Geographic Automata Systems Approaches for Simulating Forest Insect Infestation: A Case Study of the Emerald Ash Borer

by

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Abstract

Ecological phenomena like insect infestation behave as complex systems, where spatial patterns at larger scales emerge from interactions among individuals at the local level. The complexity is difficult to capture using conventional top-down approaches such as statistical or equation-based models which can be limiting in representing individual interactions, non-linearity, local dynamics, spatial heterogeneity and variation. The main objective of this study is to develop a suite of geographic automata approaches including cellular automata (CA) and agent-based modeling (ABM) to model insect infestation outbreaks over space and time. The proposed approaches were developed using emerald ash borer (EAB) infestation in Ontario as a case study. Obtained results indicate that the developed approaches capture local complex spatio-temporal EAB behavior and reproduce larger scale spatial patterns of infestation. This research advances insect infestation modeling and provides a tool to aid in the surveillance, eradication, and biosecurity to EAB infestation.

Keywords: Insect Infestation; Complex Systems; Geographic Information Systems; Cellular Automata; Agent-Based Modeling

This thesis is dedicated to my beautiful mother, who taught me not to give up on the things we love, even when they seem impossible to hold onto.

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Chapter 1.

Introduction

1.1. Introduction

Forest ecosystems are shaped by natural and anthropogenic disturbances. Among these disturbances are insect infestation outbreaks, where population densities become significantly high and have substantial effects on forest composition, structure, and function (Liebhold, 1994). Invasive forest insect infestation, where the state of the forest is changed or impacted by non-native insect species, is of increasing concern to forest managers in maintaining forest ecosystem health as global trade and travel has exacerbated the successful establishment of alien insect populations. These infestations have devastating environmental, social, and economic consequences (Liebhold & McCullough, 2012) and as such, considerable effort should be made to reduce their impacts. Forest pest management, formerly reliant on the use of harmful pesticides for pest management and eradication, has recently evolved to encourage the implementation of alternative strategies. This is known as integrated pest management (IPM). IPM emphasizes better understanding and control of the growth, composition, quality and health of the forest ecosystem through the integration of information to aid in the decision making processes for forest pest management (Liebhold, 1994).

The recent increased availability of geospatial datasets has new opportunities for geographical analysis of insect infestation, improving decision making processes in IPM, referred sometimes to as spatial decision support systems (SDSS). The development of spatial models can aid in pest management and can be used to forecast where and when an outbreak may occur. Spatial models provide the potential to develop tools that can be used to evaluate costly eradication measures, ensure long term forest sustainability (Varma et al., 1999), and provide insight to infestation dynamics through the generation of “what if” scenarios (Perez & Dragicevic, 2012) to determine how a population will respond to changes in their spatial environment e.g. population response to a changing climate.

Ecosystems and ecological phenomena typically display non-linear dynamics (Parrott, 2010). Linear systems are predictable where small or large changes at the local scale results in corresponding small or large changes at higher scales. However, non-linear systems are sensitive to small changes or sudden behavioral modifications of system elements that results in larger impacts on the entire system and this is often difficult to predict (O'Sullivan and Perry, 2013). Non-linear systems, commonly referred to as complex systems, are therefore difficult to be represented using standard spatial statistical methods (Parrott, 2010) and are more adequately represented by the means of computer simulations (O'Sullivan, 2008).

Complex systems are characterised by bottom-up processes, where small scale dynamics characterized by heterogeneous and adaptive behavior generate complex patterns at larger scales. For example spatio-temporal patterns of insect infestation are influenced by feedbacks, adaptation, self-organization, bifurcation, heterogeneity, and randomness at the local scale i.e. the heterogeneous invasive species whose adaptive behavior is driven by reproduction, the spatial arrangement and biological complexity of its resource base, the changing climate conditions, bifurcation such as forest fire, and a changing landscape structure as a result of urban development. The non-linearity in the system coupled with complex life cycles and a network of varying interactions among heterogeneous individuals can sometimes amplify heterogeneity within the system generating surprising behavior of the system as a whole, making these types of systems challenging to represent and predict, especially with conventional mathematical and top-down models (Batty & Torrens, 2005; Liebhold, 1994).

Box (1979) has questioned the purpose of modeling stating that all models are wrong, but some are useful. Mathematical and empirical models are the most widely used approaches for modeling and are based on the use of equations and the concept of equilibrium to represent measurable system components that change over time in response to system dynamics (O'Sullivan & Perry, 2013). Although these types of models can be very useful, complex systems such as social or ecosystems are typically studied as a closed linear system. In addition, due to their top-down nature, mathematical models are challenged in representing the variation among system individuals and the heterogeneity across the landscape, important factors in understanding ecological processes such as pest-host interactions (Parunak et al., 1998). The simulation modeling approaches can theoretically reproduce the quantitative relationship among system variables or elements thus representing complex systems and its behaviour. Therefore,

the latter models are suitable to represent the insect infestation phenomenon as a complex system.

Insect infestations have both a spatial and temporal component. Geographic factors such as landscape heterogeneity or host availability within the environment determine pest “invasibility” which impact patterns of local dispersal over time (Tobin et al., 2014). The use of geospatial data and geographic information systems (GIS) to collect, store, retrieve, transform, display, and analyze spatial data, can be useful in the generation of spatially explicit models in representing the spatial distribution of insect populations (Liebhold, 1994). Although a GIS approach tends to produce static spatial representations of geographic phenomena, these approaches can be integrated with other modeling approaches to generate spatio-temporal representations of insect infestation that address the behavior elements of complex systems.

In the late 1940s, mathematician, John von Neumann, and later John Conway, established the theoretical background of cellular automata (CA) and the “game of life”, a modeling method for simulating complex systems (von Neumann, 1996). Although initially used in disciplines such as physics, biology, and chemistry, the CA approach was particularly successful in representing behaviour of geographical systems including land use and regional change and simulating urban growth (Batty & Xie, 1994; White & Engelen, 1997). Subsequent work in CA in a geographical context generated interest in related automata approaches including agent-based modelling (ABM). These approaches can be linked to geospatial data and applied in geographical context are often called geographic automata systems (Torrens & Benenson, 2005). They provide mathematical representations of complex geospatial systems using bottom-up approaches capable of capturing interactions at the local level and producing spatial patterns at larger scales. The methodologies have an advantage in modeling phenomenon with limitations in data availability as data to represent the local dynamics is often easier to obtain than data representing the entire population (Latombe et al., 2011).

The main characteristics of a CA include a grid of cells used to represent geographic space, a set of states, a definition of a neighborhood of a cell, a set of transition rules to determine the state of each cell, and a sequence of time steps (White & Engelen, 2000; Torrens and Benenson, 2005). An advantage in using CA to model complex geographic systems is its ability to be easily coupled with raster based geospatial data and GIS. The method does not require the use of mathematics or physics to provide valuable and useful results. Instead of using complicated equations to represent dynamics between system elements, spatio-temporal dynamics are

simulated through the application of simple transition rules applied to each cell at every iteration (Torrens & Benenson, 2005). The transition rules are functions that represent the processes and interactions which influence the change of state of a cell within geographic space, representing the process and interactions within the complex system i.e. changing the state of a tree in reality, a cell in the CA, from not infested to infested. Despite the simplicity of these rules representing simple relationships at the local level, CA models generate complex patterns at larger scales to represent the phenomenon under study (Batty, 2005).

The integration of geospatial data and CA allows for the spatio-temporal representation of the phenomenon within its real-world environment. Although more popular in modeling the changing urban environment (White & Engelen, 1997), the value in using CA as an approach in modeling ecological phenomena has also been recognized. Widely accepted by ecologists as a useful tool, ecological CA models have emerged in application to spatio-temporal vegetation dynamics (Balzter et al., 1998; Colasanti & Grime, 1993; Cannas et al., 1999; Grist, 1999) and population dynamics (Molofsky, 1994; Hill & Caswell, 1999), embraced for its usefulness generating “what if” scenarios where researchers can observe influences of changes in climate, ecosystem structure, and landscape composition for improved ecological management (Silva et al., 2008).

Integration of GIS and CA has been more recently applied in the context of insect infestation, most notably as an approach to simulating insect infestation within a changing forested landscape (Bone et al., 2008; Mathey et al., 2008; Perez & Dragicevic, 2010). CA works by representing the dynamics between insect and host, generating patterns of insect infestation at a landscape scale. Some studies use fuzzy reasoning to address uncertainty associated with data unavailability and to represent the phenomenon of interest in a spatial and temporal context (Dragicevic, 2010). For example, a fuzzy constrained CA has been developed to simulate the propagation of the MPB in response to various management scenarios even with a lack of data availability (Bone et al., 2008). Fuzzy set theory is used in order to manage the uncertainty of cell states, specifically in determining the susceptibility of the pine tree hosts to MPB infestation (Bone et al., 2006). The relationships between the biological or spatial characteristics of the tree and the attacking insect are determined by expert knowledge and represented using fuzzy functions to calculate a pine trees membership between not susceptible or most susceptible to MPB attack.

Work with CA for autonomous simulation and the advancement in computational software development catalyzed geographer’s interests in agent-based modeling (ABM), another bottom-

up complex systems modeling method that overcomes some models inabilities to explicitly represent the individual (Grimm & Railsback, 2005). Where CA represents the dynamics between system individuals, an ABM is capable of representing discrete individuals, real-world interacting entities referred to as “agents”. Agents are programmed with artificial intelligence by combining elements of learning, adaptation, evolution, and fuzzy logic (McLane et al., 2011). ABMs commonly simulate spatio-temporal phenomena to demonstrate how local to interactions between agents and their environment generate global patterns of behavior over time (Li et al., 2008; Crooks et al., 2008; McLane et al., 2011). Like CA, ABMs can be integrated with GIS to represent the environment that the agents interact with.

ABMs have been used extensively in ecological modeling in the past in application to fish, forest dynamics, population dynamics, and species conservation (DeAngelis & Mooij, 2005). These models were developed in response to the ecological principals that (1) the genetic and environmental influences specific to every individual generates unique physiology and behavior and that (2) interactions between individuals are local and result in global collective behavior (Bousquet, 2004; Gimblett, 2002; Brown et al., 2005). Particularly, ABM development in ecology addresses the concern that the individual has been underrepresented in classical ecological modeling which largely ignores influences of individual variability, decision making, discreteness, heterogeneous lifecycles, and non-linearity on the system as a whole.

Insect infestation dynamics have been modeled in the past using an ABM approach which brings to light the importance of representing system heterogeneity. Myers (1976) developed one of the first ABMs to represent how an insect’s biological heterogeneity affects global population dynamics. Hogeweg & Hesper (1983) developed an ABM to represent the caste structure within insect societies to generate system level behavior (Hogeweg & Hesper, 1983). Most recently, ABM models representing important insect infestations have been developed to better understand the dynamics that lead to negative ecological, economic and social impacts on the world’s forest resources. Perez & Dragicevic (2010) integrated ABM and GIS capable of capturing, representing, and examining MPB at two spatial scales, tree scale and landscape scale. Perez & Dragicevic (2011) used swarm intelligence (SI) as an artificial intelligence approach to represent the behavior of the MPB and also integrated ABM and GIS to model the dynamic phenomena. Perez & Dragicevic (2012) extended existing simulations (Perez & Dragicevic, 2011) by proposing a hybrid model that can simulate forest patterns of MPB disturbance at a much larger landscape scale in addition to the dynamics at local tree-level scale. The hybrid approach consists of SI

agents incorporated into a GIS based CA model. This non-exhaustive summary of past publications on the use of bottom-up modeling approaches to simulate forest insect infestation has provided a solid foundation for future forest insect infestation modeling research. Therefore, there is a motivated agenda to further research efforts in the development of spatio-temporal models using approaches which can address and represent the complexity of insect infestation and aid in the understanding, decision making, and eradication in application to new invasive forest insect infestations.

1.2. Research Problem

The emerald ash borer (*Agrilus planipennis*; EAB), an invasive species native to south-east Asia, has been responsible for the death of millions of North American ash trees (*Fraxinus sp*.) across the United States, Ontario, and Quebec. An invasive species can be defined as a non-native species that has been transported by human-assistance beyond the limits of its native geographic limits and has successfully established its population in its new environment (Blackburn et al., 2011). The beetle was most likely introduced to North America in the early to mid-1990s in the vicinity of Westland-Garden City, Michigan (Koenig et al., 2013; DeSantis et al., 2013), but was first identified in Detroit in 2002. Lag in discovery from the time of arrival is not uncommon as invasive pests tend to remain at densities below the detection threshold until environmental or other factors lead to noticeable increases in populations (Poland & McCullough, 2006).

