APPROACHES FOR MODELING SPATIAL DYNAMICS OF FOREST INSECT DISTURBANCE: THE INTEGRATION OF GISCIENCE, COMPLEX SYSTEMS THEORY AND SWARMING INTELLIGENCE

by

Liliana Pérez
Master of Science, Pedagogical and Technological University of Colombia (UPTC)
Bachelor of Engineering, Francisco José de Caldas District University (UD)

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Liliana Perez
Doctor of Philosophy
Approaches for Modeling Spatial Dynamics of Forest Insect Disturbance: The Integration of GIScience, Complex Systems Theory and Swarming Intelligence

Dr. Nick Hedley
Assistant Professor, Geography

Dr. Suzana Dragićević, Senior Supervisor
Professor, Geography

Dr. Arthur Roberts, Supervisor
Professor, Geography

Dr. Roger White, Supervisor
Professor, Geography
Memorial University of Newfoundland

Dr. Margaret Schmidt, Internal Examiner
Associate Professor, Geography

Dr. Raja Sengupta, External Examiner
Associate Professor, Geography
McGill University

April 4, 2011
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Forest ecological systems are constantly being changed by natural disturbances such as insect infestations, fires and diseases among others. These events can result in the death of trees over areas of several thousand hectares. In western Canada, including the province of British Columbia, extensive outbreaks of mountain pine beetle (MPB) have been occurring during the last decade, raising concerns about the health of these forests and the ability to deal with these issues. For this reason, the development of forest insect infestation models has become an active research topic for scientists from many different disciplines, and geography is not apart from this issue. The insect disturbance phenomenon is a complex process that is inherently linked to space and time. Interactions between insects such as the MPB and the forest ecosystem display a wide variety of complex system properties. Accordingly, complex landscape patterns of tree mortality emerge from interacting MPB individuals that act at local host tree levels. Complex systems theory modeling approaches such as cellular automata (CA) and agent-based modeling (ABM), allow simulations of spatial interactions, which can describe the ecological context in which insect populations spread. The objective of this research is to develop and implement several spatio-temporal modeling approaches that are based on the integration of complex systems theory, swarming intelligence (SI) and geographic information systems (GIS). In particular, this dissertation introduces novel modeling approaches for generating forest patterns emerging from MPB disturbance. MPB behaviours observed in nature are simulated using SI algorithms that depict their indirect
communication, collective behaviour and self-organized aggregation in a forest ecosystem. Thesis findings demonstrate that forest patterns of MPB disturbance can be realistically depicted and simulated when collective aggregation behaviour of MPB, forest structure and spatial dynamics within the system are considered and analyzed simultaneously. Approaches are implemented in the context of MPB disturbance in British Columbia, Canada. This dissertation presents novel contributions to the study of the dynamic changes of forest cover resulting from forest insect infestations by means of complex systems theory, swarming intelligence and GIS. The thesis main contributions are in the fields of GIScience, Landscape Ecology, Environmental Resource Management and Geography.

**Keywords:** agent-based modelling (ABM); complexity theory; swarming intelligence; forest infestation, geographic information system (GIS); mountain pine beetle (MPB); cellular automata (CA).
Esta tesis está dedicada a mi mami, una mujer maravillosa quien me ha enseñado que entre más conocimiento se posee más humilde se debe ser. Para mi papi, un hombre sabio quien me enseño que la disciplina y la constancia son las claves del éxito. Por último, pero no menos importante, a mi maravilloso esposo y compañero de vida quien me ha enseñado que todo es posible con amor.

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1. INTRODUCTION

1.1 General Introduction

Natural disturbances are key drivers of forest ecosystem dynamics and natural forest development. Consequently, disturbances are highly relevant factors in the sustainable management of forest ecosystems. Natural disturbances are integral processes in the succession, functioning, and carbon cycling that occur in most forest ecosystems (Ayres and Lombardero, 2000). Disturbances such as wildfires and forest insect outbreaks can have a significant impact on forest age structure and species composition, influencing timber supply, habitat availability for many plant and animal species, and the potential for future disturbances (Dale et al., 2001; Li and Barclay, 2001).

Forest insects are the most invasive and dominating agents of disturbance in Canada's forests and during outbreaks trees are often killed over vast areas (Raffa et al., 2008). Insects such as the hemlock looper, *Lambdina fiscellaria*, cause the death of balsam firs from the Atlantic coast west to Alberta (Liang et al., 1998); while outbreaks of the jack pine budworm, *Choristoneura pinus* Freeman, kill jack pine forest stands primarily in Ontario, Manitoba and Saskatchewan, causing major economic losses (Hall et al., 1998). The mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, is the most damaging insect in western lodgepole pine forests. Specifically, in British Columbia (BC), major outbreaks have occurred in all areas with a significant mature pine component. The first recorded infestation took place in the Okanagan and Merritt areas, in 1913; throughout the past 80 years, over 500 million trees were killed by the MPB
(Unger, 1993). This extensive tree mortality shifts the forest toward younger age-classes, which contain less biomass, and are less resistant to insect attacks (Maclauchlan, 2006). As with mature stand risk, risk to young stands is highly dependent upon the level of insects’ activity in adjacent stands or proximity to an ongoing outbreak (Raffa and Berryman, 1980). A fundamental question is how the frequency, duration, and intensity of insect disturbance change the spatial pattern and structure of forest ecosystems. The damage patterns caused by these forest insects and the resulting uncertainties directly affect depletion forecasts, pest hazard rating procedures, and long-term planning for harvest queues and pest control requirements (Seidl et al., 2009). Insect attacks increase the potential for wildfire, and uncertainties in future insect damage patterns magnify uncertainties in fire regimes (Li and Barclay, 2001). In general, insects disturbance shape forests by influencing their composition, structure, and functional processes. For this reason, monitoring, assessment and future predictions of the forest ecological systems (FES) structure represent a key point for environmental policy making and for the adequate management of forest resources.

For the better part of the past decade, BC has been experiencing the largest MPB infestation in its recorded history; it had affected 164,000 ha of forests by 1999 and more than 13 million ha by 2008 (Wulder et al., 2009). MPB outbreaks are regulated by different components such as temperature, topography, wetness, susceptible trees and MPB population levels, all of which act together at local scale and generate over time complex spatial patterns of tree mortality at landscape and regional scales (Bone et al., 2007). This disturbance represents a catastrophic natural disaster as it can appear over vast areas and triggers widespread mortality of lodgepole pine, *Pinus contorta*, one of the
most abundant commercial tree species. MPB outbreaks not only cause tree mortality, but also impact water quality, change wildlife habitat, increase forest fires risk, as well as threaten the stability and long-term economic well-being of many communities (Nealis and Peter, 2008). Understanding the MPB disturbance phenomenon in FES represents one of the most important and challenging research issues faced by researchers and government agencies during the last decade in Western Canada; the need to forecast and manage forest infestations has triggered the development of several methodological approaches (Campbell et al., 2007; Carroll, 2007; Robertson et al., 2007; Wulder et al., 2010). Life habits and environmental requirements of the beetle and its host represent the core of these studies. Therefore, key elements of the lodgepole pine ecological system such as heterogeneity and complex dynamics between insects are not accounted all together. Likewise, forest structure and created spatial patterns of forest damage, are not considered due to difficulties to integrate all these aspects in a single study.

Complexity of FES often results from the nonlinear interactions of environmental factors among a large number of system components which frequently lead to emergent properties, unexpected dynamics, and characteristics of self-organization (Pascual, 2005). Environmental variables interact with systems in such a complex way that the whole system achieves a broader functionality that cannot be deduced by considering individual environmental factors. In order to gain insight into this functionality and complexity the observation of individual factors affecting the system in question is important (Jørgensen et al., 2009). FES dynamics are of primary concern not only for theoretical considerations, but also management and conservation practices. Therefore, to describe
the system and its inherent interactions, mathematical and computer-based modeling approaches have been used (Chen et al., 2010; Riel et al., 2003; Safranyik et al., 1999).

Models are approximations of the reality, but contain the essential features that are of interest for the scientific problem. An ecological model is a set of assumptions about an ecological system expressed in mathematical language (Gurney and Nisbet, 1998). Ecological modeling studies have traditionally been concentrated on the use of differential equation models, where mathematical statements represent the rules governing ecosystem changes (Patten and Jørgensen, 1994). Traditional models based on a system dynamics approach provide useful ways to represent and comprehend changing behaviours in time, but they do not adequately represent processes with space and time components (Safranyik et al., 1999; White and Powell, 1997). Space is an important domain of ecological models; especially, ecosystems exhibit strong spatial heterogeneity and localized behaviour, resulting in distinct and eminent spatial patterns (i.e. patches). While space is not the final frontier in ecology, it is certainly the current focus of research interest (Campbell et al., 2007; Mladenoff and Baker, 1999). With the purpose of capturing the inherent complexity and nonlinearity of ecological systems, computer-based models gained popularity (Pascual, 2005; Tan et al., 2006) and have progressed over the past ten years to incorporate space and time as central components of the ecological process in order to handle the complexity of the phenomenon. Computer-based models developed to incorporate multiple factors have resulted in enhanced realism of the model; however, these models require efficient approaches for both handling and processing information.
Contrary to ecology, geography is considered a spatial discipline. Evidence of this is the First Law of Geography which states that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Tobler’s Law has influenced groundbreaking work in fields as diverse as spatial analysis, migration studies, spatial interaction modeling, and geographic information science (GIScience) (Sui, 2004). In a sense, computer-based models for FES found, in GIScience’s methods and tools, the means to integrate and handle the spatial component. Through the use of geographic information systems (GIS) these models were provided with storage, analysis and display capabilities adequate for managing spatial digital data (Auger, 1995; Fall and Fall, 2001; Mladenoff and Baker, 1999).

For the purpose of forest disturbance modelling, GIS are especially useful for integrating and overlaying multiple datasets of forest attributes as individual spatial units, which can undergo spatial analysis for evaluating and determining land cover and land use patterns; however, GIS maintain an inherently static view of the world and fail to capture dynamics of the real system (Dragićević, 2010). Hence, there has been an emergent interest in geography to provide insights into the relationship between spatio-temporal system processes and the resulting spatial patterns through the adoption and integration of complex systems theory principles (Batty and Jiang, 2000; Bousquet and Le Page, 2004; Parker et al., 2003).

The use of complex systems theory in spatio-temporal GIS-based modeling provides a dynamic component to GIS by programming natural processes such as forest insect disturbance into computer models that can access and modify data in order to simulate the dynamics that influence forest structure and spatial distribution. While there
are numerous models that attempt to simulate MPB infestations and their impact on the landscape, each with its own approach and set of assumptions, the vast majority of them disregard the effect that diverse local scale interactions have in the emergent patterns at landscape scale and the complexity of the process. Therefore, there remains a need for enhancing methodological approaches that allow us to investigate and better understand the spatio-temporal mechanisms of the underlying process of such a dynamic and complex system.

The subsections that follow provide a brief overview of different approaches to MPB disturbance modelling.

1.2 Mountain Pine Beetle (MPB) Models

Unprecedented devastation to the lodgepole pine forests of western Canada has been caused by MPB infestations during the last decade (Aukema et al., 2006; Carroll, 2007). In order to assess the impact that this phenomenon has in forest ecological systems, different methodologies have been proposed. Remote sensing, equation-based, GIS-based and complex systems theory approaches have been developed and applied to detect, model, and predict the spatial distribution of the MPB population and attack patterns. Only some of these methodological approaches are used as decision aids in forest management in order to help the development of preventive forestry practices to reduce losses from the MPB disturbance (Fall et al., 2002, 2003; Shore et al., 2008).

1.2.1 Remote Sensing Approaches

Aerial overview surveys are the oldest and most widely used remote sensing tool for mapping damage caused by tree killing agents such as MPB (Wulder et al., 2006a).
These provide sufficient information to characterize the general location of the damage, approximate the gross area of damage, and indicate general trends in damage from one year to the next. However, one of the major drawbacks of these surveys is the high subjectivity involved in the capture of the information, making the accuracy of results dependent on the knowledge, experience, and skill of the observer.

Multispectral digitally converted aerial photography and satellite sensor imagery have been also used as a remote sensing technique to detect and map MPB outbreaks. Refining image processing and classification procedures have permitted reliable early detection of spreading MPB outbreaks using digitally converted multispectral and normal colour aerial photography (Roberts et al., 2003). Digital satellite remote sensing benefits include the capacity to cover large spatial areas, making them an excellent tool for monitoring and assessment of forest cover changes at a landscape scale (Wulder et al., 2010). Nevertheless, satellite detection of MPB outbreaks still faces challenges due to their relatively low spatial resolution which make them unable to identify the low to moderate levels of forest damage.

In general, remote sensing has been used as a tool for collecting data needed to support decisions and action programs to mitigate the effects of forest insect disturbance; extensive research has been conducted into the use of remotely sensed data for the detection, monitoring and mapping of the MPB outbreaks impacts (Wulder et al., 2006a). For instance, QuickBird satellite images have been used to characterize stands’ attributes in order to determine the likelihood of areas traditionally outside the beetle's biological range to sustain MPB outbreaks (Coops et al., 2006). Furthermore, Landsat images and
ancillary spatial data have been combined in order to predict the likelihood of MPB re-attack and damage in forest stands at a landscape scale (Wulder et al., 2006b).

1.2.2 Equation-based Models

Equation-based models (EBM) rely on a set of mathematical equations involving their execution and evaluation (Parunak et al., 1998). EBMs used for studying MPB disturbance range from simulation models based on pheromone ecology at the stand level (Logan et al., 1998; Powell et al., 1996) to the atmospheric models of long-range dispersal across landscapes (Campbell et al., 2007; Logan and Powell, 2001; Logan et al., 2003). Forest stands’ structure and absolute risks have been also considered to analyze the MPB outbreak dynamics (Lewisa et al., 2010; Nelson et al., 2008). These models have provided important conceptual and mechanistic insights into the configuration and distribution of MPB outbreaks. One of the most structured EBM is the one created by Safranyik (1999) to simulate MPB population dynamics. Its ability ranges from predicting lodgepole pine growth and yield—based on previously published yield tables—to simulating attack dynamics within and among trees. However, this model did not consider the influence of environmental and spatial factors in the forecasting of future MPB attacks. Ultimately, it is important to highlight that the general trend in computational models developed to depict, predict, assess and manage MPB outbreaks has been equation-based models, even though they neglect the inherent spatial and temporal components of the process.
1.2.3 GIS-based Models

GIS started to play an important role in forest assessment in the earliest 1990s, due to their capacity to integrate large spatial datasets and the ability to analyze them in order to discover forest cover patterns (Cassel-Gintz and Petschel-Held, 2000; He et al., 1998). Nonetheless, literature does not report many research efforts towards development of GIS-based models to assess or predict MPB outbreaks. Hot spot analysis methods have been used for characterizing spatial interactions between MPB and the environment and understanding how the mountain pine beetle utilizes resources over large areas (Nelson et al., 2007). Spatial statistic methods such as K-means cluster analysis have been used to determine MPB spatial distribution (Campbell et al., 2007). More recently, landscape metrics and GIS functions have been integrated to model the spatial distribution of MPB infestations (Gamarra and He, 2008).

1.2.4 Complex Systems Theory Models

Despite the fact that EBMs have been the approach leading the way in the development of models to study MPB disturbance, science fields concerning ecological and geospatial modeling began to experience a paradigm shift towards new approaches and areas of research. Artificial Intelligence, ecological informatics and complex systems theory approaches offer an improved prospect to address the complexity of FES and their disturbance processes (Bousquet and Le Page, 2004; Green and Sadedin, 2005).

Complex systems theory conceptual framework focuses its attention on many characteristic behaviours of dynamic systems such as self-organization, emergence, non-linearity, path dependence, and sensitivity to initial conditions (Brown et al. 2005) amongst others, which had previously been neglected or simplified in many disciplines
Forest ecological systems show complex patterns in both time and space. Different behaviours of individuals interacting in a geographic space (i.e. forest), give origin to complex patterns that can be analyzed under the principles of complex systems theory. Complex systems theory is suitable for incorporating both the complexity and the spatio-temporal significance in spatial ecological processes, and can provide results that enhance ecological knowledge for resource management and decision support (Railsback, 2001). Likewise, advance of complex systems theory in the specific domain of spatial-modelling in geography can provide a new vocabulary for a better understanding of complex interactions in geographic spaces, as well as new methods and techniques to model complex geographic processes.

With the aim to model and uncover laws governing the behaviour of complex geographic phenomena, two popular approaches currently used in geography and ecological modelling are Cellular Automata (CA) and Agent-based modelling (ABM).

1.2.4.1 Cellular Automata Models (CA)

CA models make use of simple rules governing the relationships between cells in a neighbourhood to produce emerging patterns over time that cannot be estimated by simply observing the initial cell states (White and Engelen, 1997). Fall et al. (2001) developed a model called SELES-MPB which built on Safranyik (1999) model. The SELES-MPB has GIS capabilities and includes a CA to simulate MPB outbreak impacts and management strategies on real raster-based landscapes with unique climatic and topographic characteristics. Mathey et al. (2008) built a model to spatially allocate and simulate management activities. The object-oriented CA model in a GIS represents a decentralized bottom-up forest planning approach (Mathey et al., 2008). Bone at al.,
(2005) developed a model that integrates the concept of fuzzy set theory with remote sensing and raster-based GIS in order to produce susceptibility maps of insect infestations in forest landscapes. These susceptibility maps (Bone et al., 2005) were the input of a GIS-based cellular automata (CA) model proposed to simulate spatio-temporal dynamics of MPB attacks in order to simulate tree mortality distributions (Bone et al., 2006). In addition, the potential of GIS-CA modelling approach was used for evaluating the complexities of forest management practices (Bone et al., 2007). Although these models account for some of the dynamics in the MPB disturbance process, complex spatio-temporal interactions happening between MPB attacking behaviours at tree scale and their impact at larger scales have not been yet well portrayed.

1.2.4.2 Agent-Based Modeling (ABM)

ABM consists of a system of agents and the relationships between them and their environment or geographic space (Sengupta and Sieber, 2007). Agents can be simply defined as self-contained programs that collect information from their surroundings and use it to make decisions based on a set of rules (Batty, 2005; Bonabeau, 2002). In addition, agents may be capable of evolving, allowing unanticipated behaviours to emerge (Bousquet and Le Page, 2004). Sophisticated ABM sometimes incorporates fuzzy logic (Gimblett et al., 2002), Bayesian networks (Kocabas and Dragičević, 2007), genetic algorithms (Bennett and Tang, 2006; Huse et al., 1999), reinforcement learning (Bone and Dragičević, 2009b), evolutionary algorithms (Manson, 2006), or other learning techniques to allow realistic simulation of agents' learning and adaptation.

Whereas some models define agents in terms of their mobility (Anwar et al., 2007; Batty, 2001; Batty et al., 2003; Bennett and Tang, 2006), some others consider not
only this characteristic but also their interaction with their environment (Bone and Dragićević, 2009b; Brown and Robinson, 2006; Deadman et al., 2004; Evans et al., 2006). No matter how they are treated, most studies have focused on agent autonomy, concerning the agent goals and behaviours. Additional characteristics of agents such as reaction, interaction, adaptiveness and communication, among others have been also recognized in the process of designing models that mimic dynamics of complex systems (Aumann, 2007; Parker et al., 2003; Weiss, 2001).

Moreover, the ability to model the emergence of phenomena through the interaction of features or individuals within a GIS over space and time, has been investigated by GIScience researchers (Brown et al., 2005; Parker, 2005). Coupling of GIS and ABM permits the development of models where agents are associated to real geographic locations, thus allowing the simulation of objects or agents and their spatial patterns as a result of interactions and changes in space and time (Batty, 2005).

Given that in ABM individual agents make decisions that affect their environment, forest ecologists and resources managers have found in this type of models an important approach to handle the numerous and interrelated processes between man and nature in order to use renewable resources in a sustainable way (Bone and Dragićević, 2009a; Deadman et al., 2004). All the aforementioned characteristics and potentials make ABM a suitable approach to conceptualize MPB as autonomous agents interacting and behaving based on their environment’s characteristics. Nevertheless, complexities of forest insect disturbance have not yet been studied by means of this approach.
1.3 Research Problem and Questions

The literature review reveals limitations of existing theoretical and modeling approaches for simulating forest disturbance by MPB and the emerging spatial patterns. Remote sensing methods, equation-based and GIS-based models do not consider the dynamic forces that influence forest patterns over time and space. Local collective behaviour between MPB individuals and its impact in the spatial distribution of outbreaks has not been considered, neither has the influence that climatic and topographic factors have in the ecological process. Such dynamics have an impact on the health status and structure of the system and can dictate the emergence of forest cover patterns. Overall, the spatio-temporal complexities of forest ecological systems at tree scale and their effect at a landscape and regional scale are not captured by these models. In order to address this problem, complex systems theory and modeling approaches can provide a theoretical and methodological framework for both gaining insights into the relationships between MPB disturbance and emerging patterns in forest, and understanding the effects of climatic and topographic factors in the spatial propagation of the outbreaks.

Even though research using complex systems theory modeling approaches (e.g. CA) for addressing forest ecology issues is gradually emerging, there are no reports in the scientific literature of developed ABM approaches to simulate MPB behaviours in a disturbance process and the effect of these in the forest structure at different scales. Therefore, there is a need for methods that allow conceptualizing MPB as autonomous agents that interact locally and make decisions based on the condition of the forest environment, generating spatial patterns of infestations at larger scales. MPB attacking behaviour depends on signals emitted from other MPB with the purpose to aggregate;
aggregation behaviour is maintained in order to make more efficient the process to overcome the defences of a host tree (Raffa, 2001). For this reason, it is also essential that these methods capture the collective aggregation behaviour of MPBs, and swarm intelligence (SI) theory (Abraham et al., 2006) can be used as a way to address these issues.

Swarm intelligence (SI) is an approach that deals with collective behaviour and interactions of simple agents within a system, which generates different emerging patterns (Bonabeau et al., 1999). SI theory was developed based on biological examples of swarming, flocking and herding phenomena in vertebrates (Bourjot et al., 2003). A swarm can be defined as a group of agents that communicate with each other by interacting in their local environment (Hoffmeyer, 1995). In order to achieve a global objective, each agent plays a key role in the resulting behaviour of the swarm. Thus, the system complexity is the result of the interactions between individual agents in both space and time (Engelbrecht, 2005, 2007). Hence, the SI approach can be used to study the behavioural aspects collective attack aggregation of MPB.

For the purpose of simulating spatio-temporal dynamics of MPB disturbance, the integration of ABM with swarm intelligence (SI) offers a promising approach to simulate MPB behaviour. This can be accomplished by acknowledging reactive, adaptive and communicative characteristics of MPB represented as agents, which allow them to respond and adjust their behaviour according to both other agents' signals and the environment to fulfil their goal in the system. SI has been used in solving GIScience research problems, mostly related with spatial optimization (Li et al., 2009b; Li et al., 2010; Parunak et al., 2006) and network analysis (Li et al., 2009a; Teodorović, 2003,
In spite of this, coupling SI with complex systems theory modeling approaches (i.e. CA and ABM) for generating forest patterns, over space and timer, from MPB disturbance, has yet to be developed.

Given the lack of research literature in the subject and the possible solutions that can be proposed for the study of MPB disturbance in forest ecological systems, this dissertation brings up the following research questions:

1. **Can GIS-based ABM be used to simulate spatial patterns emerging from MPB outbreaks at different scales?**

2. **How can a GIS-based ABM of MPB disturbance be used to evaluate different management strategies in the presence of forest insect disturbance?**

3. **Can GIS-based ABM be enhanced to simulate collective aggregation behaviour in MPB populations through the integration of SI, for improving modelled forest cover patterns?**

4. **Can a SI-ABM for modelling MPB disturbance be tested and qualified to be used as a tool to simulate forest cover patterns emerging from insect infestations?**

5. **Can a SI-ABM be integrated with CA to simulate forest patterns resulting from not only interactions between insects and the forest, in a MPB infestation, but also from the influence of topographic and climatic factors -from the tree to the landscape scales?-**
1.4 Research Objectives

The literature gap in MPB disturbance modelling and particularly those with agent-based approaches and challenges in studying the complexities of the phenomenon, together with the research questions outlined in previous sections, define the purpose of this dissertation. Accordingly, the overall aim of this research is to develop spatio-temporal modelling approaches for generating forest patterns emerging from MPB disturbance by integrating GIScience, complexity systems theory and swarming intelligence. Complex systems theory models can help to depict and examine how MPB behaviours in forest ecological systems drive changes in forest structure and patterns. Thus, this dissertation adopts ABM and CA modeling approaches in the context of forest insect disturbance. Specifically, a novel approach is proposed in order to build reactive, communicative and adaptive agents using SI to simulate agents’ indirect communication by modifications in the environment, and collective aggregation in a disturbance process.

The integration of ABM and SI offers a very robust approach to simulate forest insect disturbance at a very detailed scale such as tree level; however, such detail comes with a cost in terms of processing time and the size of the study area to be used for implementation purposes. For this reason, this dissertation also incorporates a GIS-based CA coupled with ABM and SI to model forest insect disturbance process at larger spatial scales considering the influence of environmental factors such as topography and climate. The methods developed in this dissertation draw from literature on complex systems theory, GIScience, swarming intelligence, forest and MPB ecology and forest management.
However, this dissertation is not an endeavour to answer all the questions related to forest insect disturbance from the above fields, but instead represents an effort to understand the underlying dynamics of forest insect disturbance, particularly MPB, and the changes in the spatial structure of forest ecological systems. To achieve this aim, the following objectives have been formalised:

1. **To propose novel spatio-temporal modelling approaches based on GIScience, complex systems theory and swarming intelligence to account for the dynamics of forest ecological systems associated with MPB disturbance from small to larger spatial scales.**

2. **To implement and evaluate these modelling approaches by assessing their response to varying parameter values and by comparing the results to known conditions in order to gauge its predictive accuracy.**

3. **To apply the proposed modelling approaches to real-world scenarios in order to predict the potential impacts on forest ecological systems and assess models applicability in decision-making and environmental resources management.**

In order to achieve these objectives, this dissertation uses the context of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, disturbance process in British Columbia, Canada.

1.5 **Study Sites and Data Sets**

Diverse study sites are used throughout this dissertation to implement and test the proposed approaches. The data used in Chapter 2 pertains to a forested area of Kamloops
Forest District in the central interior of British Columbia, which were provided by the Government of British Columbia (GeoBC, 2008). This location was selected because it is an area of great interest and concern to the forest industry and sustainable forest management due to significant amounts of tree mortality caused by MPB outbreaks (Taylor and Carroll, 2003). Chapter 3 employs a dataset for a forested area of approximately 560 ha, located in North-Central Interior of British Columbia, Canada. The data was obtained from the aerial photographs collected during the summers of 2001-2003 from Remote Sensing Lab at Simon Fraser University. Auxiliary cartography was also used to verify classification of average tree species and tree sizes within a stand, and whether or not a stand had been attacked by MPB (Westfall and Ebata, 2008). In Chapter 4 three different sites of a study area located in the Cariboo Regional District in Central Interior British Columbia, Canada, were used to implement the ABM-SI approach (ForestSimMPB). The locations of MPB in 2001 were derived from 2002 aerial photographs and forest cover attributes data sets were obtained from GeoBC (GeoBC, 2008).

