Fuzzy values can also be used to represent the degree to which land parcels are developed, and the resulting information can be used to project land use change with a fuzzy-constrained CA.

In closing, the methods presented in this research demonstrated that the presence of uncertainty and incomplete knowledge inherent in geospatial data do not have to restrict the type of applications that can be performed in GIS research. Regardless of the quality of the data used for spatio-temporal modelling, some degree of uncertainty will persist in terms of what exists at particular locations in space. Knowledge of spatio-temporal processes will never be complete. Therefore, it is necessary to acknowledge the presence of these issues and to develop suitable techniques in order to overcome the obstacles that they present. Remarkable advances have been made within RS and GIS over recent decades due to the ability to utilize methods and techniques from various fields of research in order to solve problems that can otherwise hinder the progress of GIScience. The future of both RS and GIS will thus only be limited by the creativity responsible for its progress.

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