EAB targets common species of ash trees native to North America. All sixteen species of ash are attacked and killed such as the green ash (*F. pennsylvannica*), black ash (*F. nigra*), and white ash (*F. americana*). Blue ash (*F. quadrangulata*) is also susceptible; however the sub-species has demonstrated resilience to EAB infestation (Poland & MCCullough, 2006). EAB is not a threat to ash species in Asia as host trees have chemical defensive mechanisms that provide resistance (DeSantis et al., 2013) and EAB populations are maintained by natural predators such as a variety of stingless wasp species. In North America, where ash is abundant and populations of natural predators are far too low to control EAB population, infestation of the ash is fatal in as little as one year (Poland & McCullough, 2006). EAB larvae feed on the interior of the tree, disrupting the flow of water and nutrients essential for the trees survival (BenDor et al., 2006; DeSantis et al., 2013).

EAB insect infestation is difficult to detect and detection is an important component in pest eradication. Detection of infestation can be delayed up to a year as external symptoms such as characteristic D-shaped exit holes, chlorosis, crown thinning and dieback, epicormic shoots, and bark splits (McCullough & Mercader, 2002) are not always evident. The difficulty in the surveillance of EAB infestation threatens the biosecurity and economics of North America as a whole. Eradication of EAB has been unsuccessful. Current strategies are limited to the removal and replanting of ash tree species, clear cutting and incineration, restriction of firewood movement across county and state borders, and biological eradication using EAB natural predators.

The beetle has spread rapidly across the U.S., Ontario and Quebec and poses major economic, environmental, and social impacts to affected communities. Six species of ash are commercially important. White ash in particular are used for products such as tool handles, baseball bats, furniture, cabinets, crating, cardboard, and paper (Poland, 2006). Additional economic impacts include the cost of replacing damaged trees from city and suburban landscapes. Aside from the negative economic consequences, ecological impacts will likely include altered forest composition structure posing negative effects on associated wildlife and ecosystem function (DeSantis et al., 2013).

EAB exhibits characteristics of a complex system, with populations interacting at local small scale and producing complex patterns of tree infestation at larger spatial scales. The emergence of large scale patterns of infestation is a result of the local dynamics between the heterogeneous EAB population and spatially and biologically varying ash trees. These pest-host dynamics are governed by a combination of EAB preferences and constraints. Current modeling approaches to EAB infestation are split between equation-based models and spatially explicit raster-based (or cellular) methodologies. Equation-based models of EAB infestation have been constructed to represent the diffusion rates of EAB spread using ordinary differential equations (ODE) (Barlow et al., 2014), logistic regression (Siegert et al., 2010), and probabilistic modeling (Marshall et al., 2011; Muirhead et al., 2006). Spatially explicit models which use differential equations to represent theoretical EAB spread from cell to cell were developed for DuPage County, Illinois (Bendor et al, 2006; Bendor & Metcalf, 2006). In addition a raster based GIS model representing EAB spread in response to the heterogeneity in host arrangement was developed by Mercader et al. (2010). Prasad et al. (2010) developed a hybrid model that uses both equation-based and spatially explicit methodologies to generate EAB infestation in Ohio, Illinois. Most of these studies are focused on a US context.

Characterizing EAB infestation as a complex system has not been addressed in EAB modeling approaches and as such many existing EAB models do not address factors of non-linearity, adaptation, heterogeneity, bifurcation, and the relationship between insect and its environment across multiple scales. Existing models take assumptions of linearity of the EAB propagation, determine the probability of infestation on a large scale based on EAB preferences, are aligned with conventional mathematical approaches that are based on equilibrium, and often are unable to treat concurrently spatial and temporal components of the phenomena. Therefore, there is a clear need to address EAB insect infestation as a complex adaptive system and to develop a spatio-temporal modeling approach that addresses the variability and non-linearity inherent to insect infestation in pest-host dynamics.

In order to address the limitations in existing EAB modeling methodologies and aid in better understanding and management of EAB forest insect infestation in a Canadian context, the following research questions are the main drivers of this thesis:

1. Can geographic automata systems be used to represent forest insect infestation propagation, specifically in the case of the EAB insect infestation?

2. Can multi-criteria evaluation techniques and artificial intelligence be used to enhance automaton decision making processes in the developed approaches?

3. What can be learned about EAB propagation dynamics from implementation of these approaches?

1.3. Research Objectives

In order to answer the research questions, the main objective of this thesis is to develop and implement a suite of models that uses complex systems approaches and geographic automata theory enhanced by soft computing and multi-criteria evaluation in order to represent EAB infestation at multiple scales.

This thesis aims to meet the following objectives:

1. The design and development of a GIS-based CA to model the propagation of EAB at a regional scale.

2. The design of development of a GIS-based ABM to represent the refined local dynamics between the EAB and its ash tree host.

3. To implement the proposed approaches on geospatial datasets.

Therefore, complex system approaches have been applied to EAB infestation in order to address and capture the complexity in forest insect infestation. The suite of models will act as a potential tool in the future for forest management, surveillance and biosecurity, improve eradication measures by assessing host vulnerability, and provide the ability to test regulatory efforts: quarantines, pesticide use, and biological control. An improved understanding of the species behavior and propagation, the use of spatio-temporal computer modeling, and the employment of realistic methods for the quantification of insect infestation can improve future eradication programs.

1.4. Study Sites and Datasets

A high proportion of non-native insect infestation occurs in North America due to increases in global trade and travel in the region (Liebhold et al., 2013). Detroit Michigan, with its high-traffic international airport, is a major hub of global trade and is assumed by researchers to be the epicenter of EAB infestation. Once established in this region, the invasive species quickly spread east into Canada. There are currently no studies that explicitly model or address the problem of EAB in a Canadian context. Due to data availability limitations, this thesis uses two Canadian study regions to model EAB infestation: the City of Windsor and the Town of Oakville, Ontario, Canada (Figure 1.1). The City of Windsor was chosen for the first study as it is the region where EAB infestation initially became established in Canada. The Town of Oakville provided data containing detailed tree inventory GIS datasets for its urban forest, essential for capturing the small scale local interactions in the ABM.

A MCE- based CA model is developed to represent regional patterns of EAB infestation across three different landscape types and is based on datasets from Windsor. Geospatial

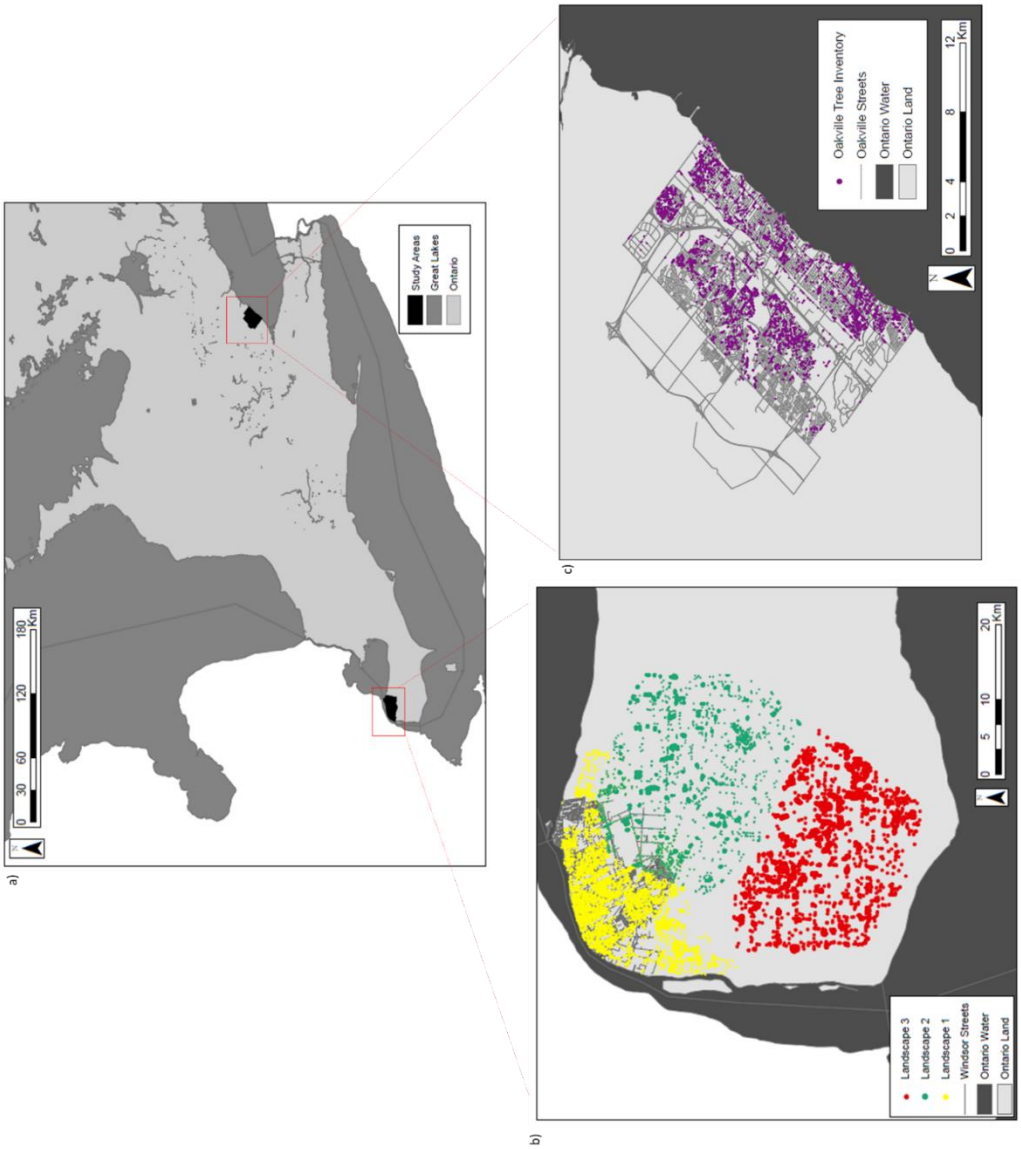

Figure 1.1. **Study sites of the thesis in south-western Ontario (a) including the City of Windsor (b) with three forest landscape types including urban (landscape 1), rural-urban fringe (landscape 2), and rural (landscape 3); and the Town of Oakville (b).**

datasets containing real geospatial data were used to develop GIS raster files of 10 meter spatial resolution where each cell found positive for ash represents one ash tree. The raster file represents ash tree distribution across various landscape types for the region of Windsor. The data sites were created using vector land use data acquired from Land Information Ontario (LIO) and transformed into a raster GIS format. Three hypothetical landscapes of varying types including urban, rural-urban fringe, and rural were extracted from the dataset for the City of Windsor and were used as inputs for the developed CA model to test how different landscape types impact EAB infestation propagation.

The GIS-ABM uses datasets from the Town of Oakville as a study site. The site was chosen for the availability of Oakville's tree inventory and the extensive collection of additional resources describing EAB infestation in the region, valuable in ABM development, calibration and validation. The tree inventory dataset represents the distribution and variability of the urban forest in Oakville, a key component in representing local dynamics in ABM.

1.5. Thesis Overview

This thesis contains four chapters. Following the introduction, chapter 2 details the design and development of the GIS-based CA approach for modeling the propagation of the EAB across three different landscape types: urban, rural-urban fringe, and rural. The model is composed of two parts: (1) the development of ash tree susceptibility using a MCE approach and (2) insect-host dynamics simulation. Fuzzy reasoning is used to develop susceptibility functions that determine to what degree each ash tree is susceptible to insect infestation on a scale from 0 to 1 where 0 is not susceptible and 1 is most susceptible. Host susceptibility is calculated based on the biological characteristics each individual ash tree (individual criteria), geographic characteristics (location based criteria), and temporal characteristics (criteria which change over time) and overall susceptibility is determined by combining the criteria using multi-criteria evaluation techniques and analytical hierarchy process through a pairwise comparison between criteria. Dynamics between pest and host are then generated using the CA. The developed GIS-CA model is calibrated by comparing the simulated patterns of EAB propagation with real-world rates of spread.

Although able to represent dynamics between host and pest, the CA approach is unable to represent the individual as a discrete entity and as such cannot take individual based factors

such as population count and life cycle of the EAB into account, which are important components in representing EAB infestation propagation at very fine scale representations. Therefore, chapter 3 presents the design and development of the GIS-based ABM model which aims to fill the gap in the literature for individual based models or ABM of EAB infestation. The GIS-ABM allows for the representation of refined EAB-ash tree interactions and the discrete representation of an adaptive, decision-making individual. The chapter addresses the potential in explicitly representing the heterogeneity and complexity of the individual and how the dynamics between the individual generates aggregate behavior, characteristic of the system as a whole, providing system level patterns. The model integrates EAB biology, lifecycle, dispersal, and host selection preferences in order to represent the behavior of the EAB as an individual. Autonomous beetle agents are programmed using Java in Repast Simphony (North et al., 2013) using aspects of artificial intelligence and integrated into a geospatial environment. The logic of the model is in accordance with EAB attack behavior and the model is calibrated and validated using spatial datasets delimiting the extent and severity of EAB infestation.