The model testing in Chapter 5 was carried out using datasets from different pilot areas located in North-Central Interior of British Columbia, provided by the Remote Sensing Lab at Simon Fraser University. The area was selected because it has undergone extensive MPB infestations during the last decade, causing significant problems to the forest ecosystem (Pantel, 2006). To cover a larger landscape, a hypothetical dataset was created from the land cover map of BC (GeoBC, 2008) in order to implement and test the GIS-based ABM-CA model proposed in Chapter 6.
1.6 Structure of Dissertation

This dissertation starts with the Introduction, where literature review, theoretical framework, research problem, questions and objects are provided. The following five chapters address the objectives of this dissertation through the development of modelling approaches that integrate GIS, ABM, CA and SI.

Chapter 2 presents the development and implementation of a GIS-ABM that simulates MPB outbreaks at the tree and landscape scales, providing spatiotemporal information of annual distribution and patterns of the infestation. MPB and pine trees are represented by two types of agents that interact to mimic dynamics between the insects and forest that influence and result in the spread of the outbreak. This is carried further in Chapter 3 in order to explore the use of the GIS-based ABM to simulate MPB disturbance and tree mortality when different forest harvesting policies are implemented in order to control the infestation. Three different scenarios are created; the first one uses no management while the other two scenarios implement sanitation and salvage harvesting methods to study the effects on the outbreak patterns.

In order to enhance the developed GIS-ABM approach, swarming intelligence (SI) reasoning is added to the model and this is presented in Chapter 4. SI offers the capability to model and simulate collective aggregation behaviour of MPB populations. The more complex model ForestSimMPB is developed and implemented at a tree scale, which allows a very accurate depiction of MPB behaviours and the resulting spatial patterns of the outbreak. A Graphical User Interface (GUI) is developed to allow the implementation of different scenarios by changing input parameters in the simulation. The model performance at local scale is satisfactory, at this stage; however, it is not
suited to be used at larger spatial scales that require larger datasets due to high computational requirements.

Chapter 5 outlines the process of formal testing the ForestSimMPB model. Through experiments with real data modelling testing stages such as verification, sensitivity, calibration, validation and qualification are performed. The model testing allows establishing whether or not the model is transferable to other systems and, therefore, how reliable its predictions are likely to be.

The need for development of the model that can operate on landscape and regional spatial scales has lead to further extension of ForestSimMPB. Chapter 6 presents a CA-AB model that takes in consideration both scales from small to large. This new approach to MPB disturbance’s simulation at tree and landscape scales allows the inclusion of environmental factors such as topography and climate. Topographic and climatic variables play an important role in the dynamics of the forest ecological system and have an effect in the forest patterns and MPB outbreaks at scales larger than the tree level. CA is found to be helpful to simulate the complexity of the ecological process at larger spatial scales without the computational burden.

The final chapter, Chapter 7, draws concluding remarks about the research as a whole. It documents the dissertation findings and contributions and also suggests possible avenues for future research.

1.7 References


2. MODELING MOUNTAIN PINE BEETLE INFESTATION WITH AN AGENT-BASED APPROACH AT TWO SPATIAL SCALES

2.1 Abstract

Extensive outbreaks of tree-killing insects have been occurring in many parts of North America, including the province of British Columbia, raising concerns about the health of pine forest ecosystems. The dynamic phenomenon of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, infestation outbreaks is an inherently spatial and temporal complex process. Agent-Based modeling (ABM) facilitates simulating spatial interactions that describe the ecological context in which insect populations spread. The main objective of this study was to develop a model of the MPB forest infestation dynamics. This spatially explicit model integrates geographic information systems (GIS) and ABM to simulate MPB outbreaks at the tree and landscape scales, providing spatiotemporal information of annual distribution and patterns of MPB outbreaks. This prototype was implemented with geographic data generated from aerial overview surveys carried out by the B.C. Ministry of Forests and Range for a study site in Kamloops, Canada. Results show the direct influence that vigorous forest stands and trees have on higher breeding rates, and therefore in the MPB population increment at a tree scale, in a period of 5 years. The simulation results at the landscape level help to determine the most probable locations of future MPB infestations in a time frame of 10 years.

2.2 Introduction

Assessment and monitoring of forest health represents a key point for environmental policy and for the management of environmental resources (Ferretti, 1997; Allen, 2003). Likewise, as with any other environmental resource, proper management of forests should be based on the knowledge of their status as well as on the recognition of changes and disturbances in their condition. As the importance of spatial structures and processes in forest ecosystem dynamics is well recognized (Malanson and Armstrong, 1996), it is essential to study how and why geographic space affects and is affected by disturbance agents in forest environments.

Disturbances, both human-induced and natural, shape forest systems by influencing their composition, structure, and functional processes. Among the natural disturbances, insect outbreaks are considered to have one of the greatest effects on Canadian forests (Taylor and Carroll; 2003). In order to learn about the spatial dynamics of insect colonies, it is important to acknowledge that their behaviour is robust, flexible, adaptive, self-organized, intuitive, and scalable. Therefore, it is necessary to use an approach that allows exploring the underlying interactions between insects and host trees, as well as the emergent phenomenon resulting from the ongoing relationships. Complex systems theory offers an advantageous framework for spatiotemporal modeling of forest epidemics phenomena.

Complex forest ecosystems and the dynamics taking place between host trees and insects within them at both the tree level and landscape levels form part of a complex geographic process that requires extensive theoretical and practical approaches to provide
insights for understanding and controlling the impacts of insect outbreaks. In order to comprehend and represent the internal organization of such forest ecosystems and interactions caused by insect outbreaks, bottom-up simulation models such as agent-based models (ABMs) can be used. Likewise, geographic information systems (GIS) provide a computational platform to handle the storage, manipulation and visualization of large volumes of geographic information regarding the phenomena under study. Although GIS are particularly useful for representing model input and output of a geospatial nature, GIS are not well suited to model dynamic phenomena due to their inability to adequately represent spatial changes over time. For that reason, it is important to explore the opportunity of linking (through coupling or integration) a GIS with ABM.

The agent-based approach has emerged from complex systems theory as a valuable tool in the exploration of space-time dynamics within environmental systems since it allows studying the relationships between micro-level individual actions and the emergent macro-level phenomena (Gimblett, 2002; Bousquet and Le Page, 2004). This type of spatiotemporal modelling approach is based on individual agents that behave or make decisions in a certain way that affects their environment. This ability makes it possible to simulate how the agents behaviour and interaction between each other and their environment produce emerging global patterns over time (Parker et al., 2003).

The emerging characteristics from often indirect interactions of individuals that constitute forest ecosystems are simple compared to the complexity of the entire system. Self-organization and emergence properties of forest ecosystems can be explored in forestry studies through an ABM approach to model the interaction between groups of
agents and resource dynamics, emphasizing how agents affect resources and the exchanges of information and agreements among these agents (Ekbia and Reynolds, 2006). Abundant research exists regarding the development and use of ABMs for experimenting with and exploring geographical phenomena such as land use and land cover change and the for improving the potential for linking ABM and GIS (Gimblett, 2002; Benenson and Torrens, 2004; Parker, 2005). Other models deal with the assessment of the influence of demographic changes in deforestation and its impact on forest ecology, stream hydrology and changes in water availability (Bithell and Brasington, 2009; Smajgl et al., 2009). Likewise, ABM have been created to deal with the design of regulations related to the purchase of environmental services from agriculture as well as policies for water access rights (Smajgl et al., 2009; Viaggi et al., 2009). Another example of a geographic ABM application is the development of a multi-agent model to facilitate the sustainable management of boat traffic in the Saguenay-St. Lawrence Marine Park and Marine Protected Area in Quebec (Anwar et al., 2007).

The objective of this study was to develop an integrated agent-based GIS capable of capturing, representing and examining mountain pine beetle populations at two spatial scales. MPB interactions were modeled at the tree scale and landscape scale to represent how MPB start at micro level and create patterns of infestation that affects forest health at macro scales. Specifically, this study analyzed how insect behaviour and environmental conditions influence the distribution of attacking insect populations, their preferences of trees to attack. The approach proposed in this study depicts MPB behaviour in order to attain a better understanding of the insect’s adaptability to new landscapes and the nature of severe attacks of MPB on lodgepole pine, *Pinus contorta*, forests. MPB outbreaks
represent a catastrophic natural disaster that triggers widespread mortality of lodgepole pine, one of the most abundant commercial tree species in British Columbia, Canada. This study demonstrates the emergence of spatial patterns as a product of this phenomenon, in order to predict forest disturbances of MPB infestation.

2.3 Existing Modeling Approaches of MPB Infestations

Various methods have been proposed to model the spatial distribution of mountain pine beetle populations and attack patterns. To monitor forest health conditions over space and time, remote sensing methods provide information for identifying forest landscapes at risk to medium or long-term changes. Detection and mapping of attacked trees makes it possible to plan for mitigation activities, and can also aid in parameterizing models of epidemic outbreaks designed to reduce future hazards and impacts on forests. Advanced image processing and classification procedures have permitted reliable early detection of a spreading mountain pine beetle infestation using digitally converted multispectral and normal colour aerial photography (Roberts et al., 2003). For example, QuickBird satellite imagery were used to characterize stands' attributes to determine the likelihood of sustaining red attack damage resulting from an infestation of MPB in an area of British Columbia that has traditionally been outside the beetle's biological range (Coops et al., 2006). In addition, Landsat imagery was used to predict red-attack damage with 86% accuracy reported (Wulder et al., 2006). The outcomes of these studies indicate that for particular sites with mixed forest stands and variable terrain, remotely sensed and ancillary spatial data can be combined to create a mountain pine beetle red-attack likelihood surface that accurately identifies damaged forest stands at a landscape scale. Point data generated from global positioning system (GPS) helicopter surveys have been
used to determine the location and magnitude of mountain pine beetle outbreaks in forest landscapes of British Columbia (Nelson et al., 2006). Fuzzy sets, GIS and high resolution multispectral aerial photographs were used to derive susceptibility maps of pine beetle infestations (Bone et al., 2005).

Parallel to remote sensing methods, various equation-based models (EBM) have been created to model MPB population distributions. EBM consist of a set of equations, and implementation involves evaluating them. Models of differential equations have been proved to be a useful and practical form of mathematical models since the days before computers due to their extremely rapid execution using numerical integration.

Different equation-based simulations range from models based on pheromone ecology at the stand level (Logan et al., 1998) to the atmospheric models of long-range dispersal across landscapes (Carroll et al., 2003). To simulate mountain pine beetle population dynamics, a population dynamic model was designed to operate in a 1ha area of pure lodgepole pine (Safranyik et al., 1999). This MPB model was enhanced by adding a spatial component through the use of SELES software (Riel et al., 2003). The model SELES-MPB simulates beetle impacts on landscapes making use of climate and topography data corresponding to the zone of study, keeping the 1ha spatial resolution. Although different approaches have been used to depict, predict, assess and manage MPB outbreaks, equation-based models are generally used to model these phenomena. These models provided important conceptual and mechanistic insights into the formation and distribution of the MPB outbreaks. However, most of them have been implemented using
mathematical equations without taking into account some of the spatial dynamics that influence the phenomenon.

In terms of describing the spatio-temporal dynamics of MPB outbreaks, a Markov Chain approach was used to describe the dispersal patterns of the beetle and the effect of dispersal on infestation, and to identify the time series hotspots and cold spots of outbreaks and the conditions that contribute to the occurrence of these spots (Lewis and He, 2006). Spatial distribution of MPB has also been studied through the application of a range of spatial statistic methods (e.g. K-means cluster analysis) (Campbell et al., 2007). A GIS-based cellular automata (CA) model was proposed to simulate spatio-temporal dynamics of MPB attacks to determine the distribution of tree mortality (Bone et al., 2006). In addition, the potential of GIS-CA modelling approach was used for evaluating the complexities of forest management practices (Bone et al., 2007). However, complex spatio-temporal interactions happening between MPB attacks at tree scale and their impact at larger scales have not been yet well captured.

It is necessary to conceptualize the insects as autonomous agents that interact and make decisions based on the condition of the environment at the local tree scale and also to determine how forest dynamics are driven by these infestations at a larger landscape scale. The spatial dynamics of mountain pine beetles exhibit a behaviour that is suitable for simulating with ABM. These models offer significant benefits over equation-based models in respect to the underlying structure of a model and the ability to provide a realistic and comprehensible representation of a system (Parunak et al., 1998). Likewise, ABMs appear to be especially suitable for processes that involve individuals such as
MPB that exhibit certain intelligence that is manifested through making spatial decisions. Agent-based geocomputational models can be used to simulate spatial interactions in environmental processes in order to understand changes in disturbed landscapes. These simulation models provide norms for comparison with real behaviour, and the differences between model and reality provide the basis for improvement of our understanding of the general principles encoded into the ABMs. Therefore the main goal of this study was to propose a MPB infestation model based on complexity theory using an agent-based approach and GIS to evaluate the emerging behaviours from the interaction between MPB populations at two spatial scales.

2.4 Methods

The GIS-AB model and the prototype tool were developed in this study to implement the simulation of MPB infestation over forest landscapes consisting mainly of lodgepole pine. This model permitted to acquire understanding on how local behaviours at the local (tree) scale influence global dynamics over time, and to incorporate the elements of complex systems theory into a forest infestation model. The tree scale as well as the landscape scale model consisted of two types of agents, Beetle agent and Tree agent that permit the representation of the mountain pine beetle behaviour and the tree health evolution respectively, as well as their interaction and mutual influence within the dynamic process of the forest infestation phenomenon. The conceptual model representation is synthesized in a Unified Modeling Language (UML) class diagram that shows all the classes of the model with their attributes, functions and their relationships (Figure 2-1). Subsequent sub-sections explain the emerging, dispersal and attacking behaviour of beetles, as well as the survival rate of MPB populations growing under
different climatic circumstances, and their influences in the health of the lodgepole pine forest ecosystem.
2.4.1 Agents – Tree Scale

2.4.1.1 Agent Beetle

The behaviour of an agent type beetle was portrayed by a series of rules or steps that it had to follow in order to decide where to fly within the forest ecosystem and also to select the tree to attack and brood. Mountain pine beetle, *Dendroctonus ponderosae* Hopkins, is a small (0.5 cm) black beetle, which typically kills host trees in order to successfully reproduce (Logan et al., 1998). The beetle is a naturally occurring part of the lodgepole pine forest ecology as it exists at low population levels in all lodgepole pine forests (Safranyik and Carroll, 2006). Their beetle larvae feed on the inner bark of mature pine trees, girdling the trees and killing them (Cole, 1973). The host trees must be sufficiently large and have thick inner bark for the beetles to successfully reproduce and reach epidemic populations (Amman and Cole, 1983). When food supplies over a sufficient area and climatic conditions over a sufficient period of time are favourable, the small endemic populations undergo explosive growth resulting in a beetle epidemic (Amman, 1982). Epidemics end when the desirable food supply of large lodgepole pine trees is no longer continuous enough to support the population or when climatic conditions become unfavourable for the beetle. Climatically ended epidemics will reoccur after a period of favourable weather allows populations to rebuild (Heavilin et al., 2005). The dynamics of the beetle epidemic resemble the classic predator-prey dynamics studied in classical ecology, which attempts to predict the relationship in populations between a population of predators (i.e. MPB) and preys (i.e. Lodgepole pine) (Taylor, 1990).
In order to present the forest infestation phenomenon, multiple raster-based GIS datasets were used to represent continuous forest landscape in several GIS layers. The beetles characterized as autonomous agents were displayed in the model simulation as a GIS layer with discrete data points dispersed over the forest landscape. Cells within the GIS raster data layer of the forest represented trees. Many beetles that form a colony of beetles coexisted within the same cell, which were able to stay and initiate the feeding and reproduction process based on a set of rules that permitted them to stay in a tree or fly to another tree within the simulation environment. Agents representing mountain pine beetle had a unique attribute that allowed discriminating the beetle population by gender; therefore the simulation involved identification of female and male beetles, with a male:female sex ratio 1:2 (Safranyik and Carroll, 2006).

2.4.1.1.1 Agent Beetle Attack Behaviour - Emergence and Movement

MPB leave their currently infested trees in late July to early August in search of a new tree to attack (Figure 2-2). Females first emerge and fly varying distances in search of a new host tree. The initial flight by newly emerged mountain pine beetles tends to disperse them widely throughout the forest. Even in the presence of aggregation pheromones, the majority of beetles may disperse out of a stand (Safranyik et al., 1999). In the simulation, the initial attack behaviour was modeled using ABM where the rule for the first beetles to emerge from the dead trees – strip attacks were not simulated – was based on the query of the agent gender attribute. Nevertheless, it is important to mention that although female agent beetles should emerge first, not all emerge at the same time. In this prototype, each beetle agent had to query the Diameter at Breast Height (DBH) of the tree that it inhabits at the moment before the emergence. Therefore, the first females
to emerge were living or located in large trees, followed by female beetles that are located in medium trees, and finally the female beetles placed in small trees. Table 2-1 presents the parameters of emergence order within the mountain pine beetle population. Large female beetles tend to emerge earlier than small females, and the development of the beetles depend on the size (DBH) of the trees (Safranyik and Carroll, 2006). The emergence of the male beetles is initiated only when at least one of the females beetles have located and selected a new host.

![Mountain Pine Beetle Life Cycle](image)

**Figure 2-2. Mountain Pine Beetle Life Cycle**

**Table 2-1. Parameters of order of emergence within the beetle population.**

<table>
<thead>
<tr>
<th>Emergence Order (Initial Attack)</th>
<th>Size</th>
<th>Attribute that Determines the Size (DBH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>Big</td>
<td>43cm – 50cm</td>
</tr>
<tr>
<td>Second</td>
<td>Medium</td>
<td>23cm - 42cm</td>
</tr>
<tr>
<td>Third</td>
<td>Small</td>
<td>12cm – 22cm</td>
</tr>
</tbody>
</table>
After the emergence has been initiated, the dispersal or movement of the new adults away from natal hibernation sites starts (Raffa et al., 1997). Newly emerged beetle adults tend to be positive phototactic – i.e., moving themselves toward a source of light when leaving a breeding site (Raffa et al., 1997). The movement during the initial flight of newly emerged mountain pine beetles is fundamentally driven by host stimuli (Shepherd, 1966). This prototype models the MPB movement behaviour through random displacements in one of eight directions (northwest, north, northeast, west, east, southwest, south, and southeast) towards mature host trees with high values of DBH. The distances that the agents beetle fly are nondeterministically specified by a number of fuzzy set rules.

2.4.1.1.2 Agent Beetle Attack Behaviour – Determining the Flying Distances for Dispersal

During dispersal, most beetles fly several meters below tree crowns but above the undergrowth (Schmitz et al., 1980; Safranyik et al., 1989). The direction of this flight is normally downwind until beetles encounter an attractive host tree (Safranyik and Carroll, 2006). Beetles that do not disperse from the stand in which they develop usually locate suitable host trees within two days of emergence, but are capable of searching for several days (Safranyik et al., 1992). Studies have established that the minimum distance for a beetle to travel in order to find a suitable tree is 6 meters (Safranyik and Carroll, 2006). When beetles fly through a lodgepole pine stand the maximum distances that a MPB have to fly can reach up to 50m (Safranyik et al., 1999). However, some unpredictable flight patterns arise due to wind and terrain influences. MPB often disperses within a small radius into nearby forests but can travel several kilometres with the appropriate wind
conditions (Berryman, 1989). Although shorter dispersal flights allow greater investment of energy in reproduction, longer flights enable beetles to locate habitats with higher quality host trees (Elkin and Reid 2005). In order to define the flying distance of each agent beetle without any bias or deterministic decision, the agent beetle decides how many meters to fly based on a set of rules that make use of fuzzy logic to establish some ranges of distances for the agent to make a decision. Likewise, the model captures the influence of wind in the flying distances by allowing the agent beetle to fly ranges from 6m up to 250m.

The decision rules for determining the flying distance were created based on the fuzzification process of transforming crisp values into grades of membership for linguistic terms of fuzzy sets (Tso and Mather, 2001) of three variables that made it possible to come to a decision: 1) flying distance, 2) DBH, and 3) lodgepole proportion, as presented in Table 2-2. The first variable represents the decision that has to be made in relation to the last two variables. The last two variables were chosen because they represent the ideal source of food that can be identified by the beetle agents. Numerous authors have reported tree diameter as a landing stimulus (Hopping and Beall, 1948; Cole and Amman, 1969), and that large, dark silhouettes (Shepherd, 1966) and vertically oriented cylinders, like the lodgepole pine, are attractive to beetles (Billings et al., 1976). Likewise, other studies suggest that beetles land at random, during the first flight, on larger trees due to their larger surface area (Burnell, 1977; Hynum and Berryman, 1980).
Table 2-2. Fuzzy membership functions for flying distance of mountain pine beetles in a forest landscape. The membership function describes the membership of the different variable in the fuzzy set.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fuzzy Set</th>
<th>Fuzzy Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flying Distance</td>
<td>Short Triangle</td>
<td>6-50m</td>
</tr>
<tr>
<td>Flying Distance</td>
<td>Medium Triangle</td>
<td>30-150m</td>
</tr>
<tr>
<td>Flying Distance</td>
<td>Long Triangle</td>
<td>100-250m</td>
</tr>
</tbody>
</table>

Fuzzy membership functions to determine flying distance of MPB based on DBH

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fuzzy Set</th>
<th>Fuzzy Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBH</td>
<td>Small Linear</td>
<td>12-25cm</td>
</tr>
<tr>
<td>DBH</td>
<td>Medium Linear</td>
<td>20-40cm</td>
</tr>
<tr>
<td>DBH</td>
<td>Big Linear</td>
<td>30-50cm</td>
</tr>
</tbody>
</table>

Note: This is a Euclidian Distance, measured from the centre of the cell that represents one tree where the mountain pine beetle is located.

Fuzzy membership functions to determine flying distance of MPB based on lodgepole pine proportion in the forest landscape.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fuzzy Set</th>
<th>Fuzzy Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lodgepole Pine Proportion</td>
<td>Low Linear</td>
<td>2-8 trees (cells)</td>
</tr>
<tr>
<td>Lodgepole Pine Proportion</td>
<td>Medium Linear</td>
<td>7-16 trees (cells)</td>
</tr>
<tr>
<td>Lodgepole Pine Proportion</td>
<td>High Linear</td>
<td>14-24 trees (cells)</td>
</tr>
</tbody>
</table>

Making use of the fuzzy variables the agents’ type beetle reached a decision regarding the distance to fly in order to look for a suitable host. The decision rules were:
Rule 1:
*If* LodgepolePineProportion is *High* and DBH is *Big*
*Then* FlyingDistance is *Short*

Rule 2:
*If* LodgepolePineProportion is *High* and DBH is *Medium*
*Then* FlyingDistance is *Short*

Rule 3:
*If* LodgepolePineProportion is *High* and DBH is *Small*
*Then* FlyingDistance is *Short*

Rule 4:
*If* LodgepolePineProportion is *Medium* and DBH is *Big*
*Then* FlyingDistance is *Short*

Rule 5:
*If* LodgepolePineProportion is *Medium* and DBH is *Medium*
*Then* FlyingDistance is *Medium*

Rule 6:
*If* LodgepolePineProportion is *Medium* and DBH is *Small*
*Then* FlyingDistance is *Medium*

Rule 7:
*If* LodgepolePineProportion is *Low* and DBH is *Big*
*Then* FlyingDistance is *Medium*

Rule 8:
*If* LodgepolePineProportion is *Low* and DBH is *Medium*
*Then* FlyingDistance is *Long*

Rule 9:
*If* LodgepolePineProportion is *Low* and DBH is *Small*
*Then* FlyingDistance is *Long*

2.4.1.1.3 Agent Beetle Attack Behaviour – Selecting the Host
After pioneer beetles land on a potential host tree, the agents initiate the process of evaluation to determine if the actual tree fulfills their requirements of food and allows
them to breed. This selection process was based on four parameters: 1) health state of the
tree, 2) type of tree, 3) tree age and 4) DBH. The first rule to select the host is evaluated
consulting the characteristics of each tree, after which point a specific decision is
reached. Table 2-3 shows the detailed rules based on these four parameters.

Table 2-3. Parameters evaluated as a first step to select the host tree and then establish the amount of
eggs to be laid per tree.

<table>
<thead>
<tr>
<th>Health State of the Tree</th>
<th>Type of Tree</th>
<th>Tree Age [Years Old]</th>
<th>DBH [cm]</th>
<th>Number of MPB Flights*</th>
<th>MPB Decision</th>
<th>Number of MPB Eggs</th>
<th>State of the Agent “Beetle” after laying the Eggs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dead</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>Leave the tree</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Alive</td>
<td>Douglas Fir</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>Leave the tree</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Alive</td>
<td>White Spruce</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>Leave the tree</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Alive</td>
<td>Lodgepole</td>
<td>80 - 140</td>
<td>40-49</td>
<td>--</td>
<td>Stay in the Tree</td>
<td>60 - 80</td>
<td>Dead</td>
</tr>
<tr>
<td>Lodgepole</td>
<td>Pine</td>
<td>61 - 79</td>
<td>23-39</td>
<td>&gt; 1</td>
<td>Stay in the Tree</td>
<td>30 - 60</td>
<td>Dead</td>
</tr>
<tr>
<td>Lodgepole</td>
<td>Pine</td>
<td>20 - 60</td>
<td>14-22</td>
<td>&gt; 2</td>
<td>Stay in the Tree</td>
<td>≤ 30</td>
<td>Alive</td>
</tr>
</tbody>
</table>

*The number of MPB flights represents the number of additional times that an
agent beetle is allowed to fly to attack and/or laid more eggs in a different tree, before it
dies.

Once the agent beetle makes the decision to stay in the tree, the second rule was
applied to find out if the agent is allowed to stay in the tree to feed and breed, or if it had
to leave the tree due to overcrowding. To minimize the effects of intraspecific
competition, the mountain pine beetle has evolved a mechanism to terminate host
colonization on individual trees at or near optimum attack densities, approximately 60
attacks per m² of bark, using chemical cues (Raffa and Berryman, 1983). The second rule
that finally permits the agent to determine if it is allowed to stay in the tree was based on
a calculation performed by the agent type tree, which provides the agent beetle with
information about how many other beetles are per 1 m². The decision is taken based on
the next condition (second rule):

\[
\text{If the population density of beetle agents} < 60 \text{ per 1 m}^2
\]

\[
\text{Then the agent beetle is able to stay in the tree and initiate its feeding and}
\text{reproduction cycle}
\]

\[
\text{If the population density of beetle agents} > 60 \text{ per 1 m}^2
\]

\[
\text{Then the agent beetle has to fly again to find a suitable tree to initiate its}
\text{feeding and reproduction cycle}
\]

The *Attack Behaviour* is completed once all the ABM rules are performed for a
single iteration, which is equivalent to the time span of one day. This time length was
used with the purpose of capturing and understanding in detail the behaviour during the
three weeks of emergence and attack of the insect. In the same way, the use of this
temporal scale permit to follow-up the life cycle of the agents’ type beetle and know
approximately when each beetle emerges from a tree (Figure 2-2).