This thesis concludes with chapter four by synthesizing the overall results from the completed research, discussing the potential and the limitations of the developed approaches, and provides reflections on avenues for future work.

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Chapter 2.

Geosimulation model for propagation dynamics of the emerald ash borer across different landscapes *

2.1. Abstract

The emerald ash borer (*Agrilus planipennis*; EAB) is an exotic-invasive species native to Southeast Asia that has infested and killed millions of ash trees (*Fraxinus* sp.) across the Northeastern United States as well as Ontario and Quebec, Canada. Efforts to understand and model the insect's behavior are ongoing, however existing models are limited to approaches which do not address the complexity within the spatio-temporal dynamics of EAB propagation. Forest insect infestation is an ecological phenomenon that behaves as a complex system, characterized by uncertainty, non-linear spatial dynamics, and emergent patterns that evolve from smaller to larger spatial scales. Cellular automata (CA) is a mathematical conceptualization of complex systems that employs bottom-up modeling and can be used to understand and represent insect infestation pattern propagation over space and time. The main objective of this study is to develop a geosimulation model to represent complex spatio-temporal behavior of EAB and its spread on a regional scale. Geographic information systems (GIS), multi-criteria analysis techniques, and CA are used to build a model of EAB spread across three different landscape types: urban, rural-urban fringe, and rural. Scenarios also incorporate influences of wind and temperature. Simulation results demonstrate that the proposed geosimulation model represents the dynamics of the EAB propagation and demonstrates that ash trees in urban forest stands are of greater risk to infestation than other landscape types. The developed approach offers a model to represent the propagation of EAB infestation while addressing important components of the complexity of the phenomenon under study. The developed model has the potential to forecast spread and aid in management and eradication strategy development.

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2.2. Introduction

Since its discovery in Michigan in 2002, the emerald ash borer (*Agrilus planipennis*; EAB), an exotic-invasive species native to Southeast Asia has since infested and killed millions ash trees (*Fraxinus* sp.) across Northeastern United States, Ontario, and Quebec (Bendor & Metcalf, 2006; Bendor et al., 2006; DeSantis et al., 2013; McCullough et al., 2009). The beetle targets common species of ash trees native to North America such as green ash (*F. pennsylvannica*), black ash (*F. nigra*), and white ash (*F. americana*) whereby larval galleries feed on the interior of the ash, creating a girdling effect which disrupts the flow of water and nutrients essential to its survival (BenDor et al., 2006; DeSantis, 2013). Large trees infested with EAB may die in three to four years and smaller trees in less than one year (McKenny 2012). Detection of infestation can be delayed up to a year as external symptoms such as the characteristic D-shaped exit holes, chlorosis, crown thinning and dieback, epicormic shoots, and bark splits are difficult to identify (McCullough & Roberts, 2002).

The delay in detection of infestation has facilitated the successful establishment of EAB populations and the infestation is spreading rapidly, posing a major economic and environmental threat to trees in urban and forested areas of North America. Although there are few economic impact studies related to forest pest infestations in Canada (Krcmar-Nozic et al., 2000), it has been estimated that the US will suffer economic losses of as much as 300 billion dollars as a result of EAB infestation (Kovacs et al., 2010). Ecological threats to the urban forests are also extensive as city ash trees provide a wide range of benefits to the urban environment, including maintaining air quality, prevention of soil erosion, provision of food and shelter for wildlife, and regulation of climate (Emerald Ash Borer Management Plan, 2013). Rural forests are at risk of altered forest composition posing negative effects on ecosystem function (DeSantis et al., 2013). An improved understanding of EAB behavior, rates of spread, and impact to its environment may aid in the eradication of the pest and mitigate economic and environmental losses.

EAB outbreak can be conceptualized as a complex system where population dynamics and spatio-temporal patterns of infestation can be difficult to predict. Its complexity stems from the non-linearity within the system as a result of changing dynamical relationships between the adaptive beetles, where individual behavior is altered in order to maximize fitness and ensure survival, and their ash tree hosts. Non-linearity also stems from environmental feedback, where behavior of the EAB is influenced by elements such as wind, climate, or human interaction. In addition, the insect infestation phenomenon is subject to bifurcation, abrupt and often surprising

changes in the structure and function of the system in response to events such as forest fire, flood, climate change, and species collapse. EAB infestation is driven from the bottom up, where these interactions occurring at the local scale, generate complex, emergent patterns of insect infestation at the forest stand scale or regional scale causing important environmental, social and economic damage to host landscapes.

Models are useful tools that can be used in forecasting where and when an insect infestation outbreak will occur. The use of traditional mathematical modeling approaches in capturing insect infestation has been challenged by data availability and the complexity of the insect infestation phenomenon (Liebhold, 1994). These approaches are less capable of capturing the emergent behavior characteristic of complex systems (Parunak et al., 1998), where traditional linear modeling approaches may form an incomplete picture of the dynamic patterns (Fussman, 2007). Insect infestation rarely remains in equilibrium where populations may be abundant one year and disappear in the next, or be affected by minor changes that can affect overall behaviour of populations. It is challenging to apply classical methodologies as insect behaviour expands beyond a simple linear approach (Fussman, 2007). Even recent geographic representations of insect infestation, such as spatially explicit models using geographic information systems (GIS), generate static spatial representations and are unable to capture spatio-temporal processes, spatial dynamics, and change. Therefore, using modeling approaches which are capable of representing the non-linear spatio-temporal dynamics inherent to insect infestation seem to be more useful (O'Sullivan & Perry, 2013).

Current modeling approaches simulate theoretical EAB behaviour on local scales (Bendor et al., 2006), model EAB dispersal in a spatial context using probability exponential decay functions (Muirhead et al., 2006) and differential equations (Barlow et al., 2014). The relationship between EAB infestation and climate were examined (DeSantis et al., 2013; Vermunt et al., 2012), as well as the estimate of the economic impacts of the insect infestations (Kovaks et al., 2010; McKenney et al., 2012). These studies are limited to modeling the EAB in a US context and use the approaches which do not address the EAB infestation as a complex system.

There is a clear need for the development of a modeling approach that can help to understand and forecast the spatio-temporal dynamics of EAB spread at regional scale and represent the EAB as a complex system to incorporate important mechanisms of bifurcation, emergence, and adaptation. The modeling and analysis of EAB propagation using a complex systems approach has the potential to reveal key information regarding the underlying processes

which govern the propagation of the infestation to aid in the management of infested regions and the protection of regions not yet impacted. Cellular automata (CA) approach is mathematical conceptualization of complex system that employs a bottom-up modeling methodology, and is capable of integrating with geospatial data to represent emerging patterns of spatio-temporal phenomena.

The main objective of this study is to develop a geosimulation model capable of capturing complex emergent spatio-temporal behavior of EAB spread at the regional scale. Geographic information systems (GIS), multi-criteria evaluation techniques (MCE), and CA are used in this study to simulate EAB spread in response to ash tree susceptibility. The study uses geospatial datasets to simulate EAB propagation in Windsor, Ontario, Canada to better understand how EAB infestation behaves as it propagates across different landscapes. The model is applied to the urban landscape, the rural-urban fringe landscape, and the rural landscape in order to determine which landscapes are at high risk and why that might be. Each landscape is composed of varying distributions and biologically heterogeneous ash tree hosts and incorporates aspects of environmental variation including wind and temperature to determine the influence of these factors across each landscape.

The use of modeling approaches and the integration of geospatial data in the decision-making process is referred to as spatial decision support systems (SDSS) and is a vital component of insect pest management (Murray & Snyder, 2000). Specifically, GIS-based CA models can be used to generate “what-if” scenarios and assist in planning, policy making, and forest management to forecast the insect infestation (Bone et al., 2008). The proposed EAB CA-model can act as powerful decision making tool for this aiding in developing strategy to minimize potentially damaging and expensive pest control activities while effectively mitigating insect species spread.

2.3. Complex Systems Theory for Modeling Insect Infestation

Complex systems theory uses a bottom-up approach to analyze the behavior of a system, more specifically, to understand how local interactions between system elements with non-linear collective behavior generate patterns at a larger scale. Ecological systems, including insect infestation, are identified to behave as complex systems as they are composed of a network of heterogeneous individuals with complex life cycles, individual variability, dynamic local

interactions and varying resource bases (Wu & Marceau, 2002; DeAngelis & Mooij, 2005; Grimm & Railsback, 2013). Variations within the system are often amplified by non-linear processes, adaptation, and both individual and environmental change, fostering emergent and unpredictable behavior.

Cellular automata (CA) are a common complex systems modeling approach which can capture both the spatial and temporal dynamics inherent to complex geographic phenomena (White & Engelen, 2000). CA, discrete in space and time, is composed of a grid of cells representing geographic space. Each cell, characterized by a *state*, is surrounded by a *neighborhood* of adjacent cells which influence the state of the cell over time (Torrens & Benenson, 2005). The influences of the neighborhood occurs via transition rules, structured by simple "if-then" rules, and are designed to mimic real world interactions between system elements. The anatomy of CA mirrors aspects of complex systems theory, making the method suitable for representing complex spatio-temporal phenomena. CA can be expressed as:

$$S_{xy}^{T_{i+1}} = f(S_{xy}^{Ti}, N_{xy}^{Ti}) \qquad (2\text{-}1)$$

Where $S_{xy}^{T_i}$ and $S_{xy}^{T_{i+1}}$ are the states of a cell at a location *xy* at time T_i and T_{i+1}, N_{xy}^{Ti} represents the neighborhood surrounding the cell at location *xy,* and *f* represents the transition rules that determine how the state of a cell will change in the next time step.

Complex systems modeling approaches based on CA and another approach, agent-based modeling (ABM), have been used for simulating ecological phenomena (Dytham, 1995; Lux, 2013, Yang et al., 2009; DeAngelis & Mooij, 2005; Hinckley et al., 1996; Myers, 1976). The use of CA to model insect populations in forest communities has also been explored (Bone & Altaweel, 2014; Perez & Dragicevic, 2010; Perez & Dragicevic, 2012). At a regional scale, CA modeling has been found to be an appropriate approach for simulating complex patterns of insect infestation within a changing forested land-cover (Bone et al., 2008; Mathey et al., 2008) and mountain pine beetle propagation (Perez & Dragicevic, 2010). Fuzzy reasoning coupled with CA has been proposed to address the uncertainty associated with data unavailability, using fuzzy sets to spatially and temporally describe the phenomenon under study (Dragicevic, 2010). For example, a fuzzy constrained CA modeling approach was used to simulate the propagation of the mountain pine beetle (MPB) in order to address the lack of the tree infestation data (Bone et al. 2006).

Given that CA allows for the representation of complex dynamics between the EAB pest and its ash tree host providing the potential to reveal emergent behavior as a result of interacting with various landscape types, it is useful to use CA methodology as an appropriate choice for the representation and analysis of the spatio-temporal dynamics of EAB infestation which has not yet been reported in the literature. Using geospatial data and the CA approach, namely its cellular structure and discrete cell states, facilitates the representation of the complex dynamics between the emerald ash borer pest and its ash tree host and enables the representation of patterns of EAB infestation over space and time.

2.4. Methods

2.4.1. Study Site and Data Sets

This study uses a complex systems approach to simulate insect infestation, specifically the initial propagation of EAB across Canada, in Windsor Ontario from May 2002 to the end of August in 2003. Windsor (42°17′N 83°00′W) is the southernmost city in Canada, located in Essex County (Figure 2.1). The Detroit River separates Windsor, Ontario from the initial location of EAB infestation in Michigan, Detroit. The geospatial data used for the study area is as following:

(1) GIS data layers containing locations of EAB infested ash trees across south-west Ontario in 2002 to 2009 obtained from the Canadian Food Inspection Agency (CFIA). Although the dataset is at too large a scale to extract useful real-world regional patterns of spread and rates of infestation for Windsor specifically, the dataset provides an initial location of EAB infestation in the City of Windsor in 2002. In addition, the dataset provides large scale patterns of spread across Ontario where EAB infestation begins in the south-west part of Ontario and spreads in a north-east direction. Additional data from the literature provides information on the average rate of spread where the first North American outbreak of EAB in Michigan, US had a rate of spread of 10-11 km/year through natural dispersal (Smitley et al., 2008).

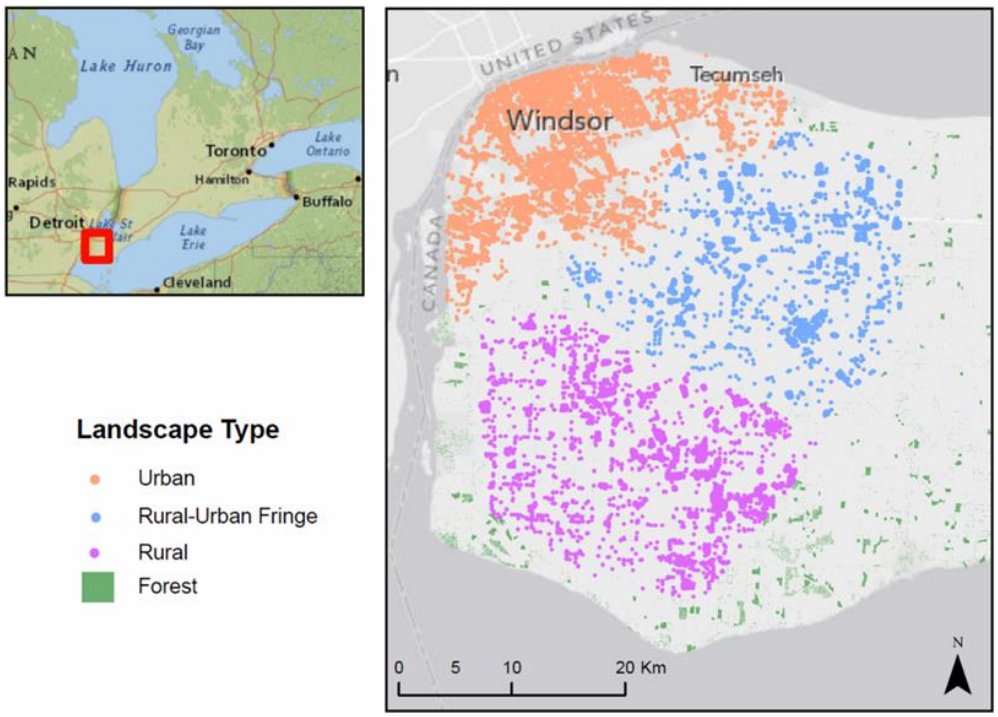

Figure 2.1. Study site, Windsor, Canada, depicting the three landscape scenarios (urban, rural-urban fringe, and rural) in the region, characterized by different spatial arrangements of the ash tree host.

(2) GIS raster files of 10 meter spatial resolution which represent three different forest landscape types including urban, rural-urban fringe, and rural in the City of Windsor, Ontario are created using vector land use data acquired from Land Information Ontario (LIO). The three landscape types are delimited through visual assessment of land use type using the land use data. The land use data allows for the generation of realistic patterns of ash tree distribution within the three landscapes, however, due to the unavailability of tree inventory data for this region, the exact location of individual ash trees are created as a hypothetical environment where the biological characteristics of the ash trees such as age and size are based off of the literature. The resulting datasets represent real-world spatial and biological patterns of ash trees within three landscape types.

(3) Weather and meteorological data for twelve stations distributed by the Ontario Weather Network. This data includes average wind direction and monthly temperature data for a period of two years.

2.4.2. Model Structure

The model structure is composed of two sub-model components, including (1) ash tree susceptibility generation and (2) insect infestation dynamics simulation (Figure 2.2). The proposed model integrates a raster-based GIS and a cellular automata (CA) approach to simulate the dynamics between pest and ash tree host which occur during the adult beetle stage, the only stage where the EAB are active during the EAB lifecycle. A multi-criteria evaluation approach was integrated to generate the degree of susceptibility of ash to infestation. The three landscape scenarios are applied to aid in furthering the understanding of the underlying mechanisms that may govern EAB spread including ash tree distribution, wind, and temperature. The details on model components are presented in the following sections.

Model Component I: Ash Tree Susceptibility

The first component of the EAB infestation model is developed to generate the values of susceptibility of ash trees to EAB infestation and is calculated using multi-criteria evaluation (MCE). Binary values of 0 or 1 were used to represent the presence and absence of trees in the raster GIS layers for the study site. Each tree is assigned a value of susceptibility to EAB infestation based on susceptibility functions and as a combination of the following criteria: (1) *tree type*, (2) *distance from infested ash*, (3) *distance from roads*, (4) *distance from highways*, (5) *density of ash in the stand*, (6) *age of ash*, (7) *size of ash*, (8) *wind direction*, and (9) *air temperature* based on values from published literature. The determined susceptibility of each tree to EAB infestation is represented on a scale from 0 to 1 whereby the value 0 represents trees with a state of non-susceptibility and 1 represents trees with a state of most susceptibility.

Tree type: Ash trees are the only tree type susceptible to EAB infestation, representing criteria 1, where susceptibility can be represented using a binary membership where cells not containing living ash trees are assigned a value of 0 and cells containing living ash are assigned a value of 1. Although evidence suggests some types of North American ash trees may be more susceptible than others, the developed model works under the assumption that ash tree type does not impact the level of susceptibility.

All remaining criteria (criteria 2 to 9) are represented using susceptibility functions (Figure 2.3, 1-8), where an ash's membership to the "susceptible" or "not susceptible" class is determined along a membership to a gradual scale rather than a binary one. Susceptibility functions were developed using fuzzy functions and their threshold values were chosen based on knowledge

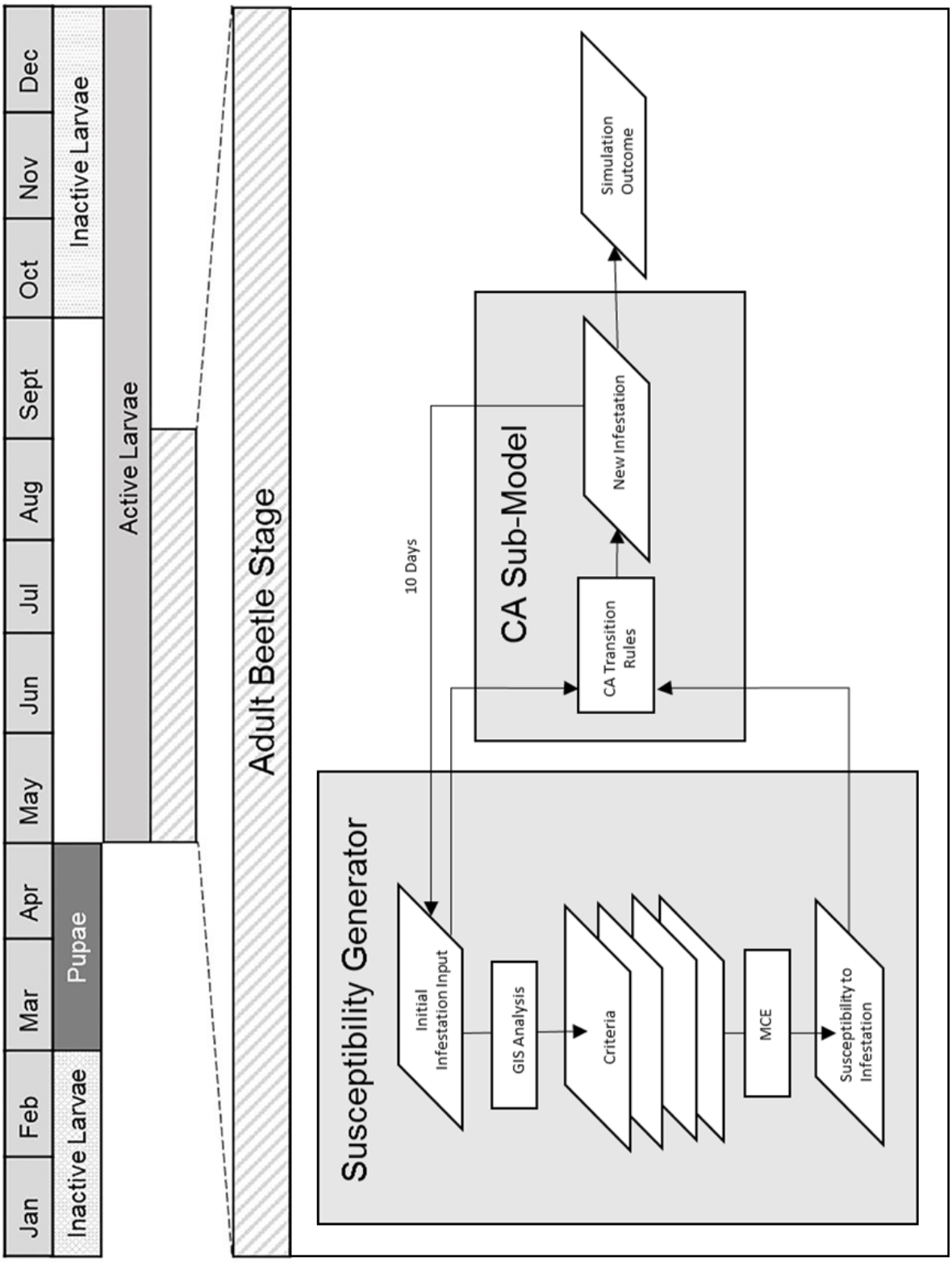

Figure 2.2. **The structure of the EAB model of infestation based on a complex systems approach. The model integrates two sub-models including a susceptibility generator and a dynamics simulator which generates EAB propagation during the adult beetle stage in the EAB lifecycle.**

collected from the literature on EAB behaviour (Figure 2.3). The decision to use linear functions was based on sensitivity analysis which determined that the use of positive or negative exponential functions either overshot or undershot the simulated rate of infestation. For example, a negative exponential function in place of the negative linear function in the distance from infested trees for the urban landscape resulted in a rate of spread that does not match the rate of spread observed in reality. This is a result of higher susceptibility values being assigned to ash trees which are close in distance to existing infestation. As distance increases, even slightly, susceptibility of ash trees decreases exponentially. The resulting effect is a decrease in rate of spread simulated by the model.

Distance from infested ash: The proximity of ash to other infested ash trees is a major factor contributing to ash tree susceptibility. Within their lifetime, migrating EAB adults have the ability to travel, on average, 1.4 km from their place of emergence (BenDor et al., 2006), indicating that the probability of infestation will decrease as the distance from infested trees increases. At a distance of 1.4 km from infested trees, susceptibility decreases to 0. As such, this relationship can be represented by an inverse linear membership function where trees are more susceptible to infestation the closer they are to trees which are already infested (Figure 2.3-1).

Distance from roads and highways: In addition to short distance dispersal, it is becoming increasingly evident that long distance dispersal plays a prominent role in spatial patterns of EAB infestation. Prasad et al. (2010) identified a correlation between roads and highways and establishment of new outlier populations of EAB, infested regions that develop ahead of the primary infestation front. These outlier populations typically grow, coalesce, and ultimately increase the speed of infestation (Mercader et al., 2011). This correlation between transportation networks and outlier populations can be attributed to human transportation of infested ash materials such as nursery stock, saw timber, and wood packaging material. In addition, firewood moves through informal pathways over long distances making infested firewood nearly impossible to identify, track, and regulate (Roberson & Andow, Working Paper). Recent research reveals that outlier populations may also be attributed to “insect hitchhiking” via attachment to automobiles (Buck & Marshall, 2008; Prasad et al., 2010; Robertson & Andow, 2009). Criterion 3 (roads) and criterion 4 (highways) represent human influence on EAB dispersal in which ash in close proximity to roads or highways are most susceptible. This relationship can be represented by an inverse linear membership function where trees are more susceptible to infestation the closer they are to transportation networks (Figure 2.3-2, Figure 2.3-3).

Density of ash: Adult beetles rely on the source of ash tree leaves for food and as a result, EAB females prefer to lay their eggs in areas with a higher proportion of ash trees in the stand (Mercader et al., 2011). This indicates that the probability of infestation will increase as stand density increases. The exact density threshold has not been identified within the literature. However, the use of a susceptibility function allows for the representation of density of ash as an influence in determining ash tree susceptibility without needing quantitative threshold values. The function simply scales the variation of ash tree densities from 0 to 1 where higher densities have a susceptibility value closer to 1. This relationship, criterion 5, can be represented by a linear membership function where stands with a higher density of ash are more susceptible (Figure 2.3-4).

Tree age and tree size: EAB are constrained by tree size and age in that ash that have a DBH of less than 5cm or are younger than 10 years of age are highly unsusceptible to infestation as the interior cambium cannot provide enough phloem to sustain larval galleries (BenDor et al., 2006). Susceptibility to infestation based on age, criterion 6, is represented by a linear membership function where trees are not susceptible (susceptibility membership of 0) if they are less than 10 years old. Susceptibility increases as ash tree age increases until the age of 170 years, representing the maximum age of ash tree species. Ash trees which are 170 years old are of the highest susceptibility and thus, have a membership value of 1 (Figure 2.3-6). Susceptibility to infestation based on size, criterion 7, is represented by a linear membership function where trees are not susceptible if they are less than 5 cm DBH. Susceptibility increases until 55 cm DBH at which time it reaches the maximum value of susceptibility with a membership value of 1 (Figure 2.3-6).