**2.4.1.1.4 Agent Beetle – Life Cycle Simulation**

Once a new host is selected, female beetles begin to construct a gallery and in the
process instigate a mass attack. A mass attack involves a complex synergism of host-
produced (kairomones) and beetle-produced (pheromones) volatile chemicals (Amman,
1982) as the female bores through the bark and releases a chemical compound that
attracts male beetles to the same tree. The tree’s defensive mechanisms are overcome
once a sufficient number of MPB have attacked the tree (Powell et al. 1998). The
aggregation pheromones result in a mass attack, and the process is normally completed in one to two days on an individual tree. In trees where attack densities are low, females may abandon their egg galleries, even after laying a complement of their eggs, and search for another tree to lay more eggs (Amman, 1982). This behaviour was captured by the AB model by allowing the beetles to fly more than one time when attacking young trees, which usually have small DBH. Table 2-3 also presents the parameters to select a host tree and establish the amount of eggs to be laid per tree. However, an agent beetle could not wander more than thirty days looking for a tree to lay and/or mate. If after this period of time the agent was not able to find a suitable tree to feed and brood, the agent died.

Inside the galleries of newly attacked trees, eggs are laid and normally hatch within a week or so following deposition and young larvae commence feeding immediately. Larvae often reach third or early fourth instars before temperatures become too low for continued development. Larvae resume feeding in the spring once temperatures are sufficiently high, at which point they complete their development and transform to pupae by June. New adults occur during late June to mid July (Figure 2-2). Within the host tree, low temperature is often the largest single source of mortality in mountain pine beetle populations (Safranyik et al., 1999).

In order to simulate the life cycle of mountain pine beetles, the ABM made use of additional rules to ensure the evolution of beetle agents’ population, which are explained as follows:

a) Once the beetle agents were within a tree, they had to query the age of the tree in order to establish the number of eggs to be laid. The number of eggs was
randomly generated once the age of the tree was stated. This random number of eggs was allocated within a range given by the Table 2-3.

b) After laying the eggs (which constituted the next generation of agents' type beetle), the parent agents die, with the exception of those agents that were attacking younger trees (20 to 60 years old). These agents were allowed to fly again and look for another tree to lay more eggs. This rule was created with the purpose to simulate newly discovered behaviours on MPB such as attacking younger pines instead of only attacking mature pines (Maclauchlan, 2006).

c) Once the new agents were created, the gender attribute was assigned maintaining the male:female sex ratio (1:2).

d) To follow the natural process of MPB life cycle, the evolution of the eggs to become an adult beetle was capture in a time period between 352 to 365 days. This range of time was randomly selected within the simulation, and it allowed accounting for those beetles that emerge early from the tree as well as for those that emerge exactly one year after being born. Different stages were accessible as an attribute of each agent beetle from the moment it is an egg to the moment it becomes a brood adult. Table 2-4 presents the mountain pine beetle life cycle stages through 365 days.

Table 2-4. Different stages of the MPB life cycle within 365 days, from the egg to the attacking adult.

<table>
<thead>
<tr>
<th>Days</th>
<th>Life Cycle Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Eggs</td>
</tr>
<tr>
<td>+7</td>
<td>Hatch</td>
</tr>
<tr>
<td>+1</td>
<td>Larva</td>
</tr>
<tr>
<td>+260</td>
<td>Pupa</td>
</tr>
<tr>
<td>+(83 to 96)</td>
<td>Brood Adult – Attacking Adult</td>
</tr>
</tbody>
</table>
e) Before reaching adulthood, the beetle agents may be threatened by cold weather. MPB experience high levels of mortality each winter when low temperatures have detrimental effects on the developing stages of the beetles. During moderate winters, it is common to have a mortality level of 80% due to low temperatures. However, under a severe winter the mortality rate may rise to 90% of MPB (Carroll et al., 2003; Safranyik and Carroll, 2006).

f) The process of emergence, flying, host selection and brood is reinitiated once the agent reached its adulthood.

2.4.1.2 Agent Tree

The agent type representing a tree was depicted by the continuous surface of cells in a raster GIS database layer where cells represent trees randomly distributed. This type of agent has its own thread of control, allowing it to identify its state and attributes and modify its behaviour. Tree agents have also individual rules and goals, making them active objects with initiative. These autonomous entities observe their own set of internal responsibilities and are capable of sending messages to the beetle type agents. These messages inform the agents of a particular event like the tree carrying capacity. The attributes of the tree (type, age, height, health state, and DBH) provide important input information to the agent-based model. The first calculation performed by the tree agents is the total bole surface area ($S_t$) in order to estimate the beetle population density per tree:

$$S_t = 0.3455 + 1.9708 \times D \times H$$

(2-1)

where the constants are regression coefficients calculated by Safranyik (1988); $H$ is total tree height (m) and $D$ is the tree diameter (m) at 1.37 m (Safranyik et al., 1999).
After computing the total bole surface area, the agent tree inquires how many beetle agents are located within it and proceed to evaluate the beetle agent population density per 1 m². The tree agent also updates its health state after the initial attack of the mountain pine beetle, consecutively through each year going from a green attack stage (once the tree is killed, but still with green foliage), to red-attack stage (approximately twelve months after the green attack) and finally to gray-attack stage (approximately three to five years after being attacked) (Wulder et al., 2006).

2.4.2 Agents – Landscape Scale

At a landscape scale, the Beetle Agent maintains its behaviour; however at this scale this agent does not represent an individual beetle but a group of insects that occupy a tree. Each group of insects has the same goal, which is to look for the most suitable forest stand. The Tree Agent does not represent a unique tree, but a forest stand with attributes of type (tree species), average age, average height, average DBH and tree health status information.

While most of the tree scale methods are kept, modifications and simplifications were necessary to portray the MPB infestation at a different spatial resolution. First, each group of agents lack the gender attribute, so they emerge only based on the DBH information obtained from each forest stand. The movement and flying distances of insect groups are determined using only the fuzzy rule for flying long distances (Table 2-2) in order to account for the influence of the winds in the spatial spread of MPB swarms. Host selection behaviour considers the evaluation of the same four variables: 1) health state of the stand, 2) type of stand, 3) average age and 4) average DBH. At the landscape scale, there is no rule to avoid intraspecific competition based on the number of beetle
agents per m$^2$, but all the beetle groups cannot attack the same stand at a time. The MPB life cycle behaviour at this scale is not simulated; it is assumed that the number of MPB swarms grows exponentially every year. However, based on the winter temperatures (high or low), these populations decrease due to the mortality rates as a result of the changes in temperature.

2.5 Model Implementation and Simulation Results

2.5.1 Model Input Data

For implementation purposes of the proposed forest MPB infestation model, simulations of the insect outbreak in a forest ecosystem were generated to apply the methodological framework. These simulations correspond to two different scenarios: 1) Scenario 1 - Landscape Scale Scenario: represents a study area of 4 km$^2$, with a course spatial resolution of 100m x 100m cell size, and 2) Scenario 2 – Tree Scale Scenario: represents two subset study areas, each of 400m x 400m, with fine resolution of 1m x 1m, where the raster cells represent trees randomly distributed. Raster was selected over a vector model due to the nature of the data; likewise, the inherent nature of raster maps (e.g. one attribute maps) is ideally suited for modelling and quantitative analysis.

The two scenarios depict two different spatial scales at which the MPB phenomenon occurs. The study area used for this study represents a forest landscape of the Kamloops Forest District in the central interior of British Columbia (Figure 2-3), which contains a high concentration of dead trees due to a number of previous MPB infestations. The forest consists of three different species of trees: 1) lodgepole pine, Pinus contorta, which dominates the landscape; 2) Douglas-fir, Pseudotsuga menziesii,
Figure 2-3. Location of study area - Thompson-Nicola Regional District, British Columbia, Canada. The subset areas (three lower windows) were used to test the model at two different spatial scales.
with relatively smaller proportions and 3) white spruce, *Picea glauca*, distributed throughout the landscape.

For the simulations, five different raster GIS datasets were used in order to feed the model with information regarding tree species, health state, diameter at breast height (DBH), tree age, and tree height. Forest cover attributes (i.e. tree species, age and height) and georeferenced data sets were obtained from GeoBC (GeoBC, 2008). The vector format file from GeoBC was converted into a raster format creating two different sets of raster files each one with different cell sizes (1m x 1m and 100m x 100m). In the absence of DBH values, these were randomly assigned based on tree age (Reid et al., 2004). Trees between twenty and sixty years old were assigned DBH between 14-22 cm; trees between sixty-one and seventy-nine years old were assigned DBH between 23-39 cm; trees between eighty and hundred and forty years old were assigned DBH between 40-49 cm (Roberts et al., 2003). The handling of the GIS data sets was carried out using ArcGIS 9.3.

The chosen study areas were extracted from the B.C. Ministry of Forests and Range datasets created by means of aerial overview surveys (Figure 2-3). These surveys record only red trees representing recent damage that is visible from the air and tend to over-estimate the numbers of trees killed particularly as the scale decreases. The dataset used in this study was mapped at 1:250,000 (B.C. Ministry of Forests and Range, 2004). The aerial overview severity codes responding to the wide-spread mountain pine beetle outbreak include five classes that describe the severity of the MPB attack over forest stands: Trace (T) (<1% attack), Light (L) (1-10% attack), Moderate (M) (11-30% attack), Severe (S) (31-50% attack) and Very Severe (V) (>50% attack) (B.C. Ministry of Forests
Two patches of dead lodgepole pine that can be observed in figure 2-5 acted as the seed trees area from which MPB disperse and search for new host trees to attack.

2.5.2 Simulation Toolkits and User Interface Developed

To implement the agent-based modeling approach, RepastS (Argonne National Laboratory, 2008) and its Java libraries were used. ArcGIS software (ESRI, 2008) and GIS libraries of GeoTools (Codehaus Foundation, 2006. In addition, the NRC FuzzyJ toolbox (National Research Council of Canada's Institute for Information Technology, 2006) for the implementation of the fuzzy rules in Java was sourced for RepastS integration.

Repast Simphony (RepastS) serves as a simulation toolkit to develop and execute AB models for applications such as forest infestations simulation within an integrated two-dimensional raster GIS environment. The implementation of the proposed model was accomplished using Java language. The programming code was written to execute the model by introducing a population of MPB agents located in a geographic space with defined spatial interactions among them, as well as with the forest environment. Thus, each agent beetle had a spatial location and was able to identify and move towards the spatial location of trees in the forest.

The graphic user interface (GUI) was created to facilitate model execution through choice of parameters as well as visual display of generated simulations (Figure 2-4). GUI permits visualization from beetle agents interacting in space, display of
histograms and charts, as well as various simulated scenarios all depicting the progress of the infestation.

Figure 2-4. Graphic User Interface developed using RepastS and Eclipse IDE software, with 2D display (dots represent Beetle Agents, different shades in the landscape represent different types of Tree Agents) and charts of mountain pine beetle simulations.

2.5.3 Implementation

The implementation of the AB model integrated with GIS was made using two scenarios: Landscape Scale Scenario (1) and Tree Scale Scenario (2). Figure 2-5 depicts the study area used in the first scenario and the localization within it of the subset areas with a finer spatial resolution. The use of two different spatial resolutions for model implementation was considered in order to provide a global and local understanding of the phenomena behaviour at two different spatial resolutions. Modeling at a more detailed scale was intended to provide specific knowledge about changes in density of attacks in small size areas such as forested areas with light attacks transforming into areas
with moderate to severe attacks of MPB. In contrast, when observed and modeled at a coarser resolution, the MPB infestation process started to exhibit an epidemic behaviour by spreading into larger areas of forest land-cover.

Initially, the simulation of a mountain pine beetle outbreak performs over the study area used in *Landscape Scale Scenario* (1), where forest stands are composed of pure lodgepole pine, Douglas-fir, and white spruce. A series of ten simulations were initialized with 100 agents each, representing groups of MPB spreading through the forested landscape. This first part of the simulation examined the emergence of the MPB outbreak spatial patterns using different MPB mortality rates observed under moderate and extreme winters. MPB experience different levels of mortality each winter when low temperatures have detrimental effects on the developing stages of the beetles. During outbreaks occurring under moderate or normal winters (e.g. -18°C), it is common to have a mortality level of 80%; however, when the temperatures are extremely low (e.g., -32°C or lower) the environmental conditions change and mortality levels increase to 90% (Safranyik and Carroll, 2006). This coarser scale provided insight about where to expect beetle infestations. One of the affected areas was used to perform the second part of the simulation at finer scale.

The simulation for *Tree Scale Scenario* (2) was generated for two selected areas (Figure 2-5) that had different MPB infestation levels. For the two subsets of forest landscape, the moderate and extreme winter mortality rates were also taken into account. A total time period of 5 years was used for the simulation of MPB infestation in the study areas that make part of the *Tree Scale Scenario* (2). This timeframe was used in order to
analyze the spread of the outbreak through time. A total of ten simulations were generated for each of the two areas taken from of the Tree Scale Scenario.

Figure 2-5. Localization of Scenario 2 two subset areas; each area had previous MPB attack. For the selected Area (1) the pest severity code reported by BC Ministry of Forest and Range is Moderate (11-30% attack) and for the selected Area (2) the pest severity code is Light (1-10% attack). Spatial resolution of Landscape Scale Scenario (1) is 100m x 100m, and 1m x 1m for Tree Scale Scenario (2). Blocky light shade shows the representation of the same areas at a coarser resolution (100m x 100m).

There are a number of factors that drive the MPB outbreaks, including tree age, stem density, basal area, year-round temperatures and drought. However, this first prototype only takes into account variables such as tree size (DBH and height), tree age and winter temperature as drivers of MPB outbreaks in order to keep the model simple.
These variables are generally considered as key elements to determine forest susceptibility to MPB attacks (Shore et al., 2000; Hicke and Jenkins, 2008).

2.5.4 Results

The findings from the simulation for Landscape Scale Scenario (1) are presented in Figure 2-6, which depicts the simulated locations of the mountain pine beetle infestation over a long term period (10 years) using both moderate and extreme winter mortality rates. These results portray that MPB during the first four years is mainly located close to the areas where previous attacks were observed; however, some spotted attacks occurred away from initial dead trees. After the fourth year, the spread consistently remains near areas with previous mass attacks; however, in year six some new infested cells are noticeable far away (upper right and left corners) from the initial infestation. These new spotted attacks are consistent with the growth of the beetle populations due to the fact that the model allows the MPB population to grow but they have to interact within the same boundaries. This produces greater populations of beetles that rapidly consume all the food resources that are available in the area.

Figure 2-7 presents simulation outcomes generated for Landscape Scale Scenario (1), these charts depict the number and percentage of MPB-killed tree stands in a time period of ten years. Between years four and six in the moderate winter, the percentage of dead stands increases by 31%. In the extreme winter, the percentage of dead stands increases only by 12%, showing how weather acts as a natural control mechanism trying to establish equilibrium within the ecosystem. Nonetheless, the lodgepole forest ecosystem continues being disturbed by the MPB infestation since the MPB populations
Figure 2-6. Ten-year simulation output of the integrated GIS-ABM model used to understand and predict spatial and temporal evolution of MPB infestation at a spatial resolution of 100m x 100m.
keep growing, and almost 80% of the trees are dead after a period of ten years from the initial attack. The reason for the increase and variation in MPB populations is that the average lodgepole pine tree diameter in the study area is 31 cm, allowing a larger rate of survival. Biologists consider that beetle survival rates are more closely related to tree diameter and phloem thickness than any other factor (Safranyik et al., 1999). Therefore when the lodgepole pine trees have a good size, beetles living in them are able to survive low temperatures better than those beetles living in thinner trees. The quantitative summary of the simulation outcomes (Figure 2-7) also indicates a range of difference between the number and location of lodgepole pine stands attacked during the infestation progress under the moderate and extreme winter scenario despite the fact that patterns were not visually identifiable.

Due to the stochasticity of the model, a series of ten simulations were generated for each geographic area that constitutes part of the Scenario (1) and Scenario (2). The replication of the simulations showed that the random components lead to different results each time. Figure 2-8 presents the overlay of the outcomes of ten simulations. This figure shows the probability of location of MPB spread after the second year of infestation for Scenario (1). Areas with the higher probability have a value of one (1), and areas with the lower probability have values close to zero (0).

Once simulations for the Landscape Scale Scenario (1) were generated, the model was executed using the Tree Scale Scenario (2) for the Kamloops area. The British Columbia Ministry of Forest and Range reported that the spatial location of the latest scenario was undergoing attack by MPB (B.C. Ministry of Forests and Range, 2004).
Figure 2-7. Percentage of lodgepole pine attacked by MPB in a time lapse of ten years.
Simulations were performed using both *moderate* and *severe winter mortality rate* scenarios. The results of these simulation outcomes for the moderate *winter mortality rate* scenario and normal climatic conditions (mean temperature of -17.9°C) are presented in Figure 2-9 and Figure 2-10, respectively, for area 1 and area 2.

The outcomes of the model simulations demonstrate the evolution of the infestation and its dependence on the structure of the landscape; likewise, it elucidates different positive and negative feedbacks observed in this dynamic process. In forested areas where previous attacks were registered, the MPB prefer to fly short distances. For
this reason, spread was not very prominent outside the previous infested zone during the first two years of the infestation, but the number of killed trees increase in areas close to previously observed attacks. However, after the second year of outbreak, the MPB populations started to spread outside the previous attacked zones. This is more evident in the area 1 where the density of previous attacks is higher than in area 2 for both moderate and severe winter mortality rate scenarios (Figure 2-11). The reason for this difference in spatial behaviour is the number of initially attacked trees in each subset. In the area 1, the percentage of MPB-dead trees is 14%, therefore the area is considered to hold a moderate attack (11-30% of trees are dead). In area 2, there is a 6% rate of MPB-dead trees, thus the area is considered to hold a light attack (1-10% of trees are dead). The density of the initial attack produces a different pattern of MPB infestation in the simulation. As a result, the areas with fewer MPB-killed trees will have an increase in mortality of the closest trees and beetles start looking for food outside the areas previously attacked after certain point is reached, resulting in longer flying distances. At the same time, MPB populations located in areas where the number of MPB-killed trees is higher tend to fly outside the zone boundaries with a high percentage of previously attacked trees. In previously attacked zones, reported to have a moderate pest code by the BC Ministry of Forest and Range, the increment in trees killed by MBP is not visually notable. However, the counts made from generated simulation maps indicate that the number of trees attacked from one year to another expands, increasing the percentage of dead trees and modifying the previously established pest codes.
Figure 2-9. Five-year simulation output of the integrated GIS-ABM model used to understand and predict spatial and temporal evolution of MPB infestation for moderate winter, Area 1 400m x 400m, spatial resolution 1m x 1m.
Figure 2-10. Five-year simulation output of the integrated GIS-ABM model used to understand and predict spatial and temporal evolution of MPB infestation for moderate winter, Area 2 400m x 400m, spatial resolution 1m x 1m.
Figure 2-11. Charts of the trees killed by MPB attack during a period of time of five years. Diagrams depict the results for the two different subset areas, considering a moderate winter scenario.
2.6 Conclusions

In this study, the integrated GIS-AB model was developed and implemented using datasets from the BC Ministry of Forest and Range. The selected study site is located in Kamloops, BC, Canada, an area known as much affected with pine beetle infestations. The obtained results revealed that MPB-induced mortality patterns can be spatially modeled using an agent-based approach due to its ability to capture the behaviour of the mountain pine beetle infestation phenomenon. The integration of GIS and an agent-based approach provides a valuable tool for exploring the space-time dynamics within the forest landscape, taking into consideration the effect of the interaction between the forest and the mountain pine beetle and also permits to simulate the robust behaviour and adaptability of MPB populations to different landscape structures. This study emphasizes the utility of ABM for modeling ecological processes where individual agents interact and self-organize at a micro-level generating specific and structured patterns at a macro-level.

One of the most important features of using AB modeling approach for forest infestation process is the capability of incorporating in the model natural behaviours observed in disturbance agents like mountain pine beetle swarms. This potential makes possible to simulate MPB population growth and life cycle, feeding and breeding habits, as well as flying and attack patterns. This study demonstrated the potential of using an integrated GIS-agent based modeling approach that permits representation of spatial dynamics of the spread of MPB outbreaks through forest landscapes. The temporal and spatial behaviour of the model outcomes are explored by analyzing the spatial allocation of new outbreaks and quantifying the new infected trees through time.
The simulation results in this study revealed the influence that higher diameter trees had on higher breeding rates, therefore in forest stands with big and mature pines new MPB population levels increased. However, as the outbreak proceeded through time, the attack of larger trees was not possible due to scarce food resources, forcing MPB to attack younger stands of lodgepole pine tree. These findings were better depicted using Landscape Scale Scenario (1), which indicates that MPB outbreaks at a landscape scale depend on the food availability and favourable weather conditions that allow higher beetle survival rates. The outcomes of the proposed model and implemented prototype using the Tree Scale Scenario (2) also depict the spatial patterns in pine mortality produced by MPB infestation. Simulation maps indicated that the areas undergoing a light MPB attack (1-10% trees attacked) turned into moderate MPB attack, due to the insects behavioural tendency to aggregate instead of flying very long distances. Conversely, the simulations for the areas undergoing a moderate MPB attack (11-33% trees attacked) depicted that the infestation spread out further.

Agent-based modeling offers a useful approach for analyzing and understanding the complexities of forest insect infestation; however, future research in this field requires a focus on the issue of model testing and validation. This involves comparing the modeled outcomes to reality, the latter being typically represented in a dataset of the same geographic area as the model input, but from an afterward moment in time. Agent based modeling evaluation and validation is a challenging research endeavour and research work in testing validation of ABM is not yet fully elaborated in the scientific literature. In respect to the MPB modeling one of the main challenges is that the information required is often unavailable. Georeferenced data sets, used in models like
the one presented in this study, contain considerable data that are extremely expensive and time consuming to collect at such detailed scale and for sustained numbers of years. Another issue regarding real data of MPB infestation is that given the spread, often governmental decisions of clear-cut were made in areas that are bigger than the infested site and all the data about the outbreaks are therefore unavailable for number of consecutive years. In addition, even if data could be collected over different periods of time, complex geographic processes are subject to feedbacks and random events that can lead to different results. In this way, a validation dataset may represent only one of a set of possible outcomes. For these reason, AB models validation requires special research efforts that are important but make part of another ongoing research study. The prototype model tool presented in this study represents the first step of a work in progress that looks forward to assuring that the model generates emergent patterns that can be used in real forest management applications. The findings from this study can help to improve comprehension of the spatially explicit spread dynamics and take better steps towards the reduction of their impact on forest landscapes. The implemented prototype of the model proposed in this study is generic and can be replicated in different study sites as long as the input information required by the model is available.

2.7 References


3. EXPLORING FOREST MANAGEMENT PRACTICES USING AN AGENT-BASED MODEL OF FOREST INSECT INFESTATIONS²

3.1 Abstract

The forests of British Columbia, Canada have undergone an unprecedented Mountain Pine Beetle, *Dendroctonus ponderosae* Hopkins, (MPB) infestation that has resulted in extensive mortality of lodgepole pine, *Pinus contorta*. The objective of this study is to apply the agent-based model (ABM) to simulate the MPB attack behaviour in order to evaluate how different harvesting policies influence spatial characteristics of the forest and spatial propagation of the MPB infestation over time. The first scenario is the no management action with the natural disturbance process leading the changes of the forest ecosystem. The other two scenarios implement sanitation and salvage harvesting methods. Obtained results indicate that the different management strategies significantly affect the MPB infestation rates. Statistical analysis of the simulation outcomes is performed to compare the three scenarios and prove that salvage harvesting is the most effective strategy. This study can improve our understanding of the effects of management strategies and assist policy decision making process when complex MPB agent-based model of forest insect outbreaks is used.

3.2 Introduction

Forest ecosystems have adapted to local climate, atmosphere and soils over many years (Dale et al. 2001). However, human activity such as resource extraction, land development and management strategies have resulted in changes to the natural environment, posing real problems for forests and woodlands. British Columbia, Canada, possesses a land area of approximately ninety-five million hectares, two-thirds of which is covered by forest that is constantly being modified by natural disturbances such as fire, diseases and insect infestations (Campbell et al. 2007, Carroll et al. 2003, Dale et al. 2001). Likewise, policies implemented by resource managers have played an important role in the modification of the landscape patterns. In a province where 15% of the economy relies on forest resources (Haley 2005), disturbances such as mountain pine beetle (MPB), Dendroctonus ponderosae Hopkins, infestation have put forest values at risk impacting the economy of many British Columbian communities; these insect outbreaks have resulted in the death of trees over areas of several thousand square kilometres (Kurz et al. 2008).

The dynamics of MPB infestation taking place between stands of host trees and insects within them, form part of a complex spatio-temporal process that requires theoretical and practical approaches to provide insights for understanding and controlling the impacts of MPB outbreaks. With the purpose of comprehending and representing the internal organization of such forest ecosystems and interactions caused by insect outbreaks a bottom-up approach using an agent-based model (ABM) has been developed (Perez and Dragićević 2010). This ABM acknowledges the robust, flexible, adaptive, self-organized, intuitive, and scalable behaviour of insect colonies. Although the model
effectively captures the emergent patterns of tree mortality due to MPB outbreaks, it has not considered how different forest harvesting management activities influence the spatial patterns of mortality tree distribution and the number of killed infested trees.

The objective of this study is to use agent-based model (ABM) to simulate the MPB attack behaviour in order to evaluate the MPB spatio-temporal dynamics under three different management scenarios. More particularly, this study evaluates how management practices, implemented through Management Agent, influence the spatial distribution and patterns of insect population and their preferences for attacked and killed trees. The model simulations are implemented using three harvesting scenarios: 1) no management, 2) sanitation harvest and 3) salvage harvest. The MPB outbreaks are considered a major natural disturbance that triggers widespread mortality of lodgepole pine, one of the most abundant commercial tree species in British Columbia, Canada. The model is implemented on a study area located in the North-Central Interior of British Columbia.

3.3 Methods

The methodology for this study consists of three main sections. The first section describes the behaviour and life cycle of MPB populations and the mechanism how these are represented with the model. The second section provides details regarding the interaction between the host (lodgepole pine) and the MPB, describing the role of pine trees in the model implementation; and finally the third section explains the different management practices and how these are implemented. The model consisted of three types of agents: Beetle Agent, Pine Agent, and Forest Management Agent that permit the
representation of the MPB behaviour, the forest environment and tree health evolution, and the stakeholder respectively.

3.3.1 Attack Behaviour of MPB and Life Cycle: The Beetle Agent

The behaviour and life cycle of the MPB are captured by the Beetle Agent which follows a series of rules or steps to decide where to fly within the forest and to select a healthy tree to attack, feed and breed. In its natural environment, MPB typically kills host trees in order to successfully reproduce (Logan et al. 1998). Their beetle larvae feed on the inner bark of mature pine trees, girdling and killing them (Cole 1973). The host tree must be sufficiently large and have thick inner bark for the beetles to successfully reproduce and reach epidemic populations (Berryman et al. 1989). MPB outbreaks end when the food supply depletes and is no longer enough to support the population or when climatic conditions become unfavourable for the beetle (Safranyik et al. 1999).

In real life, female MPB emerge from the tree before the males do and fly varying distances in search of a new host tree (Safranyik and Carroll 2006). To simulate the emergence behaviour within the model, each Beetle Agent had to query the Diameter at Breast Height (DBH) of the tree it inhabits before it starts flying. Therefore, the first female Beetle Agents to emerge are the ones living or located in big trees, afterwards the ones that find themselves in medium trees, and finally the female beetles placed in small trees. The emergence of the male Beetle Agents is initiated only when at least one of the females Beetle Agents has located and selected a new host tree. To simulate the flying distances of each Beetle Agent, fuzzy sets were used to allow them to come to a final decision. The Beetle Agent captures wind influences within the natural range of MPB flying distances. The decision rules for determining the flying distance for each Beetle
Agent are based on the fuzzification of three variables: flying distance, DBH, and tree proportion within the stand (Perez and Dragičević 2010). Once potential host trees are located, Beetle Agents initiate the process of evaluation to determine if the trees fulfill their requirements of food and allow them to start the reproduction stage. The host selection process involves the evaluation of four parameters of health state of the trees within the stand, type of trees, average age and DBH. After the assessment of the hosts, the Beetle Agents reach a decision whether to stay or fly to a different stand.

In the real-world, at some point of the MPB attack, the number of beetles per tree reaches the host tree capacity and an anti-aggregation chemical compound is released by the beetles in order to redirect the attacks towards nearby trees (Huber and Borden 2001). This specific behaviour is modeled using the Pine Agent which is in charge of calculating the beetle population density per stand and passes the information in to the Beetle Agents.

When the attack is successfully initiated, eggs are laid inside the galleries of newly attacked trees and normally hatch within a week or so following deposition and the young larvae commence feeding immediately. In the simulation, Beetle Agents have to query the age of the tree in order to establish the number of eggs to be laid; this number is randomly generated based on the average age of trees. The MPB experience high levels of mortality each winter when cold temperatures have detrimental effects on the developing stages of the beetles. During outbreaks, it is common to have a mortality level of 80% due to cold temperatures (Carroll et al. 2003, Safranyik and Carroll 2006). Winter mortality of Beetle Agents is simulated by having removed 80% of the newly created beetle population. This final stage represents the completion of one life cycle of the MPB which is equivalent to one year.
3.3.2 Lodgepole Pine Forest in a MPB outbreak: The Pine Agent

The MPB employ a specific strategy to overcome the defences of lodgepole pine. It relies upon cooperative behaviour in the form of mass attack by rapidly concentrating on selected host trees in response to aggregation pheromones; therefore the beetles exhaust the host’s defensive response (Safranyik et al. 1999, Raffa and Berryman 1983, Berryman et al. 1989). If sufficient beetles arrive at a rate that exceeds the resistance capacity of a particular tree, then colonization is successful. The Pine Agent is implemented to simulate the resistance of lodgepole pine with its own thread of control that identifies the state and attributes of each stand. This autonomous entity watches out for its own set of internal responsibilities and is capable of sending messages about tree resistance capacity to the Beetle Agents. The attributes of the tree stands (type, age, height, health state, and DBH) are also used as important input information to the agent-based model.

In order to estimate the beetle population density per tree, Pine Agents are in charge to calculate the total bole surface area ($S_t$) as follows:

$$S_t = 0.3455 + 1.9708 \times D \times H$$  \hspace{1cm} (3-1)

where the constants are regression coefficients calculated by Safranyik (1988); $H$ is total tree height (m) and $D$ is the tree diameter (m) at 1.37 m (Safranyik et al. 1999). Once ($S_t$) is calculated for each stand, Pine Agent determines the number of Beetle Agents located within the trees per stand and proceed to evaluate their population density per 1 m$^2$ (Perez and Dragićević 2010).
3.3.3 Management Practices: The Forest Management Agent

To date, there is no consensus about a unique method for suppressing the MPB infestations. Long-term mitigation of MPB outbreaks can only be accomplished through the implementation of management strategies in order to lower the susceptibility of lodgepole pine landscape (Bone et al. 2007). Management practices available for controlling MPB outbreaks depend on the size of the outbreak, the age of the stand, the size of the trees, and the conditions of the site amongst others. Generally, managing involves a reduction of susceptible and/or infested stands in an effort to prevent new attacks (Fettig et al. 2007). The most common management strategies used to minimize future resource losses from the beetle-induced tree mortality are the silvicultural treatments of sanitation and salvage harvesting. To explore the effects of management strategies in the spatial propagation of MPB outbreaks, this model simulates at stand level the two common silvicultural practices and the one with no management through the Forest Management Agent.

In the sanitation and salvage harvest silviculture strategies the Forest Management Agent evaluates each forest stand within its Moore neighbourhood. To cut down an evaluated stand, using the sanitation harvest strategy, the number of infested trees has to be greater than a set threshold. Likewise, any healthy neighbour stand is cut down whenever its average DBH value is greater than 30cm. In the salvage harvest strategy, if a stand does not register MPB attack and a predetermined number of neighbours are under a MPB attack, the Forest Management Agent proceeds to cut down the stand.
3.4 Model Implementation and Results

The model proposed in this study simulates the dynamic process of MPB outbreaks under different scenarios of forest harvesting. A forested area of approximately 560 ha, located in North-Central Interior of British Columbia, Canada (Figure 3-1) is used to implement and test the ABM previously described. The forest landscape consists of stands of small, medium and large diameter trees that are dominated by lodgepole pine, with relatively smaller proportions of Douglas fir, *Pseudotsuga menziesii*, and white spruce, *Picea glauca*, scattered throughout. The spatial resolution of the study area is 1 ha, where raster cells represent forest stands.

Figure 3-1. Study area located in the north-central interior of British Columbia, Canada, with its land cover categories.
Beetle Agents are randomly dispersed in the forest landscape as discrete data points within a raster GIS layer. Agents representing MPB have the unique attribute that allows discriminating the beetle population by gender and helps to simulate and maintain the male:female sex ratio of 1:2 as observed in reality (Safranyik and Carroll 2006).

Five different GIS raster data sets were used as input for the model simulations containing the information regarding tree species, health state, diameter at breast height (DBH), tree age, and tree height of each stand in the study area. The data is obtained from the aerial photographs collected during the summers of 2001-2003 (Roberts et al. 2003). Auxiliary cartography is used to verify classification of average tree species and tree sizes within a stand, and whether or not a stand had been attacked by MPB (B.C. Ministry of Forests and Range 2004). The thematically classified images are analyzed in a GIS, georeferenced and resampled so the spatial resolution corresponded to stand level scale. The DBH values are randomly assigned based on the tree age. The management and processing of the GIS data sets are carried out using ArcGIS 9.3. To understand the influence of management practices in the number of lodgepole pine stands killed by the MPB infestation, in the course of time, model simulations are performed for five time steps. Each time step represents a year – from the end of the first year ($T_{i+1}$) to the end of the fifth year ($T_{i+5}$). A series of thirty experiments are conducted in order to evaluate the results due to the stochasticity of some parts of the model. During the thirty simulation runs for each management scenario, none of the parameters were changed. Figure 3-2 presents the simulation results corresponding to three different scenarios: 1) Scenario 1 – MPB dispersion under no management strategy implemented, 2) Scenario 2 – MPB dispersion under a sanitation harvest strategy, and 3) Scenario 3 – MPB dispersion under
Figure 3-2. Five year simulation of lodgepole pine stands’ mortality patterns using three different management strategies (a) MPB dispersion under no management, (b) MPB dispersion under a sanitation harvest strategy, and (c) MPB dispersion under a salvage harvest strategy. Legend for land uses are the same as on Figure 3-1.
a salvage harvest strategy. These scenarios depict three different dispersal patterns, and spatial distributions of stands attacked by MPB. Furthermore, they permit to identify the effects of using forest management techniques in the presence of an insect disturbance for the study area.

The statistical analysis of the number of stands killed is provided for one simulation for each of the three scenarios in Figure 3-3 and for the aggregate of thirty different simulations for each management scenario in Figure 3-4. In average a 4% of variation amongst the thirty simulation outcomes was identified for the no management and sanitation harvest scenarios and a 2% variation for the salvage harvest scenario. The model outcomes indicate that the insect outbreak simulated without applying a management strategy results in highest overall stands infestation during the five years. Comparing the total number of stands killed by MPB in five years, the Scenario 1, Scenario 2 and Scenario 3 yielded values of 2299, 1884 and 1775 lodgepole pine forest stands respectively, which indicates that greater timber losses, in areas undergoing insect outbreaks, can be reduced through silvicultural practices. The reason for getting a higher number of attacked stands for the Scenario 1 is that more forest stands were available for a higher MPB population’s production, therefore every year the insect population increased.

The evaluation of the sanitation and salvage harvest strategies indicates that the salvage practice is more efficient in the task of diminishing the total loss of timber in a period of five years. The use of this management technique generates a reduction of 25% in the number of forest stands killed by MPB, while the sanitation harvest reduced the mortality by 19%. In the absence of a management strategy the MPB outbreak killed a
greater number of stands. The outcomes from the *salvage harvesting* scenario reveal that the implementation of this technique reduces the mortality rates of pine trees by successfully controlling MPB. The reason for this is that the outbreak is contained by cutting down all the healthy and mature trees with the purpose to reduce the wood loss.

Table 3-1 show the results of the ANOVA test that was used to establish the difference between the three management scenarios. The null hypothesis stated that there was no difference between the results out of the three different scenarios simulated; $H_0$: $\mu_1 = \mu_2 = \mu_3; H_1: \mu_1 \neq \mu_2 \neq \mu_3, \alpha = 0.05$. Given that the obtained value for $F$ is smaller than the critical ($F < F_{crit}$), therefore the null hypothesis is rejected. This statistical test confirms that different management strategies significantly affect the MPB infestation rates.

**Table 3-1. ANOVA Table.**

| SUMMARY | | | | | |
|---|---|---|---|---|
| Groups | Count | Sum | Average | Variance |
| No management | 30 | 70742.01 | 2358.07 | 6137.29 |
| SanitationHarvest | 30 | 57120.00 | 1904.00 | 4130.07 |
| SalvageHarvest | 30 | 52788.11 | 1759.60 | 857.41 |

**ANOVA**

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>$SS$</th>
<th>$df$</th>
<th>$MS$</th>
<th>$F$</th>
<th>$P-value$</th>
<th>$F_{crit}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
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<td>2</td>
<td>2925926.82</td>
<td>0.789030</td>
<td>1.73E-56</td>
<td>3.101</td>
</tr>
<tr>
<td>Within Groups</td>
<td>322618</td>
<td>87</td>
<td>3708256.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>6174472</td>
<td>89</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
Figure 3-3. Number of stands killed at each year of the model simulation for each management scenario, with standard error bars.
Figure 3-4. Box plots comparing the outcomes of thirty different simulation runs performed for each of the three management scenarios.
3.5 Conclusion

The objective of this study was to test different management strategies based on an existing AB model for simulating MPB-induced tree mortality patterns in order to evaluate the influence of different forest management practices to control insect outbreak. The model was implemented using three different scenarios on data sets from the BC Ministry of Forest, for a study site in the North-Central Interior of British Columbia, Canada. The results of the model simulations indicate that the use of different management strategies affects significantly the number of stands attacked and killed by the MPB. The importance of the model used and the scenarios developed can help with managing harvesting techniques and forest areas undergoing MPB outbreaks. The model can be used as an exploratory tool that can help to build meaningful forest management policies. In addition this study can be extended to incorporate other management strategies that can include the economic elements. Valuing the cost of using different harvesting strategies could permit to establish more effective policies to control MPB infestations with the less impact to local economies.

3.6 References


4. FORESTSIMMPB: A SWARMING INTELLIGENCE AND AGENT-BASED MODELING APPROACH FOR MOUNTAIN PINE BEETLE OUTBREAKS

4.1 Abstract

The widespread outbreaks of Mountain Pine Beetle (MPB) are responsible for infestations of lodgepole pine forests since 1990 in Canada. In British Columbia, this forest insect disturbance has resulted in losses of more than 13 million hectares of pine trees. The complexity of the MPB emergence, aggregation and attack behaviour is captured by this study, using an intelligent agent-based model (ABM) of beetle outbreaks at a local scale of individual trees. Agent-based approach permits simulation of interactions that describe the ecological context in which insect populations spread. Intelligent reasoning is introduced by a swarm intelligence (SI) algorithm integrated with the ABM that depicts indirect communication, collective behaviour and self-organized aggregation of insects in a forest ecosystem. The objectives of this study are the following: 1) to develop ForestSimMPB model that integrates SI and ABM within a geographic information systems (GIS) framework; 2) to implement the proposed model on real datasets to simulate the MPB aggregation and mass attacks on lodgepole pine trees; and 3) to determine the spatial patterns and extents of these attacks. The ForestSimMPB is calibrated by fine tuning two model parameters, and implemented using data from three sites located in the Cariboo Regional District in the central interior.

of BC. The obtained results demonstrate the aggregation behaviour of MPB to collectively attack lodgepole pines, as well as portray the spatial clustering of dead trees resulting from infestation. Simulation outputs provide analysis and predictions of spatial patterns in the forest landscape structure as a result of a MPB outbreak. The developed model can be used to assist the improvement of methods for prevention and control of MPB disturbances.

4.2 Introduction

Mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, is one of the most common disturbance agents of pine forest ecosystem in western Canada (Safranyik and Carroll, 2006). MPS outbreaks are a rapidly growing concern in British Columbia, Canada. In 1999, 164 hectares of lodgepole pine, *Pinus contorta*, were killed by beetle outbreaks, and this number rose to over 13 million hectares in less than 10 years (Aukema et al., 2006; Carroll, 2003; Westfall and Ebata, 2008). Although modeling forest cover changes in order to understand biological disturbances is very useful, it is challenging as it requires an adequate understanding of the disturbance agents' role in shaping the geographic space over time (Raffa et al., 2008). Conducive to modelling MPB populations is the fact that they can be associated with the definition of a swarm-structured collection of interacting organisms or agents (Engelbrecht, 2005; Subbotina and Oleinika, 2009). Although the interaction among the individual agents is determined genetically, the non-social interaction that achieves a global objective plays a key role in the resulting behaviour of the group. This, therefore, suggests that the global behaviour of a swarm simultaneously determines the conditions under which individual agents perform, and that every agent has an impact on the resulting behaviour of the swarm.
(Abraham et al., 2006; Bonabeau et al., 1999). Therefore, the swarming intelligence (SI) is deemed as a suitable mathematical approach to represent the behaviour of MPB. MPB interact within their colonies and their environment which results in complex patterns of dead trees. Therefore, in order to understand the complexity and emerging properties of the forest-MPB system, the use of methods that allow contextualization across both space and time is necessary. The agent-based modeling (ABM) approach coupled with the powerful analytical capabilities of a geographic information system (GIS) offers the ability to model such a dynamic phenomenon (Gimblett, 2002; Parker, 2004; Parker et al., 2003). ABM provides a way to experimentally evaluate scenarios where the forest landscape structure changes in relation to the MPB outbreaks. Hence, MPB agents are programmed as software objects with the ability to capture the spatial reasoning and interactions of beetles. The SI algorithm improves the reasoning of the agents within the ABM by providing them the capability to communicate through signals in order to accomplish a common goal.

This study offers a novel approach for simulating MPB infestations in forest ecosystems by explicitly representing MPB spatial reasoning, indirect communication and aggregation behaviour. The ForestSimMPB model integrates SI and ABM within a GIS framework, and is implemented on a study area located in the Cariboo Regional District in central interior British Columbia, Canada. Model simulation outcomes are examined to determine the spatial patterns extents of the MPB attacks in three selected sites.
4.3 Swarm Intelligence and Decision-Making in Non-social Insects

Swarm Intelligence (SI) theory was developed based on biological examples of swarming, flocking and herding phenomena in vertebrates (Bonabeau et al., 1999). A swarm is defined as a group of agents (usually mobile) that communicate with each other (either directly or indirectly) by acting on their local environment (Hoffmeyer, 1995). Therefore, a swarm's internal complexity is the result of the interactions between the individuals agents in both space and time (Engelbrecht, 2005, 2007a). SI is an innovative distributed intelligent paradigm for solving optimization problems that has been applied in data clustering, transportation planning and geospatial reasoning, among others (Abraham et al., 2008; Engelbrecht, 2007a; Parunak et al., 2006; Teodorović, 2003). Consequently, SI is used in this study as adequate approach to simulate the decision-making and aggregation behaviour of MPB.

4.3.1 Decision-Making of Swarms

Decision-making in social insects suggests the ability of ants, bees, wasps and termites to capitalize on each other's actions, drawing benefit from cooperative effects. Thus, this collective behaviour is algorithmically implemented in computational models (Abraham et al., 2006; Bonabeau et al., 1999; Engelbrecht, 2005). This collective behaviour is accomplished after individual agents observe signals from other agents and specific responses or actions are triggered as a result. The triggered response may reinforce or modify signals to influence the actions of other individuals. The term stigmergy was introduced to define the indirect communication between individuals, mediated by modifications in the environment (Grassé, 1959). To date, many different algorithms derived from social insects have been proposed to model decision-making.
4.3.2 Swarming Behaviour of Non-social Insects: Chemical Signals for Aggregation

SI approach can also be used to study the behavioural aspects feeding and/or attack aggregation of non-social insects. Swarms of non-social insects such as the bark beetles (e.g. *Dendroctonus ponderosae* Hopkins) differ from those observed in social insects because they are not characterized by overlapping generations, cooperative care of the young, and reproductive division of labour (Alcock, 1982; Coulson, 1979). Nevertheless, non-social insects communicate shared information in the form of signals, measurable in terms of physics or chemistry, which enables the alteration of the response patterns among the individual insects (Byers, 1989; Matthews and Matthews, 2009). In the specific case of the bark beetles these signals are emitted with the purpose to aggregate. These aggregations are formed and maintained for a number of reasons one of which is a larger group of co-specifies – two or more individual organisms that belong to the same species is more efficient in overcoming active or passive defences of a tree (Raffa, 2001; Schlyter and Birgersson, 1999).

4.3.2.1 Mountain Pine Beetle Aggregation Behaviour in the Real-world

The MPB life cycle begins with hatching from eggs laid in barks of dead trees and ends with migration to and colonization of new host trees. Female beetles emerge first, in
the absence of pheromones they fly and randomly spread throughout the forest (Raffa and Berryman, 1980; Safranyik and Carroll, 2006). Pioneer beetles locate suitable hosts using a combination of random landings guided by visual response to dark silhouettes followed by detection of the correct feeding stimulus. Once a host is selected, these beetles release aggregating pheromones which, together with host volatiles, attract beetles of both sexes and result in host colonization (Safranyik and Carroll, 2006). Female MPBs perceiving the volatile chemical mating call from another female choose to follow the signal to find a suitable host (Schlyter and Birgersson, 1999). The host tree strength and active defences dictate the number of aggregated beetles needed for a successful infestation.

MPB populations are capable of overcoming the active defences of healthy host trees by means of pheromone-mediated synchronous attack by numerous individual insects (Alcock, 1982; Raffa, 2001; Safranyik et al., 1999). The MPB pheromone calling system for mate attraction uses an aggregation pheromone that empowers them to defeat healthy tree defences by synchronous attack of multiple beetles (Raffa, 2001; Schlyter and Birgersson, 1999). At the same time, the attack density is regulated by the production of an anti-aggregation pheromone (Pureswaran and Borden, 2003). The inhibitory effect of the anti-aggregation pheromones affects the distribution and density of attacks within a specific tree rather than among trees (Bentz et al., 1996; Raffa and Berryman, 1983; Renwick and Vité, 1970), while plumes of the aggregation pheromones that encompass neighbouring trees are responsible for the redirection of attacks.

The aggregation behaviour of non-social insects such as the MPB can be simulated by means of mathematical models. The purpose of such a model is to describe the decision-making of MPB swarms in the forest-MPB system and integrate it into the
SI algorithm that allows the modeling of the dynamics of the MPB infestations. Hence, the main objectives of this study are to propose and implement the ForestSimMPB model based on an SI algorithm integrated with a GIS-ABM to describe the stigmergetic characteristics of the MPB swarm-entities. Moreover, the proposed model is applied to the real datasets to simulate the MPB aggregation and mass attacks on lodgepole pine trees, to characterize the extent and spatial patterns of the MPB outbreaks.

4.4 Methods: ForestSimMPB Model

The ForestSimMPB model is an agent-based model (ABM) structured within a GIS framework consisting of two essential components: Agents and Artificial Pheromone Structure (APS) (Figure 4-1). The model input consists of five different data layers related to trees’ health states, susceptibility, height, age and diameter at breast height (DBH) and the output in the form of simulated forest health maps. Each physical entity of the model corresponds to one single agent such as a beetle or a tree, and its individual characteristics. Male and female MPB start their life cycle by emerging from previously dead trees followed by the search for a new host trees in which to mate and die. Pine trees serve as hosts for the MPB. Their health state attribute is modified if their defence mechanisms against insect colonization are defeated. The APS is a mechanism used to store and administrate the simulated chemical cues that lead the interactions between agents and their environment. The following sections explain the specifics of each type of agent and component within the model design.
Figure 4-1. Flow diagram for the ForestSimMPB model integration.
4.4.1 Agents and Their Roles

There are three types of agents in the proposed ForestSimMPB model: Beetle Agents (AB) and Tree Agents (AT), representing the MPB and the lodgepole pine trees respectively; and Place Agents (AP) which are the ones in charge of managing the APS.

4.4.1.1 Beetle Agents: Representing MPB Behaviour

Emergence from dead trees represents the beginning of the MPB life cycle, and this behaviour is represented in the ForestSimMPB by A_B. These agents have a unique attribute that allows gender distinction in order to simulate the first flight of the MBP population which is initiated by the female beetles (Safranyik and Carroll, 2006). During the first flight, the A_B with a female gender attribute fly randomly in the forest ecosystem to locate an adequate tree in which to start the mating and feeding phases. Although the tree selection procedure is random, the A_B first examines its susceptibility to an attack. For the ForestSimMPB, the susceptibility of a tree depends on the tree's Diameter at Breast Height (DBH), age and distance to previously attacked trees. Subsequent to the susceptibility query, the health state is taken into account by A_B before it starts attacking the tree and depositing the attracting chemical cue (aggregation pheromone) which would direct other male and female A_B towards the selected host. Figure 4-2 presents the flow chart describing the evaluation and selection process of the appropriate host tree during and after the first flight. Following the first flight of the females, A_B with a male gender attribute begin flying towards the tree with a higher pheromone concentration within their local neighbourhood (neighbourhood dimension corresponds to observations made by experts) (Safranyik and Carroll, 2006; Safranyik et al., 1999).
Figure 4-2. Beetle Agent behaviour flowchart.
In the real-world, MPBs usually locate suitable host trees within two days of emergence, but are capable of searching beyond that (Safranyik and Carroll, 2006). For that reason, $A_B$ in the ForestSimMPB are allowed to fly up to 10 days until they find a suitable host. The model operates within the boundaries of the physical size of the study site which corresponds to the size of the available digital data layer. Edge effects are considered and addressed in the model implementation through the use of a torus surface to allow unbounded behaviour of $A_B$. Although $A_B$ cannot physically emigrate outside the simulated study site like in the real world, the model accounts for a 10% probability that an $A_B$ flies outside the study area to look for a tree to be attacked (Safranyik et al., 1999). Thus, $A_B$ populations are annually reduced by a percentage of 10% in the ForestSimMPB model. Once an $A_B$ finds a host, it has to mate, deposit the eggs and finally die. Each female $A_B$ will deposit a random number of eggs which is calculated according to the parameters presented in Table 4-1 (Safranyik et al., 1999). These eggs constitute the new generation of MPB that will emerge the following year. However, before reaching adulthood, beetles are threatened by cold weather and experience high levels of mortality each winter because low temperatures have detrimental effects on their development stages. During moderate winters, it is common to have a mortality level of 80% due to low temperatures. On the other hand, under a severe winter, the mortality rate of MPB may increase up to 90% (Carroll et al., 2003; Safranyik and Carroll, 2006), and for this reason the ForestSimMPB has the capability of incorporating either of these rates when calculating the new population of $A_B$ based on the user’s selection preference in the model.
Table 4-1. Parameters evaluated to set up the number of eggs to be laid per each female Beetle Agent.

<table>
<thead>
<tr>
<th>Type of Tree</th>
<th>Tree Age [Years Old]</th>
<th>Number of MPB Eggs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lodgepole Pine</td>
<td>80 - 140</td>
<td>60 – 80</td>
</tr>
<tr>
<td>Lodgepole Pine</td>
<td>61 - 100</td>
<td>30 – 60</td>
</tr>
<tr>
<td>Lodgepole Pine</td>
<td>12 - 60</td>
<td>≤ 30</td>
</tr>
</tbody>
</table>

4.4.1.2 Tree Agents: Representing Lodgepole Pine Forest in a MPB outbreak

The AT are responsible for regulating the strength of the trees' active defences and to determine how many beetles are needed for a massive attack to be successful (Safranyik and Carroll, 2006). The attributes of AT are age, height, DBH and health state. The first three attributes are used to calculate the total bole surface area (St) of each tree and therefore estimating the beetle population density per tree. If enough beetles colonize the host - the near optimum number of attack densities is approximately 60 attacks per m² of bark (Raffa and Berryman, 1983) -, the tree health is updated from alive to dead (Figure 4-3). On the other hand, the AT is not only in charge of updating its health state based on a successful MPB colonization, but also allows the simulation of the anti-aggregation pheromone release. The ForestSimMPB uses the AT rather than the AB to simulate the production of the anti-pheromone to avoid intraspecific competition within a host tree. Hence, after the AT calculates the MPB population density, if number exceeds the permitted amount of MPB per tree, the anti-pheromone is laid.
Figure 4-3. Tree Agent behaviour flowchart.
4.4.1.3 Place Agent: Managing the APS

The $A_p$ plays the role of manager of the *Artificial Pheromone Structure*. This agent is in charge of performing the actions described in section 4.4.1 which are in summary: 1) calculate pheromone strength $\Delta s_{ij}(t)$, 2) propagate the pheromone, 3) evaporate the pheromone and 4) evaporate the anti-pheromone.

4.4.2 Artificial Pheromone Structure (APS): Simulating MPB Aggregation

The APS is a multi-agent system inspired by the behaviour of non-social insects. In this study, the approach that has been developed adopts the basic principles of natural systems like non-social insects to design an ABM capable of depicting the robustness, flexibility, and adaptability of biological disturbance agents in natural forest ecosystems and the interactions amongst the members of the population. The APS approach is bound to apply the actual insects' coordination mechanisms to aggregate for feeding and mating purposes (Figure 4-1). It seeks to capture the underlying logic of the biological and geographical complexity of the system and its coordinated global behaviour.