Wind: During the month of June, when the adult beetles fly to find food and reproduce, the primary wind direction in the Essex region is to the north-east. Although capable of flight upwind, insect species that respond to pheromones, such as at the EAB (Ryall et al., 2012), will typically fly downwind until pheromones are encountered (Pasek, 1988). Similar to the criterion, density of ash and temperature, the use of susceptibility functions does not require a threshold value. As such, susceptibility to infestation based on wind, criterion 8, can be represented by a linear membership function where trees which are north-east of infested trees are most susceptible (Figure 2.3-7).

Temperature: Microclimatic factors such as light, temperature, wind, and turbulence all influence insect dispersal (Pasek, 1988). EAB development and emergence as an adult beetle is

highly dependent on weather conditions. In particular egg hatch and flight is limited to occur during warm and sunny weather conditions. EAB emergence begins with a base temperature of 10 ºC (McCullough & Siegert, 2007). The use of susceptibility functions to represent the influence of temperature on EAB infestation does not require threshold values. Therefore, susceptibility to infestation based on temperature, criterion 9, is represented by a linear membership function where trees are most susceptible in warmer temperatures (Figure 2.3-8).

Each fuzzy criterion (*F1, F2, … Fn*) is weighted based on the significance of their role in influencing the susceptibility of an ash tree to EAB infestation in comparison to other criteria. The sensitivity analysis explores how different weights impact the performance of the model. For example, sensitivity analysis has been performed when all the factors were weighted equally and it was determined that up to +/- 2.1% difference of infested landscape has been identified. As such, factors were weighted based on knowledge gained from the literature to attribute higher weight to more important factors.

$$y = MCE(F1, F2, F3 \ldots Fn) \qquad (2\text{-}2)$$

According to a study that explored which abiotic and biotic factors have the most to least impact on EAB habitat selection, both logistic regression and Maxent modeling identified the distance to known locations of the EAB as considerably more important than any other variable influencing the spread of the EAB (Huset, 2013). This was reflected in the susceptibility generator by assigning the highest weighting to the criteria *distance from infestation*. Additional factors such as highways (Figure 3.3 4), more frequently travelled by vehicles carrying infested commercial products are assigned higher weights in the MCE calculations than roads as there is evidence that highways experience a faster rate of spread and more susceptibility to infestation (Straw et al., 2013; Buck & Marshall, 2008). The weighted criteria are combined in the following order of significance from the most weighted criteria to the least weighted factor: distance from infestation, wind and temperature (once added), age and size, highway, roads, and density. The MCE generates output *y*, a geographic representation of the total susceptibility of ash to EAB infestation on a scale from 0 to 1 as a function of all the criteria. The map of calculated levels of overall susceptibility of ash trees to EAB infestation is presented in Figure 2.3.

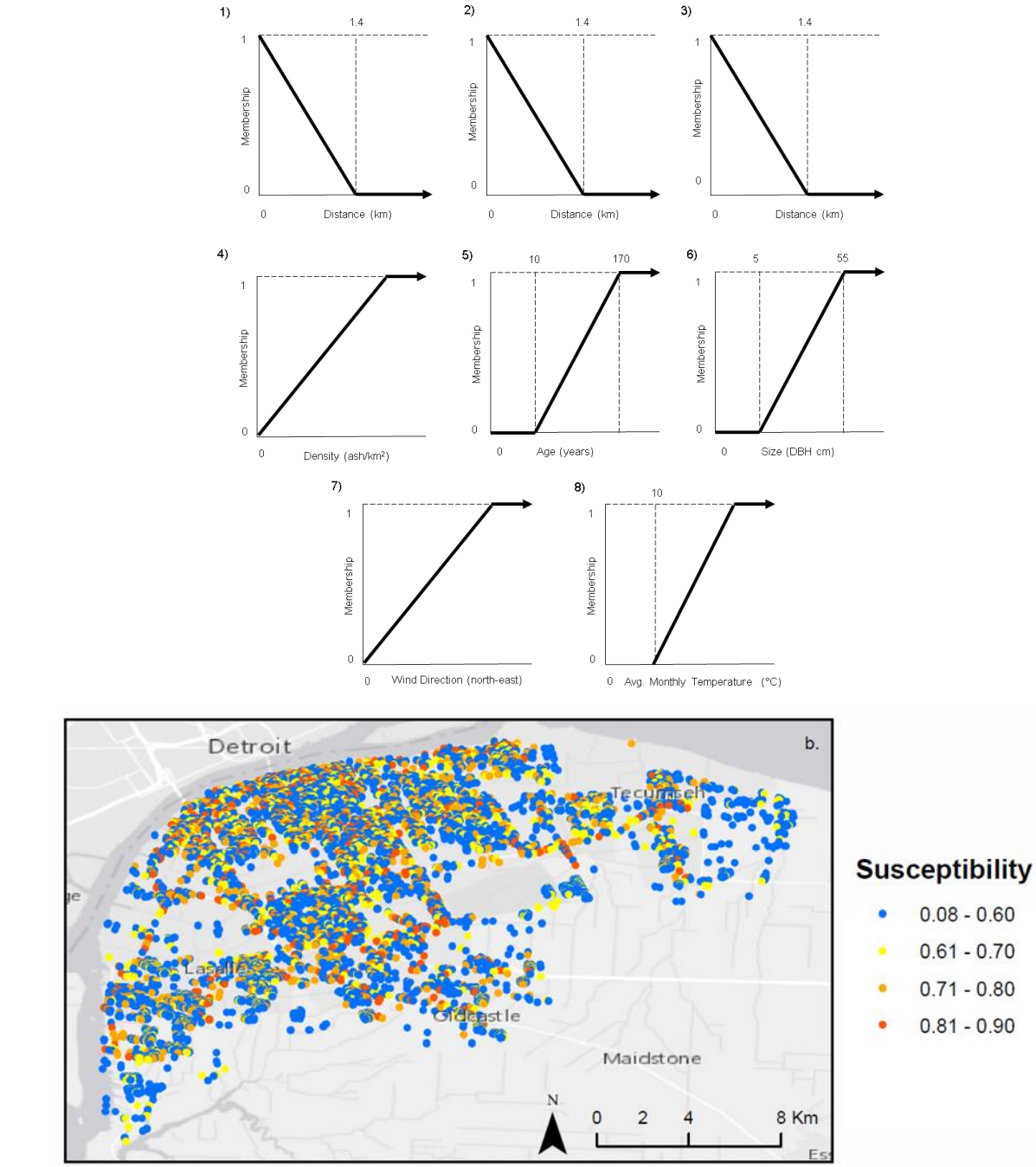

Figure 2.3. **Susceptibility functions representing criteria for the susceptibility of ash trees to EAB infestation based on criteria (1) distance from infested trees, (2) distance from roads, (3) distance from highways, (4) ash tree density in the stand, (5) ash tree age, (6) ash tree size, (7) wind, and (8) air temperature, combined to calculate overall susceptibility (bottom).**

Model Component II: Simulating Spatial Dynamics

The second component of the EAB infestation model generates the spatio-temporal dynamics of EAB spread in response to the susceptibility values generated for ash trees in Component I within the landscape. The model is calibrated using real world rates of spread identified within the literature. The CA in Component II uses the transition rules *f* based on the following: if there are non-infested ash trees within the neighborhood of an infested ash tree, then ash which are of the highest susceptibility to infestation will become infested. High susceptibility is defined as having a value greater than 0.6. Trees with a susceptibility of less than 0.6 will not become infested. Trees which are already infested stay infested and will eventually die.

The epicenter of EAB infestation in Windsor, Ontario is chosen to initialize the simulation. This location was acquired from the geospatial datasets obtained by the CFIA. The model runs for a total of 24 iterations (T_{i+24}), with a temporal resolution of 10 days per iteration. EAB spread only occurs from the months May to August, when EAB adults take flight to lay their eggs in the most susceptible trees and thus T_{i+24} is equivalent to the propagation of spread that would occur over two years. As each iteration takes place from May 2002 (T_{i+1}) to August 2003 (T_{i+24}), new ash trees become infested, changing the susceptibility of non-infested trees as a function of their proximity to other infested ash, their age, and their size.

2.4.3. Scenarios

Landscape Scenarios

In order to represent the realistic environment in which the EAB propagates through, three landscape scenarios were developed based on the different spatial arrangements and biological characteristics of the ash tree host found across southwestern Ontario using geospatial data and the literature. Each landscape scenario is unique with respect to the characteristics of the trees in terms of its spatial characteristics including age, size, and distribution (Figure 2.1).

Urban Landscape Scenario: The urban landscape is represented by the City of Windsor. Windsor is predominantly composed of residential, commercial, industrial, and some recreational space, namely Malden Park and Mic-Mac Park located in the west end of the city. Popular along city streets, on private property landscapes, and throughout urban parks and open spaces, ash trees are the principal tree species of urban southwestern Ontario (Emerald Ash Borer

Management Plan, 2013). Urban ash trees are typically 10 years of age or older when they are planted, deeming the majority of urban ash 10 years or older with a DBH of 5 cm or more.

Rural-Urban Fringe Scenario: The rural-urban fringe consists of the boundary which lies between Windsor, Ontario and agricultural land along its borders. This region is composed of a mosaic of the urban landscape including residential and commercial regions, crops, pastures, large tracts of abandoned farmland, fallow lands and forested regions. Forested regions are typically composed of a minimum of 7% of ash tree species which are randomly and widely dispersed across the landscape and loosely connected through the small corridors of trees along roadways, between agricultural plots, and along waterways.

Rural Landscape Scenario: The rural landscape scenario consists mainly of patches of forested areas and agricultural land, including crop and pasture land. Forested regions are connected by corridors of trees along agricultural fields, roads, and waterways. Rural ash trees live on average up to 170 years with a maximum DBH of 55 cm.

Climate Scenarios

Wind Scenario: In order to represent the spatio-temporal factors that influence EAB infestation, a wind scenario was applied. The dominant wind direction during all summer months from May to August is north-east (Ontario Weather Network, 2014). An additional CA sub-model simulates the effect of wind on EAB propagation where all ash tree located north-east of an infested ash tree is of increased susceptibility.

Climate Scenario for years 2002 & 2003: In order to better represent the spatio-temporal factors which influence EAB infestation and account for the way in which climate impacts EAB propagation in the real world, scenarios were developed to represent the influence of surface temperature and wind on adult EAB movement at the regional scale. Adult EAB are only active during the summer months from May through to August, As such, two temperature scenarios have been applied to the model using monthly temperature data from 2002 with an average temperature of 22 ºC and from 2003 with an average temperature of 26 ºC. Weather and meteorological data was used from twelve Ontario weather stations in the region with GIS interpolation using inverse distance weighting (IDW) to represent surface temperature continuously across each landscape scenario at a 10x10m resolution.

2.4.4. Initialization and Calibration

CFIA datasets provided coordinates for the epicenter of EAB infestation in Windsor, Canada in 2002 and was used for initialization of the model. Components of the model which were calibrated include the following: (1) the temporal resolution of the model; (2) the most suitable use of neighborhood sizes for each landscape scenario and; (3) the appropriate value of susceptibility whereby a tree may transition from uninfested to infested.

From the calibration process it was determined that the representation of EAB spread over a period of two seasons including May, June, July and August from both 2002 and 2003 was represented by 24 iterations whereby each iteration has a temporal resolution of 10 days. Each landscape was calibrated to use different sizes of neighborhoods to apply transition rules which would enable EAB spread across the landscape with different densities and distributions of ash tree host. For the *Urban Landscape, Rural-Urban Fringe, Rural Landscape Scenarios* the extended Moore neighborhoods, a grid neighborhood with 1.5 km x 1.5 km, 2 km x 2 km and 1.7 km x 1.7 km dimensions respectively were used to apply the transition rules. Neighborhoods of smaller size does not facilitate a continuous propagation of the infestation, rather the infestation propagation stops altogether.

A susceptibility value of +0.6 was chosen where only ash trees with this value or higher have the potential to become infested. This value was determined using sensitivity analysis by testing different susceptibility values. The value of 0.6 ensures that EAB infestation patterns which are simulated close to reality.

The calibration process uses rates of spread identified within the literature. The first North American outbreak of EAB in Michigan, US had a rate of spread of 10-11 km/year through natural dispersal (Smitley et al., 2008). Distances of 20+ km, up to a maximum recorded distance of 42 km has been observed in some regions. These long distances of EAB spread can only be explained through the mechanism of human assisted movement through the transport of ash infested products or the hitchhiking of EAB on vehicles (Muirhead et al., 2006; Prasad et al., 2010). These rates of spread match the baseline rates of spread for each landscape, without any influence of wind and temperature. The average rate of spread between all landscapes simulated for 2002 was 9.9 km with a maximum distance of 31 km. The average rate of spread between all landscapes simulated for 2003 was 10.5 km/year with a maximum distance of 32 km. The rate of spread obtained with model outputs is consistent with real-world rates of infestation.