The APS introduces a simple algorithm to represent the stigmergy of MPB populations during the process of emergence and host colonization (Figure 4-1). The purpose of APS is to capture and mimic the self-organization and complexity of the biological entities and to characterize the spatial patterns that emerge as a result of local outbreaks within the forest ecosystem. In the APS the pheromone and anti-pheromone are represented as the square grid of digital data layer that also represents the environment where the chemical cues disperse (Figure 4-4).
Each cell of the grid has an $A_P$ that is in charge of performing the actions as follows:

1. Calculate pheromone strength $\Delta s_{ij}(t)$ as

$$\Delta s_{ij}(t) = \sum_{k=1}^{n} \Delta g_{ij}^{k} + \Delta s'_{ij}$$  \hspace{1cm} (4-1)$$

$$\Delta s'_{ij}(t) = \sum \Delta s_{i-1,1-j} + \Delta s_{i-1,j} + \Delta s_{i-1,j+1} + \Delta s_{i,1-j} + \Delta s_{i,j+1} + \Delta s_{i+1,1-j} + \Delta s_{i+1,j} + \Delta s_{i+1,j+1}$$  \hspace{1cm} (4-2)$$

where $\Delta s_{ij}(t)$ is the amount of pheromone ($g$) laid on the cell $(i,j)$ by the $k$th beetle between the time $t$ and $t+1$; $\Delta s'_{ij}(t)$ is the amount of pheromone laid in the cell's $(i,j)$ Moore neighbourhood – i.e. the eight cells surrounding a central cell between $t$ and $t+1$. 

Figure 4-4. Graphic representation of the Artificial Pheromone Structure (APS) (a) Illustration of how the Agent Place ($A_P$) calculates the pheromone ($g$) strength ($\Delta s_{Ap}(t)$) of the cell $(i,j)$, (b) APS graphic representation of pheromone evaporation in a Moore neighbourhood
If the value of the pheromone strength is positive (representing that there is a presence of aggregation pheromone) in the cell \((i,j)\), the \(A_p\) will propagate the pheromone.

If the value of the pheromone strength is negative (representing that there is a presence of anti-aggregation pheromone) in the cell \((i,j)\), the \(A_p\) will evaporate the pheromone.

2. Once a positive value of pheromone strength is found, the eighty percent of the pheromone in cell \((i,j)\) is equally propagated to the eight immediate neighbours in the Moore neighbourhood.

3. The remaining twenty percent value of pheromone in cell \((i,j)\) has to be evaporated, every time step \((t)\), using an evaporation constant \((E)\).

\[
\Delta s_{ij}(t + 1) = \frac{1}{5}\Delta s_{ij}(t) \times E \tag{4-3}
\]

4. Once a negative value of pheromone strength is found, the anti-pheromone in cell \((i,j)\) is not propagated; however, the pheromone will be evaporated, every time step \((t)\), using the evaporation constant \((E)\).

\(A_p\) use only the information available in their immediate vicinity and thus operate at a local scale. However, the propagation of attractive pheromone in step two provides some spread of information over time.

4.5 Model Implementation

The algorithm of the proposed model was developed in the Java programming language by using the Recursive Porous Agent Simulation Toolkit (RepastS) developed
by the Argonne National Laboratory (Argonne National Laboratory, 2009). The ForestSimMPB model adopts a tightly coupled architecture using the GeoTools Java library (OSGeo, 2009) for GIS data management and visualization functionality and is available for use within the RepastS development platform. The input geospatial data layers were managed in ArcGIS software (ESRI, 2009), and then imported into RepastS as ASCII files. In order to account for the edge effects, the model was programmed to read the data layers as the torus shape (i.e. cells at the edges of the map are directly adjacent to those on the opposite edge), hence the agents behaviours in the environment are unbounded. The following sections describe the simulation results carried out using the developed graphical user interface (GUI) of the proposed model.

4.5.1 Study Site

For implementation purposes of the ForestSimMPB model, simulations of the beetle infestation within a local forest ecosystem were generated. These simulations corresponded to three different sites of a study area located in the Cariboo Regional District in central interior British Columbia, Canada (Figure 4-5). Each of the three study sites represents the area covering one hectare of mixed forest (lodgepole pine and deciduous trees). Every forest site has its own particular characteristics that give the specific conditions for scenario design as follows: 1) Site 1: Pure Lodgepole Scenario, 2) Site 2: Geographic Barrier Scenario and 3) Site 3: Mixed Forest Scenario. Different areas are selected with the purpose to observe MPB infestation simulations using scenarios with diverse spatial structures. Forest areas are represented by GIS raster data structure in which forest trees are encoded as individual cells of one meter resolution. Each forest tree has information on tree susceptibility, tree age, tree DBH, tree average
height and health status of the tree (dead or alive). The model simulates a MPB outbreak for 5 years using yearly time steps.

4.5.2 Data Management

In order to generate simulation results, five different raster GIS data sets were used as the model input. These raster files contained information on tree susceptibility, health state, age, height and diameter at breast height (DBH). The health state attribute of the trees was obtained using high resolution aerial photographs. The locations of MPB colonies in 2001 were derived from 2002 imagery data. The one metre spatial resolution was selected to represent the information for each cell that was aggregated from the remote sensing (RS) images of higher resolution in order to fit the scale of the size of the average interpreted tree crown surface area. The forest cover attributes (age and height) and the georeferenced data sets were obtained from GeoBC (GeoBC, 2007). The BDH values were calculated based on the tree age (Reid et al., 2004). Trees in the age group of twenty to sixty years old were assigned a DBH between 14 and 22 cm; trees from sixty-one to seventy-nine years old were assigned a DBH between 23 and 39 cm; trees from eighty to one hundred and forty years old were assigned a DBH between 40 and 49 cm. The handling of the GIS data sets was carried out using ArcGIS 9.3. The susceptibility of the trees to be attacked by MPB was calculated based on Bone et al. (2005) using three criteria: (1) tree size, (2) distance to the nearest tree attacked in the previous year – i.e. the year 2000, and (3) age of the tree.
Figure 4-5. Study sites in the Cariboo Regional District in central interior British Columbia, Canada.
4.5.3 Graphic User Interface (GUI)

The GUI was developed to facilitate the use of software routines programmed for ForestSimMPB. Figure 4-6 depicts the main components of the GUI that permit model parameters configuration, simulation runs and visualization of model outputs. The GUI was created using the RepastS simulation toolkit. It integrates all the model components consisting of three parts. The forest landscape is displayed as a GIS raster layer where raster cells represent trees randomly distributed their health state (dead/alive). The first part configures the parameters and runs the simulations of the ForestSimMPB model (Figure 4-6 A, 4-6 B); the second part displays the simulation results (Figure 4-6 C) as well as provides histograms and charts to visualize the simulation progress (Figure 4-6 D, 4-6 E). Finally, the third part is a report console that provides detailed information about the exact coordinates of each tree, how many beetles (males and females) are attacking the tree, what is the carrying capacity of the tree as well as some other useful information (Figure 4-6 F,4-6 G).

4.5.4 Model Calibration

The initial numerical values of the model’s parameters were based on the well documented biological studies related to the MPB populations’ behaviours in the forest environment. The model calibration procedure was performed in order to simulate meaningful patterns of tree mortality comparable to those that were extracted from the aerial photographs. The first step was to determine the initial number of $A_B$ that have to be added at the beginning of the simulation (year 2001) to obtain results in terms of attacked trees that were most similar to those observed from the actual 2006 data set.
Figure 4-6. Screenshot of the developed ForestSimMPB model Graphic User Interface: (A) Model scenario tree, (B) Configuration parameters, (C) Raster-based GIS display, (D) Pine mortality histogram, (E) Beetles population histogram, (F) ForestSimMPB Java sources and documentation and (G) Model report console.
This was accomplished by running the model five times, representing yearly increments, to allocate different numbers of beetles per dead tree. The mortality patterns observed in the 2006 dataset were visually compared to patterns produced by different values in order to find the most suitable value. The second step was to determine the appropriate neighbourhood for the Beetle Agent to search higher concentrations of pheromones. Different neighbourhood sizes were tested and it was found that the model simulated results most similar to real data when neighbourhood size had dimensions greater than 20 cells x 20 cells. Smaller neighbourhood sizes resulted in reduced spread of MPB as increased intraspecies competition (involving members of one species) caused high mortality of the MPB population, thus reducing the number of dead trees after each simulation. For this reason, a 25 x 25 cells Moore neighbourhood with a spatial resolution of one metre was used for model implementation. Once the model was calibrated to simulate results similar to tree mortality patterns extracted from aerial photographs, a five-year simulation was performed to determine whether the ForestSimMPB model produced results in accordance with real MPB attack behaviour in the natural environment.

4.6 Results

Simulation results were obtained for five year MPB outbreaks and three different forested sites and their corresponding scenarios: (1) Site 1: Pure Lodgepole Scenario, (2) Site 2: Geographic Barrier Scenario and (3) Site 3: Mixed Forest Scenario. Sites with landscapes containing different spatial features were selected to study variation in both the spatial patterns and the spatial extents of MPB attacks.
Figure 4-7 presents the spatial distribution of lodgepole trees killed by the insect infestation. The results indicate the simulated locations of trees killed by the MPB infestation under climatic conditions of moderate winter. During moderate winters, an average of 20% of the offspring survive each year to initiate a new attack, whereas in a severe winter the survival rate may decrease to 10% of MPB (Carroll et al., 2003; Safranyik and Carroll, 2006). For each of the three sites selected to implement the model, the results indicate that the number of initial infested trees, the spatial distribution of initial infested trees, the diversity of the area, the presence of artificial barriers and other aspects do influence the spatial advancement of the outbreak.

Figure 4-8 presents a chart with the simulation outcomes of the three different sites depicting the number of new MPB-killed trees per year and the cumulative values in a time period of five years. Looking at the Pure Lodgepole Scenario, which is based on an area with only lodgepole pine trees, the number of dead trees increased from 296 at the beginning in year 0 to 1404 at the end of simulations after 5 years. This represents a 64% of the total number of trees in the study area. For this specific site, it is evident that first flights by the Beetle Agents during the first year behave as observed in nature. As MPB population increases and spreads out from previously killed trees in search of a suitable host, they select the closest trees to obtain more food with less effort. This behaviour facilitates MPB overcoming the trees’ defences due to the larger number of insects. After five years, a considerable number (1024 out of 2204) of pine trees died as a result of the MPB outbreak, which makes this the worst MPB infestation scenario.

The results for the Geographic Barrier Scenario illustrate how landscape fragmentation, in this case the result of a man-made barrier, affects the creation of
different patterns and distributions of MPB during outbreaks at a local scale. A road, going through the whole right section of the site, prevented the outbreak to spread into the trees located in the upper right corner of the area. Within this site, the insect infestation simulation started having 210 dead trees and the total number of MPB killed trees was 876 after five years (Figure 4-8), meaning that 58% of the available trees were attacked by the beetles. The visual inspection of simulation outcomes indicates that the beetle population spread out from two noticeable clusters of dead trees from the input dataset. Subsequent to the spread in year 2, a corridor linking the two clusters of dead trees can be observed during the 5 year period.

The Mixed Forest Scenario was the area with the most trees killed by MPB at the beginning of the simulation. The high initial number of dead trees was 508, resulting in a wide spatial distribution of dead trees visible from the second year on. The total number of dead trees reached a value of 1470 after the five year simulation (Figure 4-8), which corresponds to 78% of the total healthy population of lodgepole pine trees in the area. The patch observed in the lower part of the site corresponds to an area with the presence of deciduous trees and therefore is not attacked by MPB.

Analysis of the progress in the number of newly killed trees per site indicates that: (A) for the Pure Lodgepole Scenario, there is a constant annual increment in the number of killed trees; (B) for the Geographic Barrier Scenario, there is a connectivity convergence to two different clusters of killed trees; and (C) for the Mixed Forest Scenario, over time the number of newly killed trees starts to decrease since the peak point in the infestation had already been reached in the beginning.
Figure 4-7. Five-year simulation results of the ForestSimMPB model for three different scenarios. Total area per site is 1 ha and spatial resolution is 1 m x 1 m.
Figure 4-8. Summary of total annual numbers of trees killed by MPB attack simulated for a five years time period.
This behaviour can be explained by the relationship between food availability and the constrained number of MPB that can developed from it.

Within the ForestSimMPB model, the first flight of the female Beetle Agents and location of a host is randomly performed for the very first time in the simulation. As a result, the stochastic nature of the model can be observed every time a simulation is performed. Therefore, a series of thirty simulations were generated for each of the three geographic areas, in order to evaluate model convergence. Figure 4-9 presents the overlay of thirty simulation outcomes. This figure depicts the likelihood of finding locations of MPB-killed trees after the third year of infestation for the three study sites. Areas with the highest probability of being attacked by MPB have a value of one (1) and areas with the lowest probability have values close to zero (0).

The summary of MPB-killed trees values obtained during the simulations after three years is provided in Figure 4-10. Descriptive statistics were calculated from the thirty simulations per site; one of them was the coefficient of variation with values of 0.46%, 0.42% and 0.30% for site 1, 2 and 3 respectively. These percentages indicate that even though there is stochasticity in the model, the final results converge to the same conclusion. The similarity in the outcomes per site is due to the fact that after the first flight, the aggregation behaviour of MPB was captured by the APS allowing realistic representation of the stigmergetic communication between the MPB. Fractal dimension index (FDI), a measure of shape complexity (White 1997; White, 2006) computed for each patch and then averaged for the class (i.e. dead and alive trees), was calculated for each of the 30 simulations for the sites 1, 2 and 3. FDI of dead trees in the study areas lie in the ranges of 1.71–1.88, 1.15–1.17 and 1.10–1.14 for sites 1, 2 and 3, respectively. FDI
Figure 4-9. Likelihood of MPB outbreaks location after three years of infestation. Overlay maps of 30 simulation outcomes for site 1, 2 and 3 representing probability of dead trees due to simulated MPB outbreak.
values greater than 1 indicate an increase in shape complexity. This suggests that the spatial patterns within each site did not vary significantly over the 30 simulations.

4.7 Conclusions

The ForestSimMPB model developed in this study introduces a novel approach for integrating agent-based modeling and swarm intelligence within a GIS framework to simulate the MPB aggregation behaviour and the emergent spatial pattern of infested trees in forested areas. The model is implemented on three different study sites located in the Cariboo Regional District in the central interior of British Columbia, Canada. These sites represent three different scenarios containing different spatial characteristics which produced diverse spatial distributions of MPB outbreaks in the landscape. The modeling approach implemented provides a valuable tool for exploring the MPB space-time dynamics within a local forest landscape and visualizing the changes in forest structure. GIS serves as a mean to display the data layers as well as to help visualize the changes of the forest environment over time induced by simulated MPB attacks. This study emphasizes the utility of ABM and SI for modeling ecological processes where individual agents interact, communicate and self-organize at a micro-level generating structured patterns in the landscape. In the ForestSimMPB, only the behaviour of micro-populations (i.e. spatially located in a hectare study site) is simulated, however, metapopulation dynamics and their effects at a larger spatial scale are acknowledged and considered important in the study of forest ecological systems. This model can be extended to consider landscape or regional scales of MPB outbreak dynamics, as well as to introduce other parameters that influence the phenomena at a different level.
Figure 4-10. Summary of total trees killed by MPB attack simulated during a time period of three years; outcomes comparison of 30 different simulations for sites 1, 2 and 3.
The simulation outcomes depict the spatiotemporal behaviour of the MPB, which is examined through the visual analysis of the spatial distribution and locations of new outbreaks. The results obtained reveal that the forest composition, artificial barriers, and trees' health status have an influence on the spatial distribution of insects and the general behaviour of MPB populations during an outbreak. The model simulation outcomes were also quantified in order to assess the variability in the model as a result of its random components. Thirty simulation experiments are used for the evaluation of ForestSimMPB likelihood to predict the location of attacked trees; these experiments demonstrate that quantity of MPB-killed trees and their spatial distributions were very similar between the thirty experiments performed. The selection of Site 1 serves as a laboratory to test the model behaviour and outcomes, while the other two sites are used to obtain insights that can be helpful to managers when dealing with different conditions of the MPB outbreak. Additional scenarios and conditions such as wind and elevation effects can be developed to gain an increased understanding about the MPB behaviour phenomenon.

ForestSimMPB model effectively simulates MPB infestations through the implementation of a swarm intelligence algorithm that mimics MPB aggregation behaviour in real-world. This approach allows the complexities of MPB infestations to be analyzed and understood in different forest landscape configurations, and also serves as a reference for building management strategies. In order to integrate the model into forest decision support systems, further research efforts have to be placed in model validation. Model testing and validation of ForestSimMPB is currently an ongoing research study but it is challenging endeavour due to lack of forest data covering the study site with at wide temporal range. The findings from this study can help to improve our understanding
of spatially explicit MPB spread dynamics and to generate better management practices or mitigation techniques towards the reduction of their impact on forest landscapes.

4.8 References


5. PERSPECTIVES ON AGENT-BASED MODEL TESTING: ASSESSMENT OF A SWARMING INTELLIGENCE AGENT-BASED MODEL FOR MOUNTAIN PINE BEETLE INFESTATIONS

5.1 Abstract

Model testing procedures represent a significant challenge in the development of agent-based models (ABMs). However, they are required stages for a model to be accepted and to serve as a forecasting, management or decision-making tool. This paper presents an approach for testing ForestSimMPB, a model that is designed to simulate mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, outbreaks at the scale of individual trees. ForestSimMPB is an agent-based model (ABM) using swarming intelligence, capable to represent individuals’ behaviours and spatial interactions that influence their surrounding environment. Swarm Intelligence (SI) methods are integrated into the ABM in order to reproduce the collective reasoning and indirect communication of autonomous agents representing MPB behaviour within the forest environment. Model testing stages consisting of verification, calibration, sensitivity analysis, validation and qualification, are accomplished by simulating MPB infestations using both the ForestSimMPB model and a Random-ABM model that serves as a null model; outcomes comparison and assessment are performed using pixel-based techniques as well as spatial metrics. Aerial photographs of the British Columbia, Canada study sites are compared

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4 A version of this chapter will be submitted for publication to the *International Journal of Geographical Information Science (IJGIS)* under the co-authorship of Suzana Dragicević and Roger White
with simulation results. Overall, ForestSimMPB representations of MPB outbreaks and the spatial distribution of MPB-dead trees are significantly similar to real datasets.

5.2 Introduction

The study of the spatio-temporal dynamics of forest ecosystems, as a result of natural disturbances such as insect infestations, requires theoretical and practical approaches to provide insights for understanding and controlling the impacts of such disturbances. Interactions taking place between host trees and insects within the forest, at a tree level, form part of a complex geographic process. Geographical systems have been recognized as complex (Batty and Torrens 2005), but they can be simplified enough to build robust theory and models that can be applied to different scenarios. The use of agent-based models (ABMs) and associated tools is becoming mainstream research in a variety of disciplines such as land use planning (Ligmann-Zielinska and Jankowski 2007, Li and Liu 2009, Martens et al. 2010), resource management (McDonald et al. 2008, Bone and Dragićević 2010), criminology (Malleson et al. 2010), ecology (Anwar et al. 2007, Li et al. 2010) and landscape ecology (Jepsen et al. 2006, Entwisle et al. 2008, Parker et al. 2008) amongst others.

The majority of agent-based (AB) simulation models are built to meet practical management needs; however, following on model testing, these can also be used to represent and analyze complex dynamics, provide indicators of potential impacts and to learn about the original system (Aumann 2007). ABMs constitute an excellent tool to represent and analyze the complex dynamics of ecological systems (DeAngelis and Mooij 2005). Ecological models are built for scientific research purposes, but increasingly for forecasting and management objectives (Rykiel 1996). These models are constituted by
theoretical assumptions to represent one or many processes that occur in the real-world which transform some aspects of the geographic space through time (Batty and Torrens 2005). With the goal of using ABMs for environmental policy-making and spatial knowledge discovery, model testing procedures are essential to the model development process if models are to be accepted and used to support decision making (Refsgaard and Henriksen 2004). Model verification, sensitivity analysis, calibration, validation and qualification are important components of the modeling process (Rykiel 1996, Refsgaard and Henriksen 2004, Kocabas and Dragićević 2007, Crooks et al. 2008). Verification concerns the correctness of a model construction, making sure that model implementation matches its design (Crooks et al. 2008). Calibration involves the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set (Manson 2007). Sensitivity analysis quantifies how changes in the values of the parameters alter the value of the outcome (Kocabas and Dragićević 2006). Validation has to do with the truthfulness of a model with respect to its problem domain, both in a structural sense and in a “goodness of fit” sense (Manson 2003). Finally, a model is only valid over the domain for which it has been validated; therefore, qualification aims at discovering this domain by revalidating the model for new cases (e.g. study sites) (Rykiel 1996). All five of these steps are closely interconnected with each other; indeed the terms really refer to five aspects of a single problem.

Even though there are simulation models exploring the effects of forest disturbances such as insect outbreaks in forest cover changes (Fall and Fall 2001, Bone et al. 2006, Waldron et al. 2007, Hlášny et al. 2009, Seidl et al. 2009, Pérez and Dragićević 2010), the scientific literature does not report many studies based on complex systems
theory and their application in decision making by government agencies and forestry managers. This is probably due to the fact that no attempts to calibrate, verify or validate such models have been reported. Given that the ABM approach describes nonlinear spatial systems, it becomes difficult to use a unique approach in the model testing procedure (Manson 2007). Hence, the challenge faced in model verification, calibration, validation and qualification is to find the appropriate methods that serve to identify and minimise the errors in ABM outputs, as well as to create confidence in the simulation results.

The objective of this study is to bring perspectives and establish a series of approaches for model testing stages such as verification, calibration, sensitivity, validation and qualification, and implement them within an ABM. More particularly the ForestSimMPB (Pérez and Dragićević 2011) model is used for the purpose of the comprehensive model testing. This model simulates forest insect infestation caused by MPB, offering a novel approach for representing MPBs’ aggregation behaviour. For the purpose of testing the Random-ABM model was developed, specifically for this study, to serve as a null model. The testing procedures are implemented on a study area located in North-Central Interior of British Columbia (BC), Canada. In the following sections, the ForestSimMPB model testing steps—verification, calibration, validation and qualification—and approaches used are reported, using case-study analysis to assess the model performance. The remainder of the chapter is structured as follows. Section two summarizes the theoretical foundations of model testing. Section three outlines the ABM models used in this study and the model testing steps. What comes next is a description
of the experiments that were developed and implemented, followed by a discussion of the obtained results.

5.3 ABM Testing Theory

AB simulation models built to forecast and offer indicators of potential impacts can only serve their purpose if they stand in a certain relation of similarity or analogy to the systems represented. The trustworthiness of an AB model depends on both its ability to predict the possible behaviours of a complex system and its capacity to stimulate new insights about it. To achieve consistency when modelling, it is essential to evaluate the degree to which the model resembles the real geographic phenomena that the model is designed to simulate. Model testing and assessment allow us to demonstrate the adequacy and strengths of these abstractions of reality; the goal is to put the model and the knowledge underlying the model under evaluation (Manson 2003, Aumann 2007, Manson 2007, Musiani et al. 2010). Verification, calibration, sensitivity, validation and qualification are considered essential parts of the model testing procedure, and simultaneously important steps of the model development process (Oreskes et al. 1994, Rykiel 1996, Crooks et al. 2008).

5.3.1 Verification

Once developed, the ABM must be verified by checking that the model behaves as expected; often referred to as internal validation (or inner validity). The process of verification can be also interpreted as a technical affair that relates to how faithfully and accurately modelling ideas are translated into computer code or mathematical morphism (Rykiel 1996, Manson 2003, 2007). Verification lies mostly in driving the model’s
underlying mathematical and computational components to fail by varying model configurations according to some anticipated model inputs. Cracking open the model for verification purposes is similar to sensitivity analysis, in which parameters are varied across repeated model runs in order to observe changes in simulation performance (Grimm et al. 2005, Kocabas and Dragićević 2006, Brown et al. 2008, Ligmann-Zielinska and Sun 2010, Topping et al. 2010). Difficulties of verification are further complicated by the fact that most simulations rely on random numbers to generate the effects of unmeasured variables and random choices. Therefore, repeated runs can be expected to generate different outcomes (Smith et al. 2009). Thus, very detailed ABM verification processes have not been reported in the literature.

5.3.2 Calibration

Calibration is an essential part of model testing, and it seeks to find the values of the parameters that permit the model to best characterize the spatiotemporal behaviour of the system being modelled. Different definitions of calibration can be found in literature. Refsgaard and Henriksen (2004) define it as the procedure of adjustment of parameter values of a model to reproduce the response of reality within the range of accuracy specified in the performance criteria. In ABM, calibration is regarded as the process of improving the agreement of a programmed calculation or set of calculations with respect to a chosen set of benchmarks—choice of information that is believed to be accurate or true for use in calibration—through the adjustment of parameters implemented in the model (Manson 2003, Trucano et al. 2006). Some examples of calibration have been documented in the development of ecological AB models (Railsback and Harvey 2002, Pitt et al. 2003, Grimm et al. 2005).
5.3.3 Validation

Validation is related to building the right model (Aumann 2007); it involves demonstrating that the behaviour of the model represents the behaviour of the system with sufficient accuracy as well as determining the degree of agreement between the model and the real-world system (Rykiel 1996, Fall et al. 2003, Manson 2007). Validating a model is to demonstrate that it meets some specified performance standard under particular conditions. Some authors (Oreskes 1998, Batty and Torrens 2005) argue that absolute model validation of both environmental and social systems is impossible because the models are simplifications of open systems. Validation of ABMs depends on a distinction between inner validation and outcome validation (Manson 2003). The first one evaluates how well the model represents the process described by the model, whereas the second assess how successfully the model outcomes portray the target system.

It is not always obvious how to carry out an internal validation. One way that is useful in some cases is to find a measurable attribute that is highly conserved over long time periods, as is the case, for example, of certain fractal dimensions in urban systems, like the cluster size frequency relationship (White, 2006). Then the model can be run for a very long time period to see if it conserves the measure. If it does, then that is an indication (not a proof) that the process has been successfully represented in the model: i.e. the model has in a sense been internally validated. It is very frequently the case in actual models that the statistically best calibration, the one that will lead to a strong outcome validation, does not pass this internal validation test (White 2006, Engelen and White 2007). Fortunately, in ABMs the problem of internal validation is less severe than in most other classes of models, because as bottom up models based on primitive
behaviours of individuals, much of what is described algorithmically in the model can be observed directly.

Validation is frequently seen as the central and most problematic of the five phases of model testing. In fact it is often suggested that ABMs, together with other non-linear models with a stochastic element and multiple possible steady states due to bifurcations, cannot be validated, because it is impossible in principle to define a one-to-one relationship between an empirical data set and the model output that should mirror that data. The problem arises at several levels. At the lowest level, a stochastic element is introduced to represent the inherent variability of agents, or more generally the effect of phenomena not explicitly included in the model. The stochasticity means that every run of the model will produce a slightly (or not so slightly) different outcome to compare with the empirical data set for validation. At this level the problem is relatively trivial, since a reasonable validation can be performed by comparing the mean values of the model output with the empirical data, taking into account the associated variances.