2.5. Results

The EAB infestation model was implemented using IDRISI Selva and ESRI's ArcGIS suite of extensions for data preprocessing and analysis. Simulation results were generated for a two-year period for years 2002 and 2003 for each of the scenarios. Weather and wind scenarios were applied to each of the landscape scenarios independently and as a combination. Simulation run time was computationally intensive, whereby each simulation outcome took approximately twenty-four hours to generate.

2.5.1. Landscape Scenarios

EAB patterns of infestation in the *Urban Landscape Scenario* was simulated for May through August 2002 and 2003 (Figure 2.4). Patterns of infestation over geographic space in the *Rural-Urban Fringe Scenario* is simulated from May through to August in 2002 (Figure 2.5a) and in 2003 (Figure 2.5b). The *Rural Landscape Scenario's* patterns of infestation over geographic space is simulated in 2002 (Figure 2.6a) and in 2003 (Figure 2.6b). The patterns of infestation for each of the three landscape scenarios are presented over time, not taking climatic effects into account (Figure 2.7).

In the *Urban Landscape Scenario,* the rate of spread is high until late-July, 2002, when the majority of susceptible ash trees become infested. In 2003, the EAB rate of spread slows, however new ash trees continue to become infested until the end of the simulation. In total, 48% of ash trees become infested after two years (Figure 2.7a).

Spread of infestation in the *Rural-Urban Fringe Scenario* begins with a gradual linear increase until early-July 2002 when infestation tapers off, and little to no new ash become infested for the rest of the time until the end of the simulation in August 2003. In the *Rural-Urban Fringe Scenario,* 10% of healthy ash become infested after two years (Figure 2.7b).

The *Rural Landscape Scenario's* patterns of simulated EAB infestation differ from the other two landscape scenarios. The rate of spread increases rapidly as forested regions composed of high densities of ash trees become infested. Rates of infestation slow as EAB infest ash of lower density where forested regions are separated and then increase again once the EAB infests another forested region. The *Rural Landscape Scenario* demonstrates a total of 34% of healthy ash becoming infested after two years (Figure 2.7c).

As shown in the study's results, the *Urban Landscape Scenario* is the most susceptible to infestation, exhibiting the fastest rate of spread and the highest percentage of infestation. In contrast to the *Urban Landscape Scenario*, the *Rural-Urban Fringe Scenario* demonstrates the least susceptibility to EAB infestation, demonstrating the slowest rate of spread and the lowest percentage of infestation. The Rural Landscape Scenario rate of spread and percentage of ash infested falls between the two.

2.5.2. Climate Scenarios

Two climate scenarios, wind and temperature, were introduced both separately and combined in all three landscape scenarios with the goal of generating simulation outcomes which produce more realistic patterns of spread. Spatial patterns of EAB are influenced by monthly temporal changes in temperature and wind, rather than simply reacting to the spatially derived characteristics of the ash tree. Wind and temperature were added into the MCE and weighted just less than distance from infestation. Landscapes with no climatic effects (Figure 2.8a), with temperature effects on the landscape (Figure 2.8b), wind effects on the landscape (Figure 2.8c), and a combination of wind and climate effects on the landscape (Figure 2.8d) are compared for the *Urban Landscape Scenario* in May 2002 (T_{i+3}) and June 2002 (T_{i+6}). Since the rate of spread is most pronounced during these months, comparison is most useful during these two months to see variation in patterns.

Wind

The rate of spread was calculated for each of the three landscape scenarios over time, taking the effects of wind into account (Figure 2.8). Wind accelerated spread in some landscape scenarios and constrained spread in others. For example, in the *Urban Landscape Scenario,* wind accelerated EAB spread, facilitating the spread of EAB infestation further in distance north-east, the direction downwind from initial infestation (Figure 2.8b). As a result, a total of 65% of all ash become infested over a period of two years in the *Urban Landscape Scenario* (Figure 2.7a), 20% more than the simulation without wind.

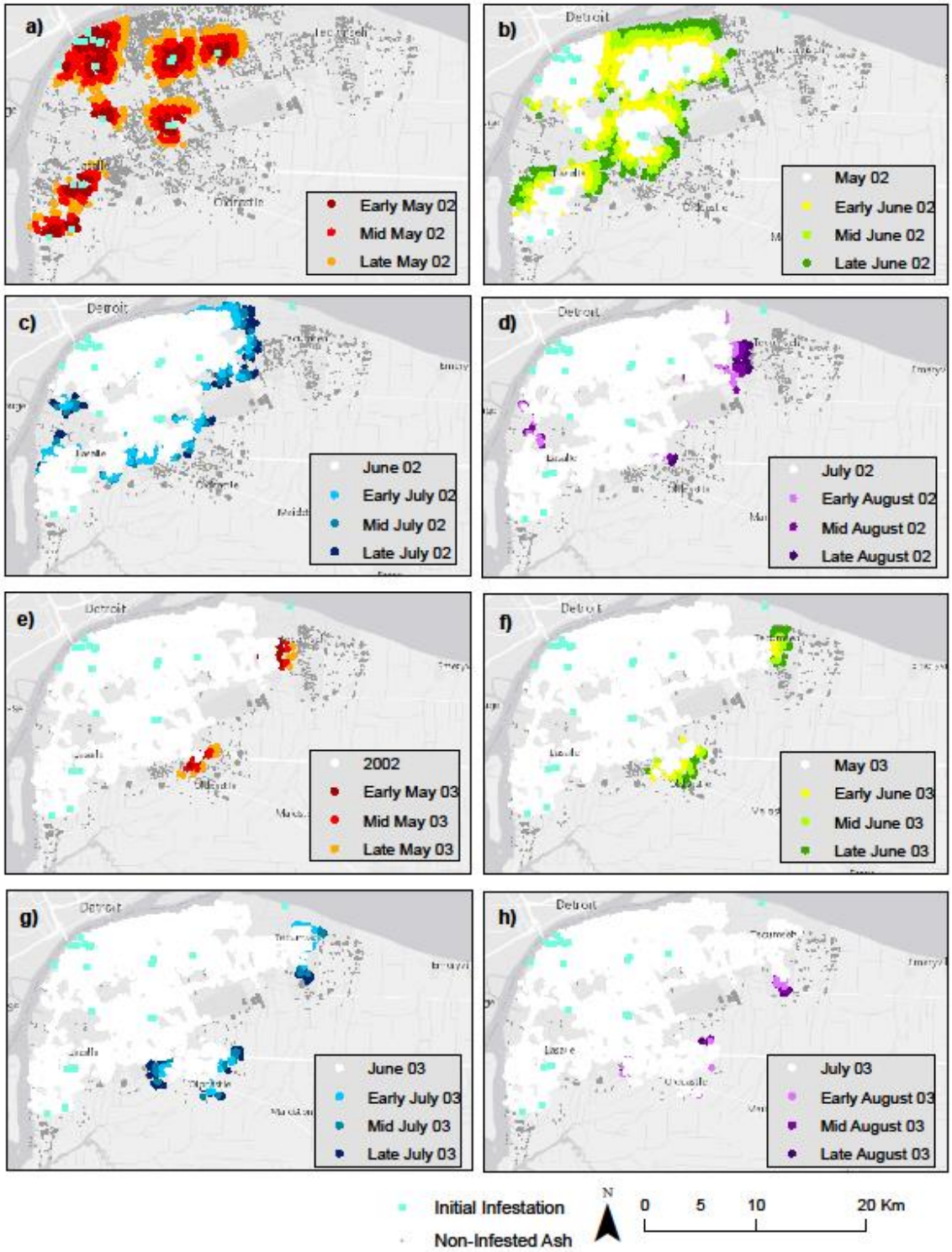

Figure 2.4. **Simulation results generated for two years for (a) May 2002, (b) June 2002, (c) July 2002, (d) August 2002, (e) May 2003, (f) June 2003, (g) July 2003, and August 2003 for the Urban Landscape Scenario. The maps show the spatial pattern of the EAB infestation propagation.**

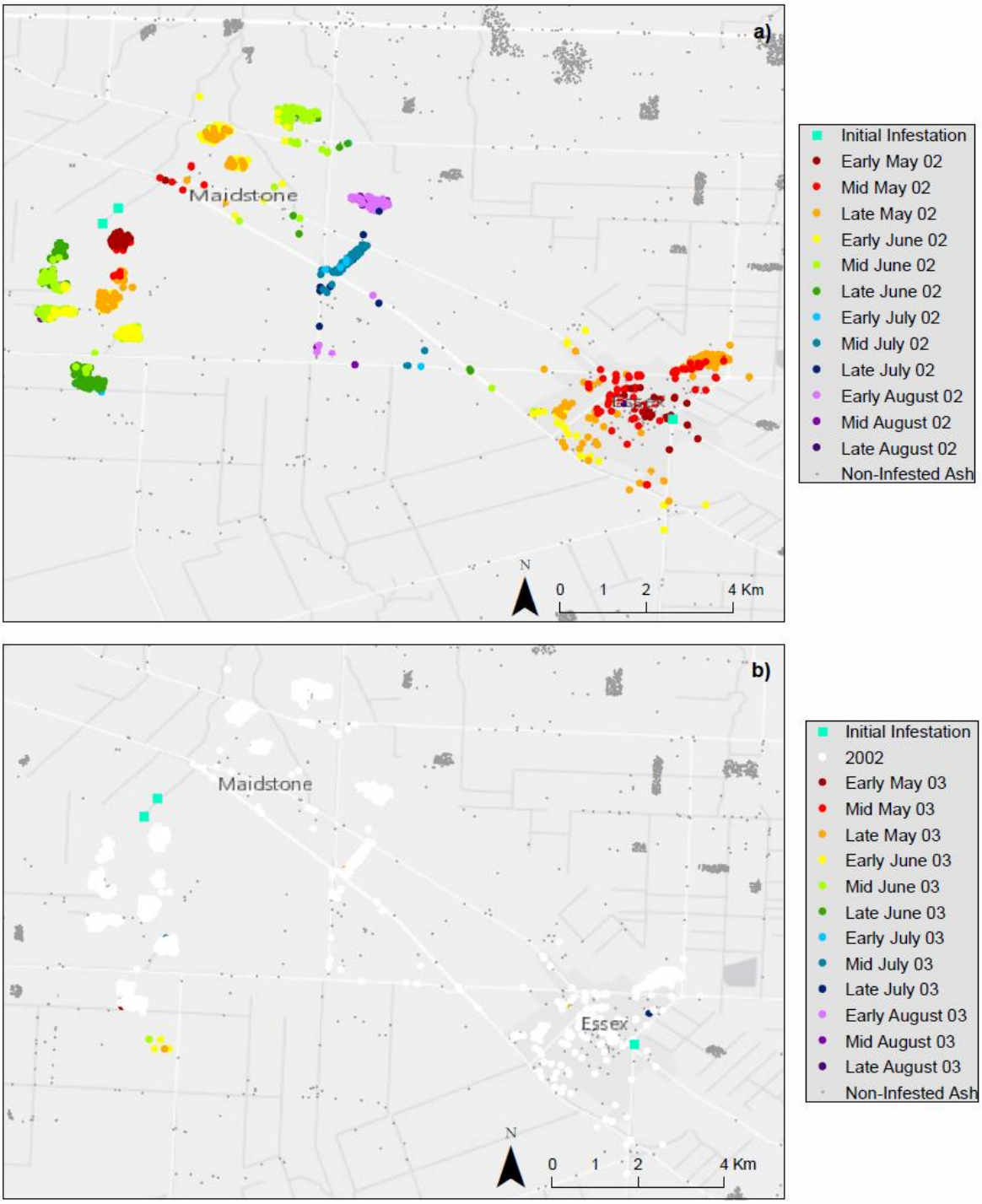

Figure 2.5. Simulation results generated for two years from (a) 2002 and (b) 2003 for the Rural-Urban Fringe Landscape Scenario. The maps show the spatial pattern of EAB infestation propagation