The more serious problem arises when the (realistic) non-linearities of the model generate bifurcations—points at which a single output value splits into two possible values. As a model may generate a number of bifurcations, it will have a corresponding multiplicity of qualitatively different possible outcomes. Given stochasticity, each of these is actually a cluster of similar outcomes, so whereas a stochastically perturbed model without bifurcations gives a unimodal distribution of possible outputs, bifurcations are manifested as increasingly multimodal distributions of possible outputs. The validation problem arises because in a given test situation, we typically can have only a single empirical dataset against which to test the model, since we cannot, in most non-
laboratory settings, re-run reality as we re-run the model. The consequence is that most outcomes of the model may be qualitatively (and hence usually quantitatively) very unlike the empirical data we are hoping to match. Validation is still possible, since the data either does or does not fall within the “error” bars of one of the qualitatively different outcome clusters of the model. However, this may seem to be a weaker validation, since with more possible outcomes, there is a greater chance that one of them will correspond to the data.

Furthermore, it is by contemplating the phenomenon of a multi-modal probability distribution of model outputs that the entanglement of validation with calibration and qualification becomes clear. In the case of calibration, the possibility of a multi-modal distribution of outputs raises serious calibration problems, as strikingly demonstrated by Brown et al. (2005), because the statistically best calibration will be the one that most frequently approximates the observed situation. And it is the one which will most likely lead to a successful outcome validation. However, the actual situation may in fact have been relatively unlikely. In that case, the best calibration would have been one that only infrequently generated outputs similar to the observed data, i.e. the best calibration would lead to a poor outcome validation. But this calibration would preserve a more accurate representation of the process that generates the outcomes, i.e. it is the one that would correspond to a better inner validation.

The concept of inner validation is in turn linked to qualification. If the real process that the model is supposed to capture is one subject to bifurcations, i.e. one that has a multi-modal distribution of outcomes, then if the process is operating in a number of different cases, e.g. different forests or cities, then the set of cases collectively should
exemplify most or all of the types of model outcomes. So qualifying a model by validating it (outcome validation) in a number of different settings is effectively equivalent to carrying out an internal validation. Of course, if the model has been over-calibrated, i.e. "optimally" calibrated to a single data set, then it will fail to qualify, which may also be interpreted as a failed internal validation.

At a more practical level, underlying the problem of validation is the complexity of the issue of how to compare a model output with an actual situation, or in other words, how to establish the accuracy of the simulation results and how to set a standard of what is enough to claim the validity of a model. To carry out outcome validation several techniques have been developed to compare simulation results against reference data. These techniques are used as a means to compare two maps and serve different purposes such as: 1) detect spatial/temporal changes, 2) assess map accuracy and 3) calibrate, validate models (Boots and Csillag 2006, Visser and de Nijs 2006). Comparison can be focused on pixel-based differences, where the measures show dissimilarities in the maps compared on a pixel-by-pixel basis; likewise, comparison can be concentrated on pattern-based analysis known as spatial metrics, where categorical maps are compared based on their differences in attribute, location, size, shape and relationships to other patterns (Power et al. 2001, Dungan 2006).

### 5.3.4 Qualification

The goal of qualification is to discover the domain over which a validated model can be appropriately used (Refsgaard and Henriksen 2004). This involves model application in more than one site and discovering if the validated model can be validated for another area. As revalidation tests are accepted, the domain of the model’s
applicability increases. When the model fails a revalidation test, its domain of applicability is qualified, implying that the model is restricted to those situations where it has been validated. The connotation of qualification is that the model remains useful for those situations for which it has been validated irrespective of its inability to pass other revalidation tests (Rykieł 1996). On the other hand, if the model can be re-calibrated so that it passes the re-validation, then it can be considered to be generically applicable, subject to re-calibration. This is a structural or inner validation, for if no suitable re-calibration can be found, then the structure of the model—its process representation—must be deficient. Failing the revalidation implies that the model cannot pass a comparison test considered essential for its credibility, acceptance, or usefulness.

5.4 Agent-based Models for MPB Infestations

5.4.1 ForestSimMPB Model

The framework for integrating SI and ABM for modelling MPB infestations is presented in Figure 5-1. The ForestSimMPB model consists of three types of agents that interact in a forest landscape: Beetle Agents (B) and Tree Agents (T) representing MPB and pine trees respectively, and Place Agent (P) which is the one in charge of estimating the amounts of chemical cues in the environment. During the first time step of the simulation, Beetle Agents emerge from previously dead trees in the search for a new host tree in which to mate and die. Tree Agents serve as hosts for the Beetle Agents and modify their health state attributes if their defence mechanisms against insect colonization are overcome. After the first time step a Place Agent is in charge of implementing the SI algorithm developed to store and administrate simulated pheromones. The SI algorithm ensure that Beetle Agents communicate by means of the
chemical cues (stigmergy) and initiate the aggregation process in order to achieve their objective—find a suitable tree to attack. In the following sections the specifics of each type of agent and components within the model are presented.

![Conceptual diagram of the ForestSimMPB framework for MPB outbreaks' simulation.](image)

### 5.4.1.1 MPB Ecology and Life Cycle: Beetle Agents

Ecology and life cycle of MPB, in the real-world, are captured and mimicked in the model by the Beetle Agents. Each simulation begins with the emergence of the Beetle Agents from previously infested trees (where they are born). These agents possess a gender attribute in order to simulate the order of emergence from a tree. Female Beetle
*Agents* fly first; once a suitable tree has been located, male Beetle Agents fly following the chemical signals from female *Beetle Agents* (Safranyik and Carroll 2006). The very first flight of the female *Beetle Agents* is random. The choice of which is the adequate tree in which to mate and feed depends on the tree susceptibility and health state. Susceptibility of pine trees to be attacked is closely related to attributes such as Diameter at Breast Height (DBH), age and distance to previously attacked trees (Safranyik et al. 1999, Bone et al. 2005, Safranyik and Carroll 2006). When a tree is selected by female Beetle Agents, the attack on the host tree is initiated. Female *Beetle Agents* deposit the attracting chemical cue (aggregation pheromone) in order to direct other male and female *Beetle Agents* towards the selected host, thereby optimizing the attack by a collective work to overcome the tree defences (Geiszler et al. 1980, Bentz et al. 1996, Heavilin et al. 2005, Safranyik and Wilson 2006). The *Beetle Agents* fly towards trees that register the highest pheromone concentration within the determined neighbourhood. Once all the *Beetle Agents* locate a host tree the attack is initiated. When the attack is successful, each female *Beetle Agent* deposits eggs inside the newly attacked tree and finally the parent *Beetle Agents* die. In the real-world, the eggs normally hatch within a week or so following deposition and then the young larvae commence feeding immediately (Safranyik et al. 1999, Safranyik and Carroll 2006). In the simulation, these eggs constitute the new generation of *Beetle Agents* that will emerge the next year to attack new healthy pine trees.

### 5.4.1.2 Forest Dynamics: Tree Agents

In the real-world, MPB employ a specific strategy to overcome the defences of lodgepole pine, *Pinus contorta*. MPB rely upon cooperative behaviour in the form of
mass attack by rapidly concentrating on selected host trees in response to aggregation pheromones; thereby the beetles exhaust the host’s defensive response (Safranyik et al. 1999, Safranyik and Carroll 2006). Within the model, Tree Agents are the ones that simulate the behaviour of trees under a MPB attack. They are in charge of regulating the strength of their active defences and determine how many Beetle Agents are needed for a massive attack to be successful (Safranyik and Carroll 2006). Tree Agents’ attributes (age, height and DBH) are used to calculate the total bole surface area (St) of each tree, in order to estimate the Beetle Agents density per tree. If the set threshold is reached, the health state of the tree is updated from alive to dead. Tree Agents are in charge of updating their own health state, based on both a successful MPB colonization, and on the simulation of the release of an anti-aggregation pheromone. The ForestSimMPB uses Tree Agents instead of Beetle Agents to simulate the production of the anti-pheromone that redirects agents to search for a different host tree. Consequently, if the number Beetle Agents within a tree exceeds the threshold, the Tree Agent releases the anti-pheromone to the environment.

5.4.1.3 Facilitating MPB Stigmergetic Communication: Place Agent

Within the ForestSimMPB, each \((x_i,y_i)\) coordinate in the simulation environment is represented by a Place Agent. These agents are in charge of the storage, evaporation and propagation of the pheromones that Beetle Agents use to initiate and coordinate the attack on a selected tree.
5.4.2 Swarm Intelligence Algorithm

The swarm intelligence algorithm is employed at every time step (equal to a day) in the simulation, to update the Artificial Pheromone Structure (APS). This structure allows the sign-based stigmergy (mechanism of indirect communication between Beetle Agents) through synthetic pheromones. The APS is used to simulate the Beetle Agents’ aggregation, after the emergence and during the host colonization, where the signs are synthetic pheromones managed by the Place Agents. The first step in this process is to calculate pheromone strength $\Delta s_{ij}(t)$, this is calculated using the equations (5-1) and (5-2),

$$\Delta s_{ij}(t) = \sum_{k=1}^{n} \Delta g_{kj} + \Delta s'_{ij}$$

$$\Delta s'_{ij}(t) = \sum \Delta s_{i-1,j} + \Delta s_{i-1,j+1} + \Delta s_{i-1,j-1} + \Delta s_{i,j+1} + \Delta s_{i,j-1} + \Delta s_{i+1,j} + \Delta s_{i+1,j+1} + \Delta s_{i+1,j-1}$$

where $\Delta s_{ij}(t)$ is the amount of pheromone (g) laid on the cell $(i,j)$ by the $k^{th}$ beetle between the time $t$ and $t+1; \Delta s'_{ij}(t)$ is the amount of pheromone laid in the cell’s $(i,j)$ Moore neighbourhood – includes the eight cells surrounding a central cell between $t$ and $t+1$. When the pheromone strength value is positive (which indicates the presence of aggregation pheromones) in the cell $(i,j)$, the Place Agent propagates the pheromone so that eighty percent of the pheromone in cell $(i,j)$ is equally propagated to the eight immediate neighbours in the Moore neighbourhood. The remaining twenty percent value of pheromone in cell $(i,j)$ is evaporated every time step $(t)$ using the equation,

$$\Delta s_{ij}(t + 1) = \frac{1}{5} \Delta s_{ij}(t) \times E$$

(5-3)
where \( (E) \) is an evaporation constant. In contrast, when the pheromone strength value is negative (which indicates the presence of anti-aggregation pheromone) in the cell (i,j), the Place Agent evaporates the anti-aggregation pheromone every time step \( (t) \), using the evaporation constant \( (E) \). Place Agents use only the information available in their immediate vicinity and thus are local; nonetheless, the aggregation pheromone is spread in the simulation environment over time.

5.4.3 Random-ABM

The Random-ABM model consists of two types of agents—Beetle Agents and Pine Agents—that permit the representation of the MPB behaviour, the forest environment and tree health evolution respectively. MPBs life cycle and their interaction with host (pine trees) mechanisms are represented within the model. The behaviour of the Beetle Agent is portrayed by a series of rules that these type of agents need to follow in order to select the host tree to initiate the attack and reproduction stages. Beetle Agents have a unique attribute that allows differentiating the Beetle Agent population by gender; therefore, simulations include identification of female and male Beetle Agents, with a male:female sex ratio 1:2 (Safranyik and Wilson 2006).

Beetle Agents with a female attribute emerge first and fly randomly in search of a new host tree. Once the host trees are randomly located, the decision to remain in tree and initiate the attack is based on the evaluation of attributes such as tree susceptibility, DBH, age and height and distance to previously attacked trees. The null Random-ABM model mimics the complete random flying behaviour and movement of MPB; however, Beetle Agents are designed to select host trees and start attacking them depending on their degree of susceptibility (i.e. starting from the most susceptible until the less susceptible
ones are reached). *Pine Agents* have the task of regulating *Beetle Agents*’ populations allowed within each host tree, in order to determine when the host tree defences are overwhelmed by a threshold number of *Beetles Agents*.

The most important difference between the Random-ABM model and the one described in section 5.4.1 regards the representation of MPB flying behaviour in the forest environment. While the ForestSimMPB makes use of a SI algorithm to simulate movement and aggregation behaviour of MPB populations to attack pine trees, the Random-ABM uses random movement behaviour to fly within forest. Hence, in this model, Beetle *Agents* fly and select trees to attack in an entirely random fashion.

### 5.5 Model Testing Approaches

The ForestSimMPB model was tested through the simulation of MPB infestation within a forest ecosystem located in North-Central Interior of British Columbia (BC), Canada (Figure 5-2). This area has undergone extensive MPB infestations during the last decade, altering landscapes and watersheds in the BC interior, bringing significant implications for a variety of ecological values, and the people that they benefit (Pantel 2006). Three different pilot test areas (Sites 2, 3 and 4) of 1 ha and one area (Site 1) of 4 ha were selected in order to calibrate, verify and validate the ForestSimMPB. Simulation results are provided for all study sites, however, maps presented correspond to Site 1. In the year 2001, this specific location registered less than one percent of dead MPB-killed trees and five years later, the same area recorded an increment of more than sixty percent in the number of pines killed by MPB (according to aerial photographs processed). The ForestSimMPB operates in discrete time steps equivalent to one year; in order to mimic
the MPB infestation observed in reality for this specific area, a five-year time period is used to execute the model.

Input data consists of five different GIS raster files that contain information on susceptibility, health state, age, height and diameter at breast height (DBH) of each tree in the study area. The health state raster file was obtained using high resolution aerial photographs; MPB-killed trees in 2002 were identified from the imagery data. In order to fit the scale of the size of the average interpreted tree crown surface 1 m spatial resolution was selected to represent the information for each cell that was aggregated from the high resolution aerial photographs. Forest attributes (i.e. age and height) and georeferenced data sets were obtained from GeoBC (GeoBC 2007). BDH values were calculated as per Reid et al. (2004) based on the tree age. Tree susceptibility was calculated using three criteria: (1) tree size, (2) distance to the nearest tree attacked in the previous year, and (3) age of the tree.

The ForestSimMPB model was coded in Java by using the Recursive Porous Agent Simulation Toolkit (RepastS) (Argonne National Laboratory 2011). The ForestSimMPB uses a tightly coupled architecture using the GeoTools Java library (OSGeo 2011) for GIS data management and visualization functionality and is used within RepastS. Handling of the GIS data sets was carried out using ArcGIS 9.3. software (ESRI 2011). For the purpose of comparing simulated results with real dataset, the
Figure 5-2. Location of different study sites in north-central interior of British Columbia. Site 1 (4ha) land cover maps for year a) 2001 and b) 2006.
The Map Comparison Kit (MCK) was used (Visser and de Nijs 2006). Each time step in the model represents a year – from the end of the first year \((T_{i+1})\) to the end of the fifth year \((T_{i+5})\). The following sections describe simulation results including verification, calibration, sensitivity, validation and qualification processes of the proposed model.

5.5.1 Model Verification

In order to assess the ForestSimMPB performance and to ensure that the model does what it is intended to do, different trace outputs (tracing is a form of debugging that allows to keep track and isolate incorrect behaviour in a model) are produced by the model (specifically spatial location of Beetles Agents, synthetic pheromone distribution map, report of attributes with spatial location of each tree evaluated and attacked in the simulation).

In reality, MPBs aggregate in large numbers when colonizing selected pine trees. These aggregations are formed and maintained in order to be more efficient in overcoming active or passive tree defences (Schlyter and Birgersson 1999, Raffa 2001, Safranyik and Carroll 2006). To prove the correctness of the model, it is shown that, in such a model, Beetle Agents, after some iterations, start to aggregate into the areas with higher concentrations of synthetic pheromone. These results are then contrasted using the outputs of a model (Random-ABM) that implements a random movement of the Beetle Agents in search of a suitable tree to attack. Visual analysis is used to evaluate the results and verify the logic and assumptions of the model.
5.5.2 Model Calibration and Sensitivity

For each ForestSimMPB model component, parameter values are estimated from the literature or via calibration and sensitivity. Calibration process is performed in order for the model to simulate patterns of tree mortality as a result of MPB outbreaks that are similar to the ones extracted from aerial photographs. Values calibrated according to the literature ensure that, within the model, the survival and growth rates of MPB agents are reasonable (Safranyik and Carroll 2006). Sensitivity procedures in the specific context of the ForestSimMPB model explore the influence of one input parameter (i.e. neighbourhood size) on the model output.

Calibration of the initial number of Beetle Agents in the simulation is essential to obtain results in terms of number of attacked trees that are very similar to those observed from the actual 2002 data set. Once more, one year of MPB outbreak is simulated, in this case varying the number of Beetle Agents at the beginning of each model test. The preliminary number of the initial Beetle Agents parameter is based on the well documented biological studies related to the MPB populations (Safranyik et al. 1999). The evaluation of these latest results is accomplished using the fuzzy polygon based matching technique, as well. Assessing the changes, when different input model parameters are used, allows the estimation of degrees of similarity in spatial patterns and percent of change. However, when representing feedback processes such as the ones involved in forest infestation phenomenon, spatial path dependence and stochastic uncertainty need to be acknowledged as some of the challenges faced in the development and testing of an ABM (Brown et al. 2005). Once the model is calibrated, a five-year simulation is performed and then the model validation is carried out.
Neighbourhood size represents the area where the Beetle Agents fly in search for a tree to attack. To determine if the ForestSimMPB model is sensitive to changes in neighbourhood sizes, and also to select the one that produces results that are most similar to the observed attacked trees, four extended Moore neighbourhoods (i.e. 5x5, 10x10, 15x15 and 25x25) are tested. This is accomplished by simulating one year of MPB forest infestation using a reference map for the year 2001 as input and comparing the results with real world data (aerial photographs) from the subsequent year. After obtaining the results, the fuzzy polygon based matching technique (Power et al. 2001, White 2006) is used to assess which of the neighbourhoods has the better ability to simulate patterns of MPB-killed trees similar to the actual patterns.

5.5.3 Model Validation

It has been argued by some authors that ABMs are never likely to be validated due to the heterogeneity of processes shown by different variables in the model (Batty 2005, Batty and Torrens 2005). But as implied in the earlier discussion of the complexities of validation, it is more realistic to think of degrees of validation rather than in the dichotomous terms of validated/not validated, or possible/impossible to validate. The ForestSimMPB is validated using map comparison approaches: a) Cell-by-cell and b) Pattern-based. Spatial output validation is based on a comparison between the last of a five-year simulation, of MPB outbreak, and real infestation data extracted from aerial photographs. Validation of the agents’ behaviour is not possible due to the lack of real and precise data about MPB movement behaviour; however, model structure is verified and its outcomes are compared against the target system (i.e. forest ecosystem undergoing a MPB outbreak).
5.5.4 Model Qualification

In order to undertake qualification of the ForestSimMPB model, this is tested and validated on a different site located in the Southern Interior of BC, Canada. ForestSimMPB model qualification was accomplished by simulating four-year MPB outbreak initiated in 2000 \( T_i \) in an area located in the Southern Interior of BC, Canada; simulation time span was selected in order to validate the outcomes versus real dataset existing for the year 2004.

5.6 Results

The model was run to simulate a five-year MPB outbreak initiated in 2001 \( T_i \). The simulation timeframe was selected to validate the outcomes against the available dataset corresponding to the year 2006. Model verification was carried out using the results from the ForestSimMPB simulation and comparing them with outcomes from the Random-ABM; both verification and calibration were accomplished by using MPB infestation data of 2001.

5.6.1 The effects of Beetle Agents aggregation behaviour: Verifying agents behaviour

The annual spatial distribution of lodgepole trees killed by the MPB infestation is presented in Figure 5-3. The map depicts the simulated locations of MPB-killed trees during a six-year time frame, as well as the remaining healthy trees in the study area. Looking at the results, the number of dead trees increased from 358 in 2001 to 7388 after 5 years. Total annual increments are presented in Figure 5-5; the analysis of these values shows an average increment of
Figure 5-3. ForestSimMPB model, five-year simulation results. Total study site area is 4ha and spatial resolution is 1 m x 1 m.
approximately 51%, with the higher percentage increase during the first year with value of 312%.

The ForestSimMPB final output (i.e. year 2006) is visually compared with the results from the Random-ABM model in Figure 5-4 as well as the annual increment in dead trees (Figure 5-5). The contrast represents differences in global pattern and number of simulated MPB-killed trees. While it is expected that the models would produce dissimilar patterns, the amount of dissimilarity in spatial distribution is not very striking. To assess differences between the two outputs, the following contagion metrics are calculated (McGarigal and Marks 1995): Aggregation Index (AI) and Landscape Division Index (DIVISION). These metrics reflect the overall clumpiness of the landscape, that is, a tendency to occur in large, aggregated or contagious distributions. Table 5-1 summarizes the values obtained for each metric.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Metric (unit)</th>
<th>ForestSimMPB</th>
<th>Random-ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregation Index</td>
<td>AI (%)</td>
<td>87.6321</td>
<td>80.5166</td>
</tr>
<tr>
<td>Landscape Division Index</td>
<td>DIVISION (proportion)</td>
<td>0.3264</td>
<td>0.6273</td>
</tr>
</tbody>
</table>

AI equals 0 when there are no adjacencies in the landscape, there it is maximally disaggregated; AI increases as the landscape is increasingly aggregated and equals 100 when the landscape consists of a single patch (McGarigal and Marks 1994). The AI values demonstrated that both simulated landscapes ForestSimMPB and Random-ABM had a high level of aggregation and a tendency to create a single patch of MPB-killed
Figure 5-4. ForestSimMPB and Random-ABM models simulation results for the year 2006.
Figure 5-5. Graph of annual increments of lodgepole killed by MPB.
trees; however, the first model global aggregation pattern was greater than the second model. DIVISION equals 0 when the landscape consists of single patch and when the landscape is maximally subdivided equals 1 (McGarigal and Marks 1994). DIVISION values for the two model outputs compared here show that the ForestSimMPB simulated landscape is very close to being a single patch, while the Random-ABM landscape pattern was more subdivided.

Overall spatial patterns from the two models are dissimilar; simulation results also reveals that the total number of MPB-killed trees, using the ForestSimMPB, is 12.9%, greater than the quantity obtained using the Random-ABM. This demonstrates that, in the ForestSimMPB, the collective behaviour of Beetle Agents that leads to aggregation behaviour simulates the behaviour observed in the real-world by which MPBs attack a selected tree and kill it by overcoming its defences (Safranyik and Wilson 2006).

The results from a set of tracing outputs, corresponding to the spatial location and number of agents per cell in the forest landscape, are presented to visually compare the distribution of Beetle Agents in Figure 5-6. The outcomes indicate that spatial dispersion of agents varies when the decision rules are changed. As expected, the Random-ABM provides unclear patterns related to aggregation or grouping of Beetle Agents; whereas the ForestSimMPB suggest a location preference by the Beetle Agents, making it more visible after iteration 240. The results and examination of the coded tracing outputs verify that the implementation matches the ForestSimMPB design.
Figure 5-6. Beetle Agents spatial distribution in the study site during different points in time (iterations) using the ForestSimMPB and Random-ABM models.
5.6.2 Tuning the model: ForestSimMPB Calibration and Sensitivity

Model simulated outcomes from implementing four extended Moore neighbourhoods: a) 5 x 5, b) 10 x 10, c) 15 x 15 and d) 25 x 25, in four different sites are compared and assessed. The fuzzy matching index \((g)\) values are summarized in Table 5-2 and illustrated in Figure 5-7(a) which indicates a relatively high degree of agreement between the model results using neighbourhood (c) and the real data from 2002 for most sites. The fuzzy matching index is polygon rather than pixel or cell based, and indicates the degree to which polygons on the two maps overlap (Power et al. 2001). Values of \((g)\) range between 0 (no similarity) and 1 (identical), indicating degrees of similarity between the two maps compared. Lower matching values were obtained for the neighbourhoods (a), (b) and (d). Accordingly, simulations presented in this study are implemented using a 15 x 15 neighbourhood.

Once the appropriate neighbourhood size is chosen for the simulations, calibration of the initial number of Beetle Agents is accomplished. Four different sizes of initial Beetle Agent population are selected: a) 300000, b) 400000, c) 600000, and d) 800000, these numbers are selected based on trial and error as well as the visual evaluation of the outcomes; testing with quantities greater than (d) resulted in unrealistic results of MPB infestation (e.g. hundred percent of the susceptible trees in the study sites were killed after one year of simulation). Figure 5-7(b) and Table 5-2 summarize the results of comparing simulated output maps with real data of 2002. Populations (a) and (b) generated lower values \((g < 0.7)\) of similarity; in contrast, the outcomes of using (c) and (d) as initial Beetle Agent populations produced results closer to those observed in reality. Sensitivity and calibration tests indicate that a neighbourhood size of 15 x 15 and an
initial Beetle Agent population of 800000 produce results closely similar to the patterns observed in the real-world; hence, they are chosen so that performance of the ForestSimMPB related to data is nearly optimal.

Figure 5-7. Graph of fuzzy polygon matching indexes for different sites, from the ForestSimMPB outputs, compared with real data from 2002 aerial photographs. (a) Using different neighbourhood sizes, and (b) using different initial populations of Beetle Agent.
### Table 5-2. Global fuzzy matching indexes summary.

<table>
<thead>
<tr>
<th>Site</th>
<th>Neighbourhood Size</th>
<th>Fuzzy Polygon Matching</th>
<th>Site</th>
<th>Initial Number of Beetle Agents</th>
<th>Fuzzy Polygon Matching</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5x5</td>
<td>0.681</td>
<td>1</td>
<td>300000</td>
<td>0.647</td>
</tr>
<tr>
<td>2</td>
<td>10x10</td>
<td>0.677</td>
<td>2</td>
<td>400000</td>
<td>0.685</td>
</tr>
<tr>
<td>3</td>
<td>15x15</td>
<td>0.798</td>
<td>3</td>
<td>600000</td>
<td>0.734</td>
</tr>
<tr>
<td>4</td>
<td>25x25</td>
<td>0.675</td>
<td>4</td>
<td></td>
<td>0.770</td>
</tr>
</tbody>
</table>

5.6.3 **Demonstrating the model accuracy: Model results validation**

Validation of the ForestSimMPB spatial outcomes (i.e. maps of MPB-killed trees distribution in a forest landscape) is accomplished through map comparison between simulation output (i.e. 2006) and the real forest infestation data for the same year corresponding to the study area located in the North-Central Interior of BC. Figure 5-8 shows two different approaches to compare the structure of the maps and relate areas of similarity and dissimilarity. The *fuzzy Kappa statistic* and the *global fuzzy matching index* (Power et al. 2001, Visser and Nijs 2006, White 2006, Hagen-Zanker 2009) are used to demonstrate the global agreement between the observed land cover in real-world and the predictions from the model simulations. The *fractal dimension index (FDI)* is also used in order to qualitatively validate the ForestSimMPB model.
Figure 5-8. Results from the ForestSimMPB model validation through map comparison techniques: Kappa fuzzy and global fuzzy matching approaches.
The fuzzy Kappa approach takes into account that there are grades of similarity between pairs of cells in two maps. Map comparison result using the Fuzzy Kappa showed an agreement between the two maps of 0.744. The global fuzzy matching index (g) value was 0.854, and the map shows areas where the pattern has changed. These results demonstrate that the ForestSimMPB is able to reproduce MPB-killed tree patterns with an 85% of similarity to what is observed in reality. The FDI looks at a global description of pattern by measuring the shape complexity of a map. The FDI value for actual tree death map was 1.11 and 1.09 for the simulated tree death map, suggesting that fractal dimension values for both maps are very similar.

5.6.4 ForestSimMPB Qualification: Does it work for a different area?

In order to assess the usefulness of the ForestSimMPB model, it was revalidated using a study site located in the Southern Interior of BC, Canada. Simulations for a four-year time span were created; validation of the final output was accomplished using the global fuzzy matching index (g) as well as through numerical comparison of total number of lodgepole pine killed by MPB in the specific area; total number of trees killed in reality was 5% greater than the number simulated by the ForestSimMPB model. Figure 5-9 depicts the location of the study area, simulation and map comparison results. A value (g) of 0.822 indicates that the ForestSimMPB output similarity is valid for different study areas.
Figure 5-9. Location of the study site in the Southern Interior of BC, Canada. Results from the ForestSimMPB model simulation and validation using the global fuzzy matching approach.
5.7 Conclusions

The goal of this study was to go through several stages of model testing using the ForestSimMPB model that integrates ABM and SI within a GIS framework to simulate the spatial patterns of MPB-killed trees in forested areas as a result of MPB infestations. The ForestSimMPB model tested here was designed to simulate aggregation behaviour via indirect communication as observed from MPBs conduct in the real-world. Combined with a SI mathematical model it represents the stigmergetic communication used by MPB through the spreading of chemical cues. In order to achieve the objective of this study, the model was implemented on four different study sites located in the North-Central Interior of British Columbia (BC), Canada and one in the Southern Interior.

As part of the ForestSimMPB model testing presented in this study, several steps were followed in order to make sure that intentions of developing an agent-based model were accomplished. These stages attempted to comply with the purpose for which the model was built, the extent to which the model can be replicated, the way the model can be verified, calibrated, validated and qualified and the way model dynamics are represented in terms of agent interactions. ForestSimMPB verification was accomplished by generating tracing files that allowed reviewing the performance and behaviour of the model. Additionally, a Random-ABM was created to compare, evaluate and verify the ability of the ForestSimMPB to represent the stigmergy of MPB populations during the process of emergence and host colonization. Sensitivity analysis and calibration involved the tuning of some of the initial parameters of the model (specifically neighbourhood size and initial agents population size), in order for the representation of the real-world patterns to be as accurate as possible. Model validation was accomplished through
different map comparison approaches for two different study areas in order to evaluate the applicability of the model in a different geographical context.

Simulation outcomes depict the spatiotemporal behaviour of the MPB, which is examined through the visual analysis of the spatial distribution and allocation of new outbreaks. Likewise, quantification of total new infected trees over five years was obtained. Model testing results revealed (visually and statistically) that ForestSimMPB implementation and performance matches its design. Validation results are promising in terms of levels of agreement between the real-world data and the simulated data. The model was qualified to be used in different spatial locations with successful results.

The ForestSimMPB approach provides a very useful tool to study the complexities of MPB infestations, and for building forest management strategies. That an initial validation was successfully accomplished is a necessary first step in order to apply the model in the forest decision support process. Nevertheless, MPB agent-based model verification, calibration and validation represent a big challenge when the information required is frequently unavailable. Georeferenced datasets used in this type of model – like the one presented in this study – contain extensive data that are very expensive and time consuming to collect at such detailed scale and for a continuous number of years. Together with the issue concerning real data of MPB infestation is that given the spread, different management practices are put in practice to control the expansion of the outbreak and therefore information on the MPB outbreak is unavailable for subsequent years. The model presented in this study is part of work in progress that looks into the development of a robust landscape simulation tool that generates emergent patterns similar to those observed in nature. The findings from this study can help to improve the
spatially explicit models that can, in turn, improve our understanding of MPB spread
dynamics and generate better practices or mitigation techniques towards the reduction of
their impact on forest landscapes.

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6. LANDSCAPE-LEVEL SIMULATION OF FOREST INSECT DISTURBANCE: COUPLING SWARM INTELLIGENT AGENTS WITH GIS-BASED CELLULAR AUTOMATA MODEL

6.1 Abstract

Forest insect disturbances have an ecological impact and are the cause of partial or complete stands mortality; hence they influence the forest cover change. The modeling of ecological processes such as insect disturbance is challenging due to the complexity of insect outbreaks in forest ecological systems, thus diverse spatial scales need to be considered in order to effectively represent these dynamic spatial phenomena. The objective of the study is to develop a hybrid model that combines swarm intelligence (SI), agent-based modeling (ABM) and cellular automata (CA) with geographic information systems (GIS) for simulating tree mortality patterns introduced by insect infestations at a landscape spatial scale. The focus is on lodgepole pine, *Pinus contorta*, tree mortality patterns caused by infestations of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins. The complexity of the insects' behaviour during forest disturbances can be captured and simulated by an intelligent agent-based model (ABM). Agents represent insects that have the ability to behave and adapt according their interactions within the forest environment at a very fine spatial scale at tree-level, and with the use of swarming intelligence approach. However, due to computational

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5 A version of this chapter will be submitted for publication to the journal *Ecological Modelling* under the co-authorship of Suzana Dragićević
complexity such model is not operational at landscape and regional spatial scales where the consequences of infestation phenomenon are most obvious. Therefore, the integration of the ABM with CA approach is proposed to handle modeling at both fine and large spatial scales. The discrete nature of CA enables integration with raster-based geospatial datasets in GIS, and can also be beneficial when modeling complex ecological processes that evolve over time. The developed model includes factors such as wind directions and elevation to demonstrate their influence in the spread patterns of the outbreaks at a landscape spatial scale. The model outcomes provide “what if” scenarios that can assist studying and controlling MPB forest disturbance.

6.2 Introduction

Spatiotemporal modeling provides the capability to explore the characteristics of complex geographic processes in which landscapes evolve through the interactions of natural entities (Bousquet and Le Page, 2004; Brown et al., 2005). The advancement of spatial modeling in forestry domain over the last decade has been facilitated through the coupling of geographic information systems (GIS) and existing dynamic modeling approaches from complexity theory such as cellular automata (CA) (Mathey et al., 2008) or agent-based (AB) models (Deadman et al., 2004; Brown et al., 2005). GIS are well known as computational tools for storing, handling, analyzing and displaying spatial data (Goodchild, 2004). As GIS are limited to providing static geographic representations, approaches for modeling dynamic phenomena can be integrated with them in order to present both spatial and temporal dimensions when analyzing complex phenomena.
Modeling environmental processes in ecological systems is challenging due to the interaction of a variety of factors, such as winds, temperatures, seasonality, elevation and slopes amongst others. Moreover, these interactions take place at various spatial and temporal scales giving rise to complex patterns (Mladenoff and Baker, 1999). In spite of this complexity, simulation models make it possible to improve the understanding and predictions of observed ecosystem functions or patterns by defining complex processes and their interactions using approaches from complex systems theory – CA and AB models. Phenomena such as fire spread (Yassemi et al., 2008), forest insect infestations (Bone et al., 2006), animal migration patterns (Bennett and Tang, 2006), invasive plant species propagation (Dragićević, 2010) and dynamics of aquatic plant growth (Li et al., 2010) among others, have been modeled and studied by means of complex systems theory modeling approaches. Modeling provides a medium for exploring “what if” scenarios in planning, policy making and environmental management; ecological systems’ models are increasingly being built for forecasting (Evans et al., 2006) and management objectives (Bone and Dragićević, 2010; McDonald et al., 2008).

CA and ABM are bottom-up approaches that have been used to study the complexities and dynamics of forest landscape change (Gebetsroither et al., 2006; Sprott et al., 2002). The spatial complexity and dynamics of forest landscape changes due to insect disturbances, for example, are represented by selecting various configurations of the basic elements of the CA and AB model design – cell space, cell size, neighbourhood size, transition rules, agents’ behaviours and temporal increments. Transition rules that determine agents’ behaviours are the most important element of these two approaches as they control the evolution of the landscape into the future states. In order to advance GIS-
based CA and AB modeling, these transition rules have been enhanced through the integration of CA and AB models with other approaches such as fuzzy sets theory (Graniero and Robinson, 2006), neural networks (Almeida et al., 2008), Bayesian networks (Kocabas and Dragičević, 2007), genetic algorithms (Manson, 2006) and reinforcement learning (Bone and Dragičević, 2009) among others.

Swarm Intelligence (SI) provides an alternative approach based on artificial intelligence that can overcome challenges such as agents reasoning, that is similar to the one in reality (Engelbrecht, 2007). Known as an innovative distributed intelligent paradigm for solving optimization problems, SI has been applied in data clustering (Abraham et al., 2008), transportation and optimal path planning (Teodorović, 2003; Li et al., 2009), protected areas planning (Li et al., 2010) and geospatial reasoning (Parunak et al., 2006) among others. This approach integrated with ABM has been particularly implemented to simulate the decision-making and aggregation behaviour of insects such as mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, in natural disturbances of forest infestations. The model named ForestSimMPB proved to be useful for modeling the spatial patterns of the forest structure as a result of a MPB outbreak at a very detailed scale (Pérez and Dragičević, 2011). However, the spatial extent of the ForestSimMPB is limited to areas from one to four hectares, constraining its use to small sites as well as not allowing the inclusion of important factors in the disturbance process such as wind, elevation, slope and aspect (Aukema et al., 2006; Jackson et al., 2005; Moore and Jackson, 2004; Safranyik and Wilson, 2006).

The objective of this study is to extend the existing ForestSimMPB by proposing a hybrid modelling approach that can simulate forest patterns of MPB disturbance at...
much larger landscape spatial scale in addition to the dynamics at the local tree-level scale. The hybrid approach consists of swarm intelligent agents incorporated into a GIS-based cellular automata model. This novel approach for simulating MPB infestations in forest ecological systems, at a landscape spatial scale, allows the addition of important topographic and climatic factors that influence the metapopulation and spatial dynamics in the insect disturbance process. The model is implemented on a hypothetical dataset in which intelligent mountain pine beetle agents make decisions to attack nearby trees while factors such as wind, elevation, slope and aspect are taken into account. The model is tested using different CA parameters to observe changes in simulation outcomes that provide insights to better understand the complexity of the spatial process.

6.3 The Intelligent CA-ABM Approach for Modeling Forest Insect Disturbance

Ecological processes such as natural disturbance (e.g. insect outbreaks, low severity forest fires), where dynamic interactions take place between host trees and insects in forest ecosystems, are complex spatial systems that change and evolve over time (Bolliger et al., 2003; Sprott et al., 2002). These processes exhibit non-linear behaviour between the system elements and the environment along with relatively simple interactions at a local scale that generally give origin to complex patterns at a global scale.

A combination of complex systems theory approaches (i.e. CA and ABM) together with artificial intelligence (i.e. SI) is used to model a dynamic spatial phenomenon (i.e. forest insect disturbance) at various spatial scales. Cellular automata can be described as an array of cells characterized with their states and local interactions,
where space and time are taken into account (Wolfram, 1994; White and Engelen, 2000). The state of a cell at consecutive time $T_{i+1}$ is a function of its state, its neighbourhood, and transition rules at time $T_i$. The cell state can be mathematically represented as:

$$S_{x,y}^{T_{i+1}} = R(S_{x,y}^{T_i}, N_{x,y}^{T_i})$$

(6-1)

where $S_{x,y}^{T_i}$ and $S_{x,y}^{T_{i+1}}$ are the states of cell at a location described with x and y coordinates at times $T_i$ and $T_{i+1}$ respectively; $N_{x,y}^{T_i}$ represents the state pattern of neighbourhood surrounding cell $x,y$; $R$ represents the transition rules that explain how the initial state will change in the next increment of time.

The repetitive application of $R$ in the local neighbourhood generates emergent, often unexpected patterns from local deterministic interactions, allowing the analysis of complex behaviours. In ecological modelling these rules represent how change occurs in the real world ecosystems. For example, 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; Matsinos and Troumbis, 2002).

Agent-based techniques extend the capabilities of CA, and allow studying the relationships between micro-level individual actions and the emergent macro-level phenomena (Gimblett, 2002). While CA models are focused on how simple rules lead to ecosystems change and evolution, ABMs focus on the interactions amongst computer-programmed agents that represent the decision making behaviours of organisms such as forest insects. Agents' decisions are not only influencing change to their environment or to the behaviour of other agents, but their autonomous behaviour influences the overall
behaviour of the system and the emerging patterns (Bousquet and Le Page, 2004). Autonomous agents need to act in accordance with a cognitive architecture that relates their objectives to the environment through their behaviour (Wooldridge, 2000).

In the specific case of simulating the behaviour of forest insects such as mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, agents can represent beetles and their cognition through reactive behaviour to system changes. Even though pure reactive behaviour seems overly simplistic, it is nonetheless considered a form of cognition if agents possess the ability to react to change (Russell and Norvig, 2010). Insects like the MPB are able to communicate by emitting chemical messages (i.e. pheromones) that induce a behavioural reaction or developmental process among individuals of the same species (Wallin and Raffa, 2002).

Although ABM represents a valuable modeling approach to simulate emerging global patterns over time, its implementation becomes challenging when specific organisms' behaviours need to be represented in order to appropriately depict the system dynamics. Artificial intelligence (AI) has been used to provide agents with improved decision making abilities in order to make their behaviour closer to the one in nature (Di Chio et al., 2006). To simulate behavioural reaction, as well as feeding and aggregation behaviour of MPB populations, the swarming intelligence (SI), an AI technique, is used in this study. Another important issue to consider when modeling MPB disturbance, is the various scales on which the phenomenon operates. MPB infestations start at a very local scale of trees, spreading to stands and then moving to larger scales such as regions. Van Vliet et al. (2009) research presents an approach to handle different spatial scales within CA models for land use change. For this reason, this study addresses modeling of
MPB outbreaks at different scales. The integration of both CA and ABM approaches with SI proves particularly useful in ecological studies because the rich behaviour of insect colonies in complex natural environments.

### 6.3.1 Model Framework

The swarm-intelligent CA-ABM model proposed in this study is composed of two main Sub-Models (Figure 6-1). Sub-Model I consists of the ForestSimMPB that operates at a small spatial scale (i.e. tree scale) and generates patterns at a local scale (i.e. areas of 1ha). The output of the submodel (ForestSimMPB) at a local scale represents the input for the Sub-Model II. The second submodel is based on CA for modeling tree mortality patterns as a result of MPB infestation, at a landscape scale (i.e. areas of 2500 ha) and considers factors such as wind direction, climatic cycles, elevation and aspect. Given that MPB have a one-year life cycle and emerge from an infested tree in search for a new healthy tree over the course of days, the modeling approach operates at two different temporal scales (i.e. daily and yearly). Sub-Model I simulates dynamics taking place between host trees and MPBs at a tree spatial scale, at discrete time steps equal to one day. The emergence, aggregation and attacking behaviour of MPB are simulated, for larger spatial extent on daily basis. The Sub-Model II generates landscape spatial scale patterns of tree mortality and MPB spread at discrete time steps equivalent to one year. The spatial patterns of tree mortality at a larger scale in the Sub-Model II emerge as a result of the local interactions between MPB and host trees simulated in by the Sub-Model I as well as the influence factors such as weather and topography.
Figure 6-1. Schematic representation of the intelligent GIS-based CA-ABM approach for modeling forest insect disturbance.
6.3.1.1 Sub-Model I - ForestSimMPB: Swarming Agents Mimicking the Aggregation Behaviour of Forest Insects

The objective of the *Sub-Model I* is to emulate the annual pattern of trees killed by MPB at a local scale (Pérez and Dragićević, 2011). A fine spatial resolution of a tree scale is selected to represent the information for each cell, which is interpreted as an individual lodgepole pine tree. The MPB life cycle, aggregation behaviour and interactions between the insects and the host trees (i.e. lodgepole pine) are captured by artificial *Swarm Intelligent Agents (SIA)* that follow synthetic pheromone plumes in order to aggregate and select healthy and susceptible host trees to attack, feed on and breed in. In their natural environment, MPB carries a blue-stain fungus, which contributes to the success of the beetles in killing trees in order to successfully reproduce. MPB leave their currently infested trees in late July to early August in search of a new tree to attack. Females first emerge from the tree and fly varying distances in search of a new host (Logan and Bentz, 1999; Logan et al., 1998). Once a new host has been selected, the female bores through the bark and releases a chemical compound that attracts male beetles to the same tree. The tree’s defensive mechanisms are overcome once a sufficient number of MPB have attacked the tree (Heavilin et al., 2005; Safranyik and Carroll, 2006), while fewer beetles are required for killing trees that are more susceptible (Safranyik et al., 1999).

Within the ForestSimMPB sub-model I, the initial flight of the *SIA* happens in a random fashion, in the bounds of a local scale (usually 1ha) of a forest ecosystem. After a random choice of tree (i.e. specific cell located at x and y coordinates with attributes), each beetle agent consults if the tree is susceptible to be attacked. In particular for
ForestSimMPB, the susceptibility of a tree depends on the Diameter at Breast Height (DBH) and the age of a tree, as well as the distance to previously attacked trees. After querying about the susceptibility and the health status of the host tree, if the tree is suitable the SIA attacks the selected host and deposits an attracting chemical cue (aggregation pheromone) which would direct other SIA towards the tree. If the health state of the initially selected host is zero (0), where zero indicates a dead host and one (1) indicates an alive host, the agent needs to locate a different one. Once the initial host trees are selected, the SIA begin flying towards the trees with higher pheromone concentrations within their local neighbourhood.

In the real-world, MPB populations have the ability of defeating the active defences of healthy host trees by means of pheromone-mediated synchronous attack by numerous individual insects (Alcock, 1982; Raffa, 2001; Safranyik et al., 1999). This pheromone calling system for mate attraction uses an aggregation pheromone (Raffa, 2001; Schlyter and Birgersson, 1999). Simultaneously, the density of the attack is regulated by an anti-aggregation pheromone produced by both, the MPB and the host tree, which helps to neutralize the aggregation pheromone (Pureswaran and Borden, 2003). The aggregation pheromone plumes influence the density and distribution of attacks within a particular tree rather than among trees (Bentz et al., 1996; Raffa and Berryman, 1983; Renwick and Vité, 1970), while the repellent effect of the anti-pheromones that encompass neighbouring trees is responsible for the redirection of attacks. Aggregation behaviour of MPB is simulated through the use of a Synthetic Pheromone Infrastructure (SPI).
The SPI models a discrete spatial dimension to enable indirect communication among the SIA in the same way MPB communicate in the real-world. It comprises a finite set of places with x and y coordinates that overlap with the coordinates of the forest ecosystem, and a finite set of pheromone types. A pheromone type is a specification of the message to be transmitted to agents: 1) aggregation pheromone and 2) anti-aggregation pheromone to aggregate or disperse. The aggregation pheromone is represented by positive values and the anti-aggregation by negative values. Each amount of synthetic pheromones is mapped to a place in the SPI. The mapping represents the spatial distribution and concentrations of pheromone.

Each of the SIA starts to deposit one unit of synthetic aggregation pheromones into the SPI once they locate a host tree and are in need of more agents to defeat the defences of the tree. When a threshold value is reached, each of the SIA located at any x and y coordinates cell (i.e. representing a lodgepole pine) begin to deposit one unit of anti-pheromone in order to redirect the agents attack to a different host. The SPI handles concentration of each pheromone type at each place in the following way:

**SIA Input:** Based on a request by an agent, the concentration \( c \) of the specified pheromone \( g \) (i.e. aggregation or anti-aggregation pheromone) is changed by adding the specified input value. Positive concentrations attract more agents to a specific place \( (p_{x,y}) \), whereas negative concentrations force agents into a different place.

**Propagation:** Assume the SIA input of a pheromone \( g \) at a place \( (p_{x,y}) \) at a concentration \( c \). The input event is equally propagated to the neighbours of \( (p_{x,y}) \).
There, the local concentration of $g$ is changed by an input weaker than $c$. The stepwise weakening of the input is influenced by the $g$ propagation parameter.

**Evaporation:** Whenever the $SIA$ input and/or propagation results in a negative concentration of pheromone $g$, $c$ is constantly reduced in its absolute value. The reduction is influenced by the evaporation parameter of the pheromone $g$.

The state of the $SPI$ changes over time through the $SIA$ input, propagation, and continuous evaporation. The following transition functions formally specify the evolution of the state.

The transition of the propagated $SIA$ input $q$ is defined as

$$q(t + 1, p_{x,y}) = F\left(r(t, p_{x,y}) + q(t, p_{x,y}) + q(t, p_{x-1,1-y}) + q(t, p_{x-1,y}) + q(t, p_{x-1,y+1}) + q(t, p_{x-1,y-1}) + q(t, p_{x+1,1+y}) + q(t, p_{x+1,y}) + q(t, p_{x+1,y+1})\right)$$

and the transition of the *pheromone concentration* $c$ is defined as

$$c(t + 1, p_{x,y}) = c(t, p_{x,y}) \times E + r(t, p_{x,y}) + q(t, p_{x,y})$$

The first transition function specifies the propagation of input events through the $SPI$ and the second function combines the input from the agents and the propagated input with a general dispersion function to determine the current concentration $c$ of the pheromone $g$. In the discrete spatial dimension of the $SPI$, $E$ and $F$ are two parameters of the synthetic pheromone; $E$ is the evaporation parameter and $F$ is the propagation parameter. The initial amount of pheromone at a place $(p_{x,y})$ inputted by $SIA$ at time $t$ is represented by $r$. Changes in the state of the $SPI$ at a time $t+1$ are determined by two
transition functions $q$ and $c$ at time $t$. The addition of each amount of pheromone propagated from each neighbour of the place $(p_{x,y})$ is represented by $q$.

Hence, pheromone concentrations change not only with the SIA input, but also with the propagation from neighbouring places.

Once all the agents find a suitable host tree, the MPB life cycle is simulated as follows. Every agent gives birth to a set number of new agents depending on the age of the tree where the agent is located (Safranyik et al., 1999). Parent agents die and the new generation of SIA is the one that is going to emerge the next year. However, in the real-world, before reaching adulthood MPB are threatened by cold weather, experiencing high levels of mortality each winter when low temperatures have detrimental effects on the developing stages of the beetles. During moderate winters, it is common to have a mortality level of 80% due to low temperatures. On the other hand, under a severe winter the mortality rate may increase up to 90% of MPB (Carroll et al., 2003; Safranyik and Carroll, 2006). For this reason the ForestSimMPB incorporates both rates within a climatic cycle and a new population of swarm intelligent agents is determined.

In the ForestSimMPB sub-model the SIA aggregation behaviour is responsible for changes in health status of trees that are part of the forest ecosystem (i.e. alive (1) and dead (0)). In the real-world, when the sufficient number of MPB attacks is reached (Raffa and Berryman, 1983), the lodgepole pine tree active defences weaken and the tree finally dies and is used by the MPB to feed and complete their life cycle (Berryman, 1989). Therefore, when the number of aggregated agents reaches the threshold value, the health attribute of each cell (i.e. representing a lodgepole pine) is updated from alive to dead.
Sub-Model I runs for every 1ha cell of the landscape map; therefore the output of this sub-model is a series of raster maps – covering the area of the extent of the local scale (1ha) at a fine resolution of tree scale (2m x 2m) – indicating the health state of every tree in the area with values representing alive and dead trees, respectively. The total number of trees killed by MPB as model output is used to calculate the Percentage of MPB Occupancy (\(H_{mpb}\)) per hectare (%) as follows:

\[
H_{mpb} = \frac{(T_{ldp} - T_{hdp})}{T_{ldp}} \times 100
\]  

(6-4)

where \((T_{ldp})\) is the total number of lodgepole pines in the area and \((T_{hdp})\) is the total number of healthy trees. The \((H_{mpb})\) values are integrated into a new raster GIS map – covering an area at much larger landscape level (2500ha) at a local scale spatial resolution (1ha) – called MPB landscape occupancy map, in order to be used as the input for the GIS-based CA Sub-Model II each time.

6.3.1.2 Sub-Model II - GIS-based Cellular Automata

An important feature of the proposed method in this study is the coupling of the GIS-based CA with the ABM, so that the effects of MPB dynamics can be observed at a landscape spatial scale. MPB outbreaks have resulted in the change of landscape patterns which can be simulated and predicted by CA models at a feasible computation time. This is one of the main reasons why the ForestSimMPB and the GIS-based CA are coupled to model forest disturbances. The purpose of the Sub-Model II is to mimic annual patterns of trees killed by MPB at a landscape spatial scale in order to consider the effects of climatic and topographic factors in the process of driving insect outbreaks at a greater scale and gain some insights in this regard. Each cell in this sub-model represents a stand.
of trees. The state of each stand (i.e. health status) at a time \( t \) is defined by the Percentage of MPB Occupancy \( (H_{mpb}) \) of the forest stand. Hence, the state of a stand ranges from 0 (dead if \( \geq \) sixty percent of the forest stand is occupied by MPB) to 1 (healthy if \( < \) sixty percent of the forest stand is occupied by MPB).

The CA transition rules are based on the assumption that aspect, elevation and the percentage of occupancy of the neighbouring cells influence the forest infestation process at a landscape-level. MPB may be transported hundreds of kilometres by the influence of wind currents during peak flight periods; this atmospheric transport is generally unidirectional (Jackson et al., 2005). Hence, wind direction is also used to test different outcomes from its influence in the spatial patterns of the outbreak. It is implemented in the CA through evaluation of the neighbouring cells that receive the influence of different wind directions (Figure 6-2). Synchronous deterministic updating of all cells is based on Equation 6-5 at each discrete time iteration. This logic of the equation is consistent with the explanation that lower elevations and south-western slopes are associated with the locations of the highest-intensity infestations (Moore and Jackson, 2004; Nelson et al., 2007; Safranyik et al., 1992; Safranyik and Wilson, 2006).

\[
S(x, y)_{t+1} = f \left[ \beta_1 \left( 1 - \frac{A}{A_{max}} \right) + \beta_2 \left( 1 - \frac{E}{E_{max}} \right) + \beta_3 \left( N_{(Hmpb)}_t \right) \right]
\]

\[
\beta_1 + \beta_2 + \beta_3 = 1
\]

Where \( S(x, y)_{t+1} \) is the cell state at a time \( (t+1) \) that changes as a function, \( f(A,E) \), of the cell aspect \( (A) \), elevation \( (E) \) and the number of neighbours \( N_{(Hmpb)_t} \), within the
neighbourhood, with a cell state equal to 0 at a time \( (t) \). Lower elevations and south-facing slopes require fewer neighbours occupied by MPB in order for a successful attack to a new area, while higher elevations and north-facing slopes require a larger \( N(Hmpb)_t \).