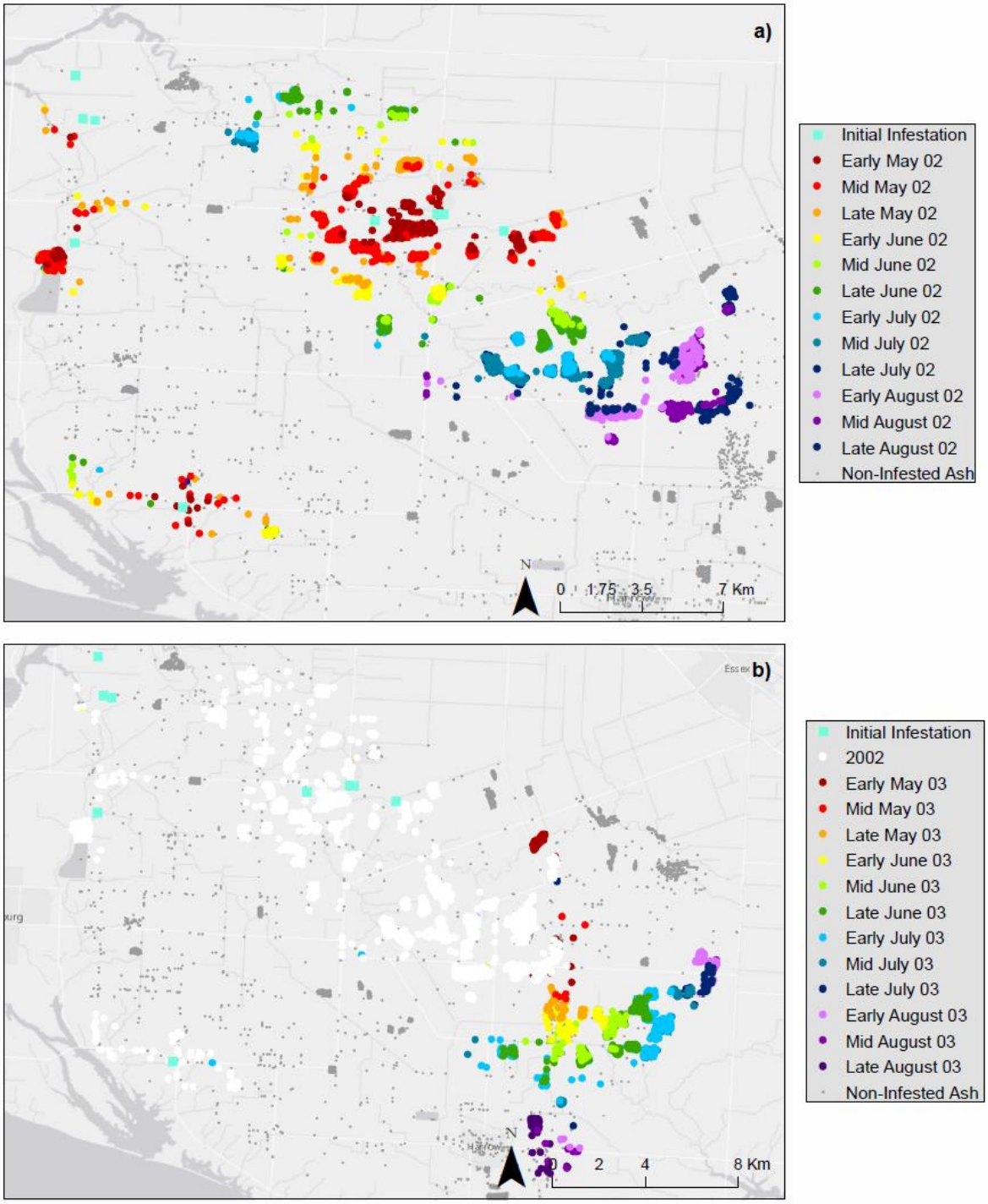

Figure 2.6. Simulation results generated for two years from (a) 2002 and (b) 2003 for the Rural Landscape Scenario. The maps show the spatial pattern of EAB infestation propagation.

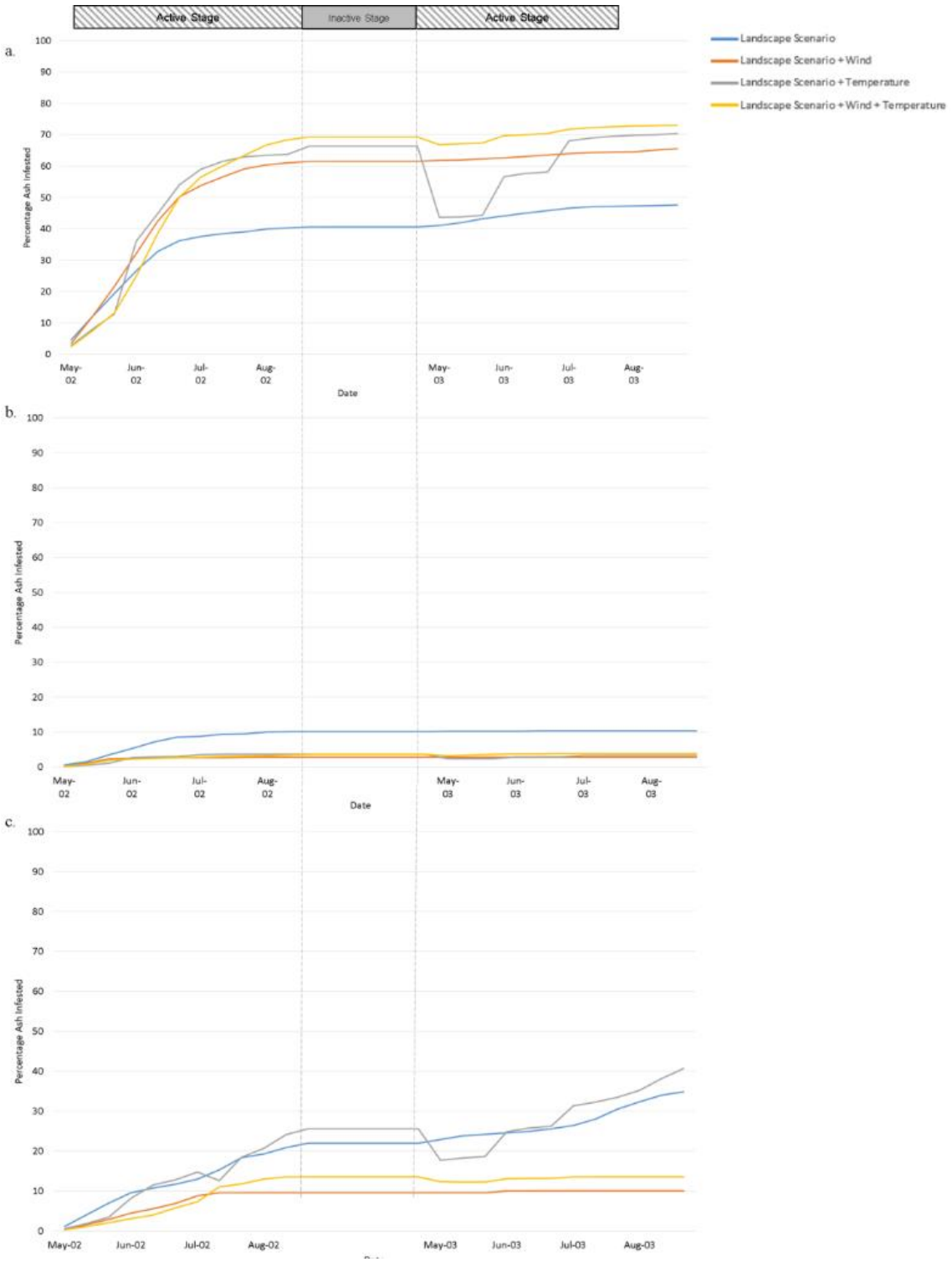

Figure 2.7. Graphs representing the percentage of all ash trees infested for all three Scenarios: (a) Urban Landscape, (b) Rural-Urban Fringe Landscape, and (c) Rural Landscape.

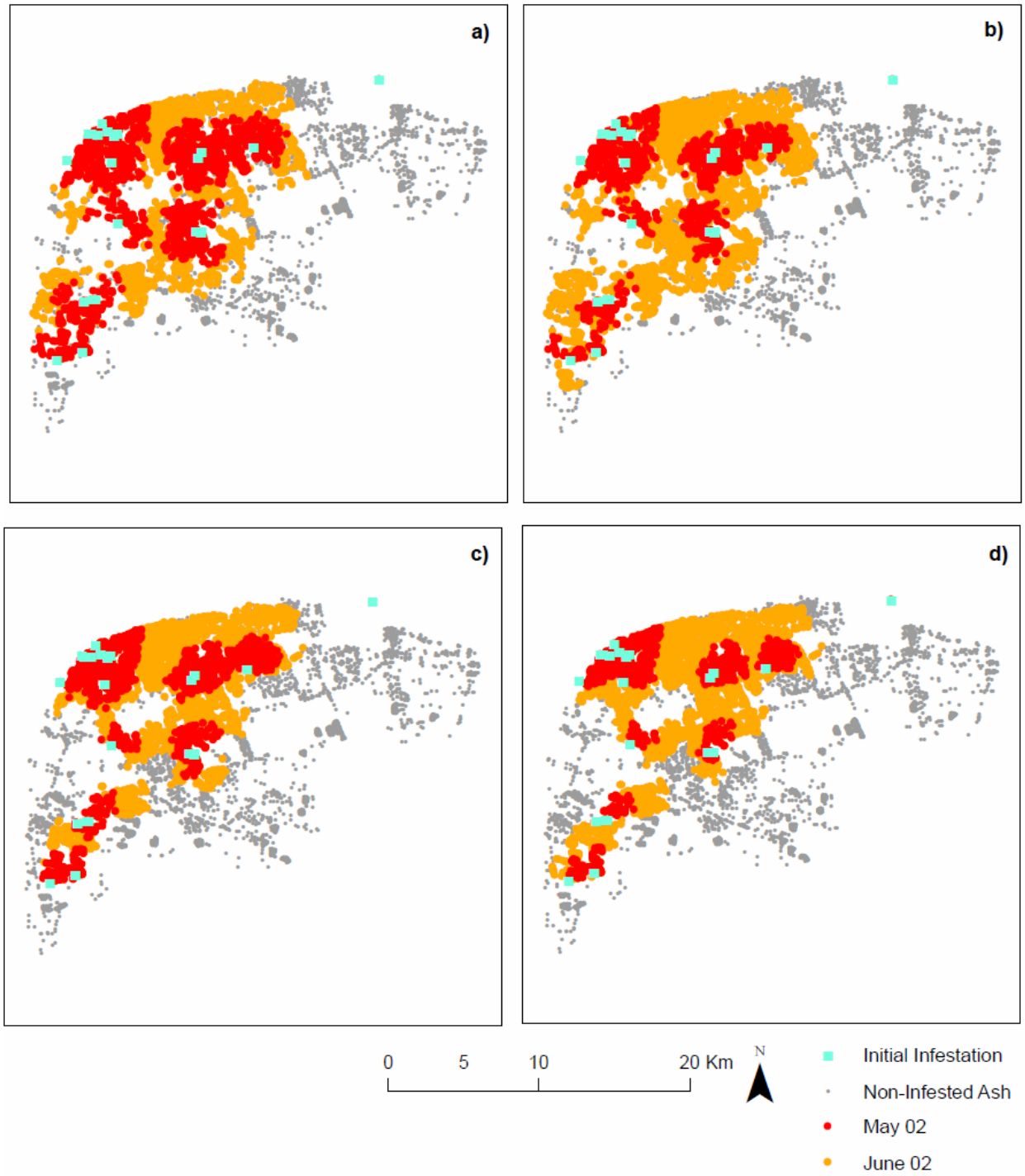

Figure 2.8. **Simulation results generated for May and June 2002 comparing spatial patterns of EAB spread for (a) Urban Landscape Scenario and its changes with (b) Wind (c) Temperature Scenarios and (d) Landscape, Wind, and Temperature.**

Wind constrains EAB spread in the *Urban-Rural Fringe Scenario*. There are less susceptible trees downwind from initially infested regions and as such, wind minimizes spread. In total, 2.7% of all ash become infested over a period of two years (Figure 2.7b), a decrease of 7% in ash infested. Similarly, wind acts as a constraint for the *Rural Landscape Scenario* with a total of 20.3% of all ash becoming infested over a period of two years (Figure 2.7c), decreasing the percentage of ash that become infested by 14%.

Consistent with the previous set of scenarios, the *Urban Landscape Scenario* experiences the highest percentage of total infestation, followed by the *Rural Landscape Scenario* and lastly the *Rural-Urban Fringe Scenario*.

Temperature

Essex County experienced warmer temperatures in the summer of 2003 than in 2002, and as such, rates of spread are higher in 2003. In our model framework, temperature constrains spread in colder months and accelerates spread in warmer months. The spatial pattern this produces is visible (Figure 2.8c) in comparison to simulation results that do not take temperature into account (Figure 2.8a). In particular, the *Rural Landscape Scenario,* demonstrates decreases in infestation in July 2002 and May 2003 reflecting the cooler temperatures characteristic to these specific months which in turn decreases the susceptibility of ash trees in the region and results in a decreased rate of infestation (Figure 2.7c).