The constants \( \beta_1, \beta_2, \) and \( \beta_3 \) are values representing the assigned weights for each of the variables that make part of the equation. These constants can be calibrated to produce realistic infestation patterns, when real datasets are available.

![Diagram showing wind direction influencing the spread of the MPB disturbance](image)

**Figure 6-2** Wind direction influencing the spread of the MPB disturbance
The output from the *Sub-Model II* is a raster layer representing the spatial location of MPB at a landscape-level; this layer contains values of \((H_{mob})\) at a time \((t+1)\). Once the landscape spatial scale simulation is generated, GIS operations are used to produce individual raster maps at local spatial scale (i.e. tree scale) with the location of the MPB trees attacked at a time \((t+1)\), that will be the input for the *Sub-Model I*.

### 6.4 Model Implementation

The algorithms of the proposed model were developed in Java by using the Recursive Porous Agent Simulation Toolkit (RepastS) developed by the Argonne National Laboratory (Argonne National Laboratory, 2011). The swarming intelligence CA-ABM approach adopts a tightly coupled architecture using the GeoTools Java library (OSGeo, 2011), which includes GIS data analysis, management and visualization functionality, and is available for use with the RepastS development platform. The input geospatial data layers were managed in ArcGIS software (ESRI, 2011), and then imported into RepastS as ASCII files.

#### 6.4.1 Study Site and Data

A hypothetical study site area of 2500ha was created to represent a forest landscape. The area represents a typical montane forest of the central interior of British Columbia, Canada (Figure 6-3). The forest landscape consists of a diverse collection of trees with varying diameters. The forest stands are typically dominated by lodgepole pine, *Pinus contorta*, with a relatively smaller proportion of deciduous aspen trees, *Populus tremuloides*, as well as some wetlands scattered throughout. The area is represented by GIS raster data layers at two scales. The tree scale, in which forest trees
Figure 6-3. Datasets of the forest landscape.
are encoded as individual cells of 2m x 2m resolution, covering the area of the extent of the local scale (1ha) at a tree level. The landscape scale where cells of 1ha resolution represent tree stands, covering an area at much larger landscape level (2500ha) at a local scale. Each forest tree has information on susceptibility, type, age, DBH, height and health status of the tree (dead or alive). Also, elevation and aspect data is registered for each raster dataset. Trees susceptibility to MPB attacks was calculated based on Bone et al. (2005) using three criteria: (1) tree size, (2) distance to the nearest tree attacked, and (3) age of the tree. Elevation and aspect values were extracted from a DEM of the central interior of British Columbia where a typical Montane forest can be located. The swarming intelligence CA-ABM approach simulates a 10 years MPB outbreak.

In order to start the simulations, eight different raster GIS data layers were used as the model input. These raster files contained information on tree type, susceptibility, health state, age, height and diameter at breast height (DBH), elevation and aspect. Each tree was represented in the database by a pixel with attributes such as the species name and values indicating its size in diameter at breast height (DBH), height and age. These values were randomly assigned based on Reid et al. (2004) in order to mimic real information previously used in local scale studies due to the lack of information (GeoBC, 2007). A raster GIS layer of lodgepole pine trees health status was created by adding different polygons in the landscape and randomly assigning the percentage of MPB infested trees within each polygon. The handling of the raster data layers was carried out using GIS.
6.4.2 Model Calibration and Sensitivity Analysis

Essential parts of spatiotemporal modeling, calibration and sensitivity analysis (SA) seek, respectively, to adjust parameter values of a model to reproduce the response of reality within a range of accuracy (Trucano et al., 2006), and quantify how changes in the values of the input parameters alter the value of the outcome.

The initial numerical values of the model's parameters were based on the well documented biological studies related to the MPB populations' behaviours in the forest environment (Carroll et al., 2003; Raffa and Berryman, 1980; Riel et al., 2003; Safranyik et al., 1999; Safranyik et al., 1992; Safranyik and Wilson, 2006). The model calibration procedure is an important consideration within the model development process and usually requires several temporally independent series of spatial data that is sometimes difficult to obtain. For this specific study, the calibration was not possible due to the required detail of information and lack of its availability. However, in order to identify which parameters of the model are critical and which ones are less likely to be important to the final simulation outcomes, a sensitivity analysis was performed.

Sensitivity analyses are essential to exploration of the behaviour of complex system models, due to the structural intricacies of the modeled process. The proposed model’s sensitivity was tested by running multiple simulations with different configurations. The intelligent CA-ABM approach has two sensitive areas: *neighbourhood size sensitivity* and *transition function weights sensitivity* (Equation 6-5). In testing the neighbourhood size sensitivity of the model, two different neighbourhood sizes (i.e. 3x3, 5x5) were used to simulate the forest infestation phenomenon at a landscape-level.
Model sensitivity to neighbourhood sizes is presented in Figure 6-4, it depicts the simulation outcomes that were obtained after running the model using two different neighbourhood sizes for a time lapse of two years (Δt=1 year, n=2). It can be seen from the figure that the result map (a), which implements a neighbourhood size of 3x3, has smaller size areas indicating trees attacked by the MPB, while map (b), which implements a neighbourhood size of 5x5, shows a broader spread of MPB with more trees killed by MPB. In the same way, results presented in Figure 6-4 (a, b) illustrate that a smaller neighbourhood size results in fewer overall trees attacked during the first five simulated years, which is confirmed by the information from Figure 6-4 (c). Smaller neighbourhoods limit the distance over which MPB disperse through the forest, while large neighbourhoods include more trees; hence more susceptible trees that are relatively distant from currently infested trees can still be attacked. The limitation of dispersal when using smaller neighbourhoods result in more localized infestations that require more time (i.e. years) in order to spread farther distances.

Additional to the neighbourhood size sensitivity, changes in the weights of the transition rules’ function were tested to explore the model sensitivity to variation of these parameters. For this purpose, three different simulations were performed using different values of \( \beta_1, \beta_2, \) and \( \beta_3 \) (Equation 6-5) as follows: a) 0.2, 0.2, 0.6, b) 0.3, 0.3, 0.4 and c) 0.6, 0.2, 0.2. These values were selected with the unique purpose to get insights about the influence of them in the final outcomes. No comparison with real data is possible due to absence of them. Figure 6-5 depicts the three outcomes, using different weights in the CA transition rules function. Visual comparison of these maps illustrates that changes in \( \beta_1, \beta_2, \) and \( \beta_3 \) do not significantly affect the outcomes of the spatial distributions of MPB.
Figure 6-4. Simulated MPB infestation at a landscape-level after 2 years \(t_{i+2}\) with: a) neighbourhood size of 3x3 and b) neighbourhood size of 5x5; c) Number of trees killed at each year of the model simulation for each neighbourhood size.
Figure 6-5. Simulated MPB infestation at a landscape-level after 5 years ($t_{i+5}$) with $\beta_1$, $\beta_2$, and $\beta_3$ (Equation 6-5) as follows: a) 0.2, 0.2, 0.6, b) 0.3, 0.3, 0.4 and c) 0.6, 0.2, 0.2.
killed trees. The graph (Figure 6-6) confirms that the simulated annual number of trees killed by MPB are not affected by changes in $\beta_1$, $\beta_2$, and $\beta_3$.

6.5 Modeling Results

The proposed intelligent CA-ABM approach was applied to the hypothetical study site with a spatial resolution of 2m and temporal resolution of 17 days for the Sub-Model I, and 1ha spatial resolution and 1 year temporal resolution for the Sub-Model II. The study site data at time $t$ was input to the model and the MPB outbreak landscape pattern was predicted for the time $(t+10)$ ($\Delta t=1$ year, $n=10$). Seven different scenarios were performed using a neighbourhood size of 3x3 and another seven using a 5x5 neighbourhood size, considering dispersions with and without the influence of winds. The values of $\beta_1$, $\beta_2$, and $\beta_3$ chosen for this study are 0.2, 0.2, 0.6, respectively. Figure 6-7 presents the simulated spatial distributions of lodgepole trees killed by the MPB infestation after three, six and nine years and for 3x3 neighbourhood. Four different scenarios depict the spatial patterns of MPB infestation when the influence of winds’ direction (i.e. no wind, N, NE and SE wind direction) is considered.

Although only four of the possible wind directions are presented, eight different wind directions were simulated as well as a scenario where no wind direction was accounted for. Visual evaluation of the results at landscape spatial scale confirm that spatial forest patterns of tree mortality fluctuate according to wind directions influencing the speed at which the outbreak spread. As expected, spatial clusters of MPB killed trees change based on wind direction. Comparing the simulated MPB infestation at landscape spatial scale with the DEM created for the area, it was possible to observe how lower
<table>
<thead>
<tr>
<th>Simulated Years</th>
<th>Number of Trees Killed</th>
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<tr>
<td>10</td>
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</tr>
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<td>3</td>
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</tr>
<tr>
<td>1</td>
<td>570228, 988565, 989285</td>
</tr>
</tbody>
</table>

Figure 6-6. Number of trees killed at each year of the model simulation for each set of different CA transition function weights: a) $\beta_1 = 0.2, \beta_2 = 0.2, \beta_3 = 0.6$, b) $\beta_1 = 0.3, \beta_2 = 0.3, \beta_3 = 0.4$, and c) $\beta_1 = 0.6, \beta_2 = 0.2, \beta_3 = 0.2$. 

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elevation areas provided corridors for the outbreak to spread faster. The use of wind and elevation information added complexity to the simulated outbreak patterns at the landscape scale.

The MPB outbreak spatial spread was visually inspected for the influence of the elevation and aspect on the outbreaks. The visual assessment indicated that MPB infestation during the first year moved first towards slopes facing south, southwest, northwest and northeast. The south and south-western ones corresponded to elevations around the 1135 m.a.s.l., while the north-western and north-eastern slopes corresponded to elevations around the 905 m.a.s.l. Simulation outcomes also revealed that the infestation process at a landscape scale was closely related to the elevation, allowing MPB outbreaks to be spotted first in lower elevations; however, when elevations are very similar, southerly slopes were first attacked.

The simulation reveals that after five or more years, winds have influenced the transportation of MPB infestation to higher elevation at the landscape scale. Figure 6-8 depicts changes in spread patterns in the presence of different wind directions (red color) compared with a scenario without wind (white color). It was found that MPB outbreak spread to higher elevations in the south winds influence scenario, while north wind scenarios presented less trees killed and the majority of them were located at lower elevations. Model realistically represent the influence of slope, aspect and elevations factors on the MPB spread. Southern and south-eastern facing slopes were more prone to MPB dispersion, whereas trees located on the northern side slopes were attacked much later than the others.
Figure 6-7. Simulated MPB infestation at a landscape scale after 3 ($t_i + 3$), 6 ($t_i + 6$) and 9 ($t_i + 9$) years, respectively for four different wind direction patterns. Highlighted areas indicate places where most change has taken place.
6.6 Conclusions

This study developed a novel hybrid modeling approach that incorporates swarm intelligence, agents, cellular automata and GIS to simulate the spatial patterns of forest disturbance by MPB at a landscape-level. The simulation results revealed that MPB induced tree mortality patterns, at landscape scale, can be simulated using a hybrid intelligent CA-ABM approach through the introduction of a swarm algorithm to represent the local aggregation behaviour of MPB populations during the process of emergence and host colonization, at a tree scale. Coupling the outcomes of the ForestSimMPB model at a tree scale with the GIS-based CA model to simulate the forest disturbance phenomenon at a landscape scale made it possible to address the problems of computation time when simulating larger geographic areas. Forest disturbance simulations at a landscape scale implemented in this study also permitted the consideration of important factors, such as wind, elevation and aspect that influence the spatial pattern of trees killed by MPB. The implementation of the intelligent CA-ABM approach within a GIS structure offers a unique tool to study and understand the spatiotemporal dynamics at tree and landscape scales in forest insect disturbance processes, as well as visualize the changes in the forest structure. GIS serves as a tool to store, process and display the geographic environment as well as to visualize the dynamic changes of the forest environment over time.

The MPB were represented by swarm intelligent agents simulating the local behaviour of the insects, which aggregate in order to attack a selected host tree and overwhelm its defences. After the local patterns of trees attacked by MPB are simulated, landscape-level patterns are simulated using a GIS-based CA. The emergence of spatial
Figure 6-8. Simulated MPB outbreak after five years; overlay of scenario with no wind (white areas) and scenarios with the presence of different wind directions (red areas)
patterns of tree mortality at landscape-level result from the local interactions between MPB and host trees and the influences of factors such as weather and topography. The model was applied to a hypothetical study site. Simulation outcomes depicted the spatiotemporal behaviour of the MPB, which is examined through the visual analysis of the spatial distribution and allocation of new outbreaks using different scenario where wind direction patterns are changed. The results in this study revealed the influence that factors such as elevation, aspect and wind have in spatial distribution of MPB infested trees at a landscape scale. Sensitivity analysis provided the evaluation of the changes occurring in the model outcomes when the neighbourhood size and weights in the CA transition function were changed. The model is sensitive to the changes in the neighbourhood size, while no significant changes were observed from changes in the CA transition function weights.

The intelligent CA-AMB approach presented in this study offers a useful tool for understanding the complexities of forest MPB disturbance at a tree and landscape scale, and can help forest management strategies for MPB outbreaks control. This modeling approach can present decision makers and other interested parties with a testing environment to explore different scenarios. In order to use the model in the forest decision support systems, very detailed information is required and further model testing is needed. Accordingly, during the model testing process it is important to get access to the real dataset that are scarce. The findings from this study can help to better understand all the factors and variables that affect and take part in the phenomenon of MPB and in general forest insect disturbances.
6.7 References


Moore, B.L., Jackson, P.L., 2004. Effects of topography upon mountain pine beetle (Dendroctonus ponderosae) transport and dispersion as indicated by mesoscale meteorological models, 16th Conference on Biometeorology and Aerobiology, Vancouver, BC.


7. GENERAL CONCLUSIONS

Forest ecological systems hold high ecological, environmental and economic importance. However, forest health is jeopardized by natural disturbances such as MPB infestations. This dynamic process makes it essential to understand the complexities inside these ecological systems and the consequences in the structure and spatial patterns of forests. This dissertation addresses forest insect disturbance modeling issues, in the context of MPB infestations, by providing a novel approach to simulating forest disturbance spatial patterns, at multiple scales. Natural collective aggregation behaviour of insects and its impact in forest cover change over time were considered. The modeling approaches developed in this dissertation draw upon knowledge from three scientific paradigms: GIScience, complex systems theory and swarming intelligence.

7.1 Summary of the Thesis Findings

This dissertation introduced novel spatio-temporal modeling approaches designed and implemented in order to simulate spatial patterns of MPB disturbance in forest ecological systems.

There is no record of other published examples of agent-based models applied to the MPB disturbance phenomenon that are able to account for the intricacies of the forest environment or the depth of the insects' behaviour exhibited by the models produced for this research. Thus, this makes this dissertation's contributions unique and novel. These models considered detailed information about the forest health, structure and
susceptibility to MPB attacks and this information was used to model MPB infestations at the most highly detailed resolution possible, that of the individual tree. Furthermore, the behaviour of the individual MPB was also modelled directly. Autonomous MPB agents aggregate thanks to a swarm intelligence framework that allows them to indirectly communicate in order to participate in massive attacks to selected host trees. Not only detailed models were produced, but also larger scale simulations including global variables were generated by integrating SI, ABM and CA.

In order to accomplish the objectives of this dissertation, an agent-based model based on reactive agents’ behaviour was built. The model presented in Chapter 2 demonstrated that emerging forest insect disturbance patterns were largely dictated by agent responses to forest attributes and structure, as well as rules set for their attacking behaviour. The ABM, which was integrated with GIS, was able of capturing, representing and examining MPB disturbance at two spatial scales. The model was able to represent the emergence of infestation patterns at macro scales from MPB outbreaks initiated at the micro-level. Additionally, model results revealed the influence that higher diameter trees and favourable weather conditions had on higher MPB breeding rates and therefore in the increments of new MPB populations.

Another important finding was that the spatial distribution of the outbreaks was influenced by shortage of food resources, which forced MPB infestations on younger stands of lodgepole pine tree. These conclusions suggested that, although forest characteristics played a very important role in determining MPB infestation patterns, the emergence of new dynamics was the product of adaptation of agents representing MPB to new conditions. Hence, if agents were adapting their behaviour based on their
environment, it was necessary to improve the agents’ abilities to communicate between them, in order to closely mimic their observed behaviours in nature.

In order to get additional insights about all the forces that drive forest patterns in the presence of MPB infestations, the GIS-based ABM for simulating MPB disturbance was used to assess the effect of harvesting policies in the dynamics of the phenomenon. The findings from Chapter 3 revealed that the application of different harvesting strategies had an impact in the forest patterns, spatial distribution of outbreaks and number of stands attacked and killed by the MPB. Specifically, it was observed that MPB populations varied depending on the harvesting strategy used. Likewise, the outcomes from two of the strategies simulated presented clusters patterns of dead trees, but with different spatial locations. The importance of these findings lies in its contribution to the development of forest resources management tools in order to build meaningful forest management policies.

The observations from the previous GIS-based ABM helped the realization that agents need to be able to communicate amongst themselves to produce patterns similar to the ones observed in reality. Therefore, SI was linked to the existing model to build swarming intelligent agents that indirectly communicate via synthetic pheromones to produce collective aggregation behaviours that allow them massive attacks towards susceptible hosts. The ForestSimMPB was tested in different study sites in order to observe and understand the outcomes of having different landscape spatial arrangements. MPB agents’ spatial distribution and the produced forest patterns for the disturbance process were the result of embedded collective behaviour in MPB agents’ population. The results revealed that agents were able to transmit messages to other agents with a
unified goal to aggregate; accordingly, distinctive forest patterns started to emerge. It was also observed that forest composition, artificial barriers, and forest health status had an effect on the spatial distribution of MPB and their general behaviour during an outbreak.

ForestSimMPB was built to realistically depict MPB behaviour by equipping agents with swarming intelligence. The model was carefully calibrated to simulate meaningful patterns of MPB disturbance, using documented biological studies of MPB populations' behaviours in forest ecological systems. Great effort was made to ensure the development of a tool that allowed exploration of “what if” scenarios where different parameters could be tested and examined at a very detailed level (i.e. tree scale). A complete GUI was created for users of such a tool, where climatic conditions and cycles can be selected; simulation progress can also be analyzed through the use of histograms and charts and a GIS output allows access to the geographic position and attributes of attacked trees.

The ForestSimMPB model presented in Chapter 4 provides a novel approach for simulating MPB infestations in forest ecosystems, at a tree scale, explicitly representing MPB spatial reasoning, indirect communication and aggregation behaviour. This approach represents an important contribution to forest disturbance modeling because it provides a means to investigate, with a greater level of detail, the complexities, dynamics and outcomes of MPB outbreaks through time and space.

An essential part of any modelling endeavour is to determine the extent to which the model is able to replicate the system it is attempting to mimic. Therefore, model testing stages such as verification, calibration, sensitivity, validation and qualification for
the ForestSimMPB were addressed by establishing and implementing a series of approaches suitable for ABM assessment. Additional to the ForestSimMPB model, a Random-ABM model was built to serve as null model. These two model outcomes were compared and evaluated to verify the ability of the ForestSimMPB to represent collective aggregation behaviours of agents. Model verification was accomplished by creating tracing files that allowed reviewing the performance and behaviour of the model. Sensitivity analysis and calibration involved the tuning of initial parameters of the model such as neighbourhood size and initial agents population size.

Model validation, achieved through map comparison approaches, revealed (visually and statistically) that ForestSimMPB outcomes match real forest patterns of MPB disturbance. Validation results were reassuring thanks to the levels of agreement between the real-world data and the simulated data. For the purpose of model qualification a completely different spatial location was used to simulate MPB disturbance. According to the obtained results, the ForestSimMPB model can be used to realistically simulate MPB disturbance and the emerging forest patterns. These outcomes represent a contribution to forest resource management by providing a tool (ForestSimMPB) useful in the forecasting of the MPB outbreaks. This tool provides spatio-temporal information of the MPB outbreak as well as a database with the exact location and attributes of each of the trees in the study area. The presented perspectives on agent-based model testing advance the literature in the specific domain of validation of complex system approaches.

Following the ForestSimMPB model testing, an enhancement of the model was needed in order to allow the simulation of larger study areas and to produce landscape
patterns of MPB disturbed forest taking into account climatic and topographic factors. Another required improvement was the reduction of simulation computing time when managing large datasets. The model upscaling from tree-level to landscape-level was accomplished by combining swarm intelligent agents and a GIS-based cellular automata model. Sensitivity analysis was carried out to explore the model for changes occurring in the simulated outcomes when neighbourhood sizes and wind directions were modified. Implemented on a hypothetical dataset, simulation findings revealed emergent landscape patterns from complex interactions at a tree scale and the influence that global factors such as wind, temperatures, elevation and aspect had in the forest disturbance patterns at a broader scale. The GUI designed for the ForestSimMPB model was updated to include new parameters that allow the user to customize different simulation scenarios.

Spatio-temporal modeling approaches described in this dissertation were successfully developed and implemented using RepastS 1.2 software and the open source Java GIS toolkit (GeoTools). All the models developed were loose coupled with ArcGIS 9.3 software. This allowed the use of ArcGIS files and functionalities in RepastS libraries. The different GUIs were also created with RepastS in order to allow users to manipulate model parameters and analyze the model outcomes.

7.2 Thesis Contributions to the Knowledge

For the purpose of modelling the dynamics of forest insect disturbance, this dissertation studies the integration of swarming intelligence and spatio-temporal modelling approaches. As a result, this thesis offers contributions to different scientific fields. First, the proposed approaches built on knowledge and research in GIScience,
particularly in the area of spatio-temporal modelling techniques, by integrating GIS, ABM and CA and enhancing them with SI for understanding spatial dynamic phenomena. To improve upon other agent-based models, which rely on reactive behaviour of agents the research conducted here, provides the additional ability for agents to indirectly communicate and adapt their behaviour based on synthetic chemical cues and collective decision-making in order to achieve their goal in the system. Likewise, swarming intelligent agents provides GIScience with a means for mimicking collective behaviour as a driver of geographic change, which is generally not supported by functionality within contemporary GIS.

This dissertation also provides contributions to research in landscape ecology as it presents a novel approach for deriving patterns of forest MPB disturbance at tree, stand and landscape scales. Whereas traditional equation-based models of MPB are only able to simulate population dynamics at stand level and across landscapes, the novel ForestSimMPB model presented here is able to generate spatial patterns of tree mortality and provide geographic locations of previous and current outbreaks. Moreover, modeling approaches developed in this dissertation acknowledge the coupling of ecological, spatial and human processes in order to understand forest disturbance patterns as a complex system.

The approaches presented in this dissertation add to the growing body of research efforts pertaining to environmental resource management; specifically to the ones concerning the understanding the linkages between MPB biology, climatic changes, forest spatial patterns, management policies resulting forest cover change. In this sense, the methods presented here can provide a computer simulation laboratory for observing
and enriching our understanding of the complexities involved in forest disturbance processes. The ForestSimMPB model represents a way to enhance forest management decision-making tools by presenting GIS results at multiple scales of the forest disturbance phenomenon, as well as a GUI that allows testing of different “what if” scenarios to explore climatic changes (i.e. temperature and wind changes) and forest harvesting practices. As a result, the modeling approaches proposed in this dissertation can be used to serve as a tool for analysis of environmental policy and forest resource management issues.

Another important field to which this dissertation has contributed is Geography, by providing the integration of multidisciplinary approaches to study, analyze and understand an inherently dynamic spatial phenomenon. In summary, this research contributed to GIScience, Landscape Ecology, Environmental Resource Management and Geography by means of complex systems theory, GIS and swarming intelligence integration to study forest cover change resulting from MPB disturbance.

7.3 Perspective on Future Research Work

Taking into account the main objectives of this research and the specifications of the proposed model, the aim of this dissertation has been therefore accomplished, particularly in developing, implementing and testing a hybrid intelligent model to simulate emergent forest disturbance patterns.

The GIS-based SI-ABM (tree scale) and SI-ABM-CA (landscape scale) approaches developed in this dissertation produce four outputs that are of significant use to forest ecology and management: (1) spatial location of agents (i.e. MPB) based on
pheromone concentrations and forest attributes; (2) annual increments of trees killed by MPB; (3) spatial location of MPB killed trees; and (4) maps of landscape patterns of MPB disturbance considering climatic and topographic factors. Consequently, it would be valuable to develop an interactive web-based application that allows model users to examine these different outputs in order to gain insight and understanding of the relationships between specific factors such as climate, forest structure, and harvesting strategies and the ability to manage forest insect disturbance.

While the modeling approach herein developed has significant potential for informing forest ecology and management, it is important to consider how it can be enhanced through further research. The forthcoming focus for ensuring successful implementation should be to develop an adequate web-based spatial decision support system (SDSS) for forest landscape ecological and management evaluations, in which interested foresters, ecologist and managers can easily follow the outcomes of interacting variables, improve the reproducibility of decisions, and document the reason why a particular choice has been made. In order to build the web-based SDSS, the first step to follow is to expand the management component of the developed model, in order to enrich it with different harvesting strategies that provide insights into the role of these policies in the spatial patterns and spread of forest insect disturbance. After the web-based SDSS is built the next step is to make the model accessible to the policy makers.

In general, future research is also needed for evaluating and improving some of the present challenges when integrating complexity approaches and SI to model large-scale geographic systems. It is important to acknowledge that comprehensive ABMs are often computationally intensive due to the complexity of geographic systems and the
need to represent massive numbers of agent-agent and agent-environment interactions. Specifically, this challenge can be addressed in future implementations by exploring the use of new computer paradigms of parallel, high-performance, grid and cloud computing in order to overcome the computational limitations of ABMs. The potential of building complex ABM approaches under new paradigms such as cloud computing is that models can be made available to users without them having access to very powerful computers to run simulations. Through these new computer paradigms the latest modeling approaches can be remotely accessed over the internet from very-large-scale data centres.
APPENDICES
Appendix A: Co-authorship Statement

Chapter 2
Title: Modelling Mountain Pine Beetle Infestation with an Agent-based Approach at Two Spatial Scales
Co-author: Suzana Dragićević
Role of co-author: Manuscript preparation

Chapter 3
Title: Exploring Forest Management Practices Using an Agent-Based Model of Forest Insect Infestations
Co-author: Suzana Dragićević
Role of co-author: Manuscript preparation

Chapter 4
Title: ForestSimMPB: A Swarming Intelligence and Agent-based Modeling Approach for Mountain Pine Beetle Outbreaks
Co-author: Suzana Dragićević
Role of co-author: Manuscript preparation

Chapter 5
Title: Perspectives on Agent-based Model Testing: Assessment of a Swarming Intelligence Agent-based Model for Mountain Pine Beetle Infestations
Co-author: Suzana Dragićević, Roger White
Role of co-author: Manuscript preparation

Chapter 6
Title: Landscape-level Simulation of Forest Insect Disturbance: Coupling Swarm Intelligent Agents with GIS-based Cellular Automata Modeling Approach
Co-author: Suzana Dragićević
Role of co-author: Manuscript preparation
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