Consistent with all scenarios, the *Urban Landscape Scenario* demonstrates the fastest rate of spread and the highest percentage of infestation. The *Urban Landscape Scenario* simulates infestation of a total of 70.5% of all ash in the landscape using temperatures from 2002 to 2003 (Figure 2.7a). The simulation results for the *Urban-Rural Fringe Scenario* indicates the lowest rate of propagation and the lowest percentage of infestation with a total of 3.3% of all ash becoming infested by 2003 (Figure 2.7b). Lastly, the *Rural Landscape Scenario* has a total of 40.7% of all ash in the landscape becoming infested in response to 2003 temperatures (Figure 2.7c).

Wind, Temperature, and Landscape

The combined effects of wind and temperature are presented for the *Urban Landscape Scenario* (Figure 2.7a & Figure 2.8d), the *Urban-Rural Fringe Scenario* (Figure 2.7b), and the *Rural Landscape Scenario* (Figure 2.7c). As noted in Section 4.2.2., wind either constrains or accelerates propagation in the landscape. This pattern remains consistent in the combination with temperature as a criterion, but also adds variation in response to monthly temperatures. The scenarios, using the combined wind and temperature criteria in the weighted MCE, generates more detailed spatial patterns of spread, where spread is constrained in colder months and enhanced in warmer months and in addition, captures the north-east direction of infestation propagation on a regional scale, consistent with real world EAB datasets.

Maintaining consistency with all other scenarios, the *Urban Landscape Scenario* demonstrates the fastest rate of spread and the highest percentage of infestation with a total of 73.3% of all ash become infested from 2002 to 2003. The simulation results for the *Urban-Rural Fringe Scenario* indicates the lowest rate of spread and the lowest percentage of infestation with a total of 3.8% of all ash becoming infested by 2003 (Figure 2.7b). Lastly, the *Rural Landscape Scenario* patterns of infestation has a total of 13.5% of all ash in the landscape becoming infested by 2003, taking both wind and temperature climate criteria into account.

2.6. Discussion

The model and chosen methodology indicate that patterns of ash tree infestation and rates of spread are influenced by the type of landscape and distribution of susceptible ash trees that the EAB propagates through. In addition, patterns of infestation and rates of spread are influenced by climatic factors such as wind and temperature. The simulation results for the *Urban Landscape Scenario* demonstrate that ash trees in this landscape are significantly more susceptible to EAB infestation than in any other landscape. This has been suggested, but not fully explained, in other studies (Kovacs et al., 2010; Huset, 2013; MacFarlane & Meyer 2005; Poland & McCullough, 2006). A closer look at the criteria contributing to generated susceptibility values included in this study indicate that this emergent behavior may be a function of several factors, one of which is the availability and distribution of ash as a resource to EAB populations in urban environments. Ash trees make up a high percentage of the City of Windsor's urban forest and are homogeneously distributed, easing any distance or resource based constraints which might

impact EAB propagation. In addition, transportation networks play an important role in the spread of insect infestation and although present in all landscape scenarios, are more prominent and frequented in urban settings. These patterns are visible in simulation outcome maps, where infestation clusters around transportation networks.

The urban environment experiences heat island effects, whereby temperatures in urban regions may be up to 8 to 10 degrees warmer than its surrounding rural counterpart (Davidson, 1988). These temperatures create a more suitable environment for the development of EAB larvae and adult emergence, but Cregg & Dix (2001) found a correlation between heat island effects and insect damage in ash tree species temperature driven evapotranspiration results in moisture stress, interfering with the tree's defence systems and increasing susceptibility to insect attack (Cregg & Dix, 2001; Mattson & Haack, 1987). In the developed model, temperature plays an important role in the rate of infestation. Most clearly seen in the urban environment, colder temperatures in May result in a decrease in EAB infestation, as emergence of new adult EAB is constrained. In warmer months the rate of infestation is increased and the percentage of the landscape infested in almost all landscapes in comparison to scenarios without the effects of temperature.

The land bordering Windsor, can be characterized by a mosaic of diverse land use types. As presented in the *Rural-Urban Fringe Scenario,* this region experiences the lowest susceptibility to EAB infestation. The contrast in land use types in the region creates a highly fragmented landscape that affects insect populations by both reducing available habitats for insect species (Burel et al., 2000) and constraining spread which is limited by dispersal ability to move throughout landscape patches (Tscharntke & Brandl, 2004). This emergent behavior in response to land cover is captured by the proposed spatio-temporal model. Additionally, the *Rural Landscape Scenario* experiences EAB propagation lesser than that of the *Urban Landscape Scenario*, but significantly greater than that of the *Urban Rural Fringe Scenario*. This may also be associated with a less fragmented landscape, far less agricultural land use, and better connectivity between forested regions.

The developed model allows for the conceptualization and representation of EAB infestation as a complex system, an approach not fully explored for this particular invasive species. The model represents the phenomenon from the bottom-up and collective behavior is generated by the CA as a response to the local and dynamic relationship between pest and ash

tree host. Non-linearity is represented in the re-calculation of tree susceptibility at every iteration in response to a changing climate, a changing environment, and the propagation of the infestation.

2.7. Conclusion

The geosimulation model composed of a GIS-MCE and CA approach based on complex systems theory provides an approach for simulating spatio-temporal dynamics of insect infestation. The obtained simulation results indicate that the developed model simulates local dynamics between ash tree host and pest and generates regional spatial patterns of EAB spread over a two-year period. The model demonstrates the urban forest is of the greatest risk to infestation and indicates that this may be a result of the distribution of ash trees, temperature, and regularly frequented transportation networks. The model can allow for the evaluation of landscapes at risk and the identification of low risk areas.

An additional limitation of the overall process is related to selecting the weighting of the criteria in the MCE which is subject to the expert opinion, however it is the choice of susceptibility functions and the thresholds from within the literature that allow for the generation of realistic EAB behavior, more so than the weighting as seen by the sensitivity analysis. Furthermore, the susceptibility functions represent membership to susceptibility as fuzzy, which helps to handle the uncertainty of the sparse tree inventory data that and allows for the calculation of the degree of ash tree susceptibility rather than just a binary representation of susceptibility e.g. the ash tree is susceptible vs. the ash tree is not susceptible.

The development of satellite populations and long distance dispersal of EAB cannot be represented using a CA approach due to the neighborhood which is used to apply the transition rules that simulate EAB infestation. This is a common problem where the CA approach is challenged in representing mobile objects (Torrens & Benenson, 2005). The study reveals that allowing for full mobility of EAB within the geospatial environment could aid in better representing long distance dispersal patterns of EAB infestation as a result of human-mediated transportation. Future work in modeling EAB infestation using complex systems approach, specifically the generation of an ABM, would not only facilitate improving EAB mobility within the geospatial environment, but also the simulation of EAB dynamics on a smaller scale with a focus on fine details such as carrying capacity, populations, and life cycles by representing the indiviudal. These models could be used to better understand how the individual and their adaptive behavior

influence patterns of infestation at a larger scale. Moreover, availability of additional datasets of infestations for model inputs would be beneficial for the spatio-temporal EAB model.

The development of a simulation model such as this typically undergoes the following processes: (1) verification, where the dynamics between the components of the system are represented in the model. In the MCE-CA model, this process is represented by determining the susceptibility of the ash trees to EAB infestation based on the literature; (2) calibration, where the model is adjusted to a reference system such as available datasets, literature, or another validated and robust model. The CA model's parameters that were adjusted during the calibration process include the susceptibility value where trees can transition from uninfested to infested (0.6), the size of the neighborhood, and the temporal resolution of the model in order to simulate the correct rate of spread in the study area; and (3) validation, where the agreement between another independent dataset and the model output is evaluated. In the case of the EAB in this particular study area, data for model validation is not available and as such the model is currently un-validated. However, the model is flexible with respect to its inputs and changes in parameters and as such, the acquisition of complete datasets makes model validation feasible. Three datasets which detail EAB infestation over a series of years would be required, in this case from 2002, 2003, and 2004, where the model could be calibrated to 2003 and validated to 2004. However, the proposed geosimualtion methodology is very useful providing the ability to calculate susceptibility of ash trees based on input data and simulates spatio-temporal dynamics of EAB infestation in response to those values, generating large scale patterns of infestation.

Although, the unavailability of tree inventory and infestation data for the region of south-western Ontario creates difficulty in model validation and the determination of the susceptibility of ash trees, this is a common occurrence when modeling complex phenomena such as insect infestation. The geosimulation model incorporating MCE, fuzzy set reasoning and CA can help to overcome some of these challenges in managing the uncertainty associated with data scarcity in determining the susceptibility to infestation and demonstrates the importance of complex systems methodologies. The integrated GIS-MCE and CA model can be useful even in the face of data scarcity and provide the potential to explore 'what-if' scenarios in application climate change, forest fire, and management scenarios and project future trajectories of infestation propagation at regional scale. They demonstrate the potential to use the developed model as a tool to assist decision makers in evaluating current and costly eradication strategies, fill in knowledge gaps with

respect to spatio-temporal dynamics of EAB spread, and assist in future city planning and forest management strategy formation.

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Chapter 3.

Geospatial modeling using an agent-based approach: representing emerald ash borer infestation*

3.1. Abstract

Agent-based modeling (ABM) is a mathematical conceptualization of complex systems that facilitates the representation of real-world, interacting entities referred to as “agents”. The ABM approach is recognized for its ability to capture the way individual dynamics between agents and their environment determines the behaviour of the system as a whole that is difficult to predict. ABM can be used to capture the complex spatio-temporal patterns in ecological processes such as insect infestation. The emerald ash borer (*Agrilus planipennis*; EAB) is an invasive species native to south-east Asia which has infested and killed millions of ash trees (*Fraxinus* sp.) across eastern United States as well as Ontario and Quebec in Canada. Efforts to understand and model the insect’s behavior are ongoing, however current models are limited to approaches that do not address the complexity emergent from dynamics and interactions between heterogeneous individuals and their varying spatial environments. The main objective of this study is to develop and implement an ABM of EAB behavior to capture complex emergent patterns of EAB spread over space and time in the Town of Oakville Ontario from 2008 to 2009. The results indicate that the developed ABM approach offers a model able to capture complex behavior of EAB and provides some insight to the underlying processes which govern EAB behavior, providing a useful tool for forest management and eradication strategies.

*A version of this chapter co-authored with S. Dragicevic will be submitted to Ecological Informatics

3.2. Introduction

The emerald ash borer (EAB), *Agrilus planipennis*, is an invasive wood-boring beetle species native to Asia that has been of increasing concern to the sustainability of North America's forested regions (Muirhead, 2006). Responsible for crown dieback, epicormic shoot growth, and subsequently the death of ash trees, non-native EAB were first identified in 2002 in Michigan, US. Shortly after, the pest was discovered in south-eastern Ontario, Canada (Tanis & McCullough, 2002). EAB targets green ash (*F. pennsylvannica*), black ash (*F. nigra*), white ash (*F. americana*) and blue ash (*F. quadrangulata*), which collectively make up a large portion of North American forests (Muirhead, 2006).

The abundance of the ash tree in North American forests poses severe ecological and economic threats to regions affected by the infestation. Ash tree species are an important ecological component in urban and rural forests (Poland & McCullough, 2006). The loss of the ash tree species threatens to alter forest composition and negatively impact ecosystem function (DeSantis et al., 2013). Not only are ash tree products a valuable export in North America, but ash tree removal, clean up, and replacement is expensive. The estimated economic impact is 2 billion dollars in Canada and over 300 billion dollars in the US (Oakville, 2011; Muirhead, 2006). As such, the spread of EAB infestation has motivated a research agenda to better understand EAB behavior and patterns of infestation which can help with EAB management, mitigation, and the prevention of future outbreaks.

Surveillance and monitoring to determine the presence and population levels of EAB is a difficult task as visible signs of infestation are minimal. Identification of EAB infestation in ash include the removal ash tree bark in order to visibly identify infestation, extensive surveys (Sargent et al., 2010; Anulewicz et al., 2007), and tracking of EAB (Knight et al., 2011; Tanis et al., 2012). These practices can be time consuming, expensive, and detrimental to the ash tree. Models provide a useful alternative and supplement to monitoring to help with forecasting infestation, population size, and patterns of tree mortality.

Early insect infestation modeling includes mathematical representations of important species such as the gypsy moth (Campbell, 1967), the winter moth (Varley & Gradwell, 1968), the spruce budworm (Morris, 1963), and the western pine beetle (Stark & Dahlsen, 1970). Methods used in these studies were accepted for use in forest management since they could quantitatively estimate pest damages to the forestry industry, but like all modeling approaches faced many challenges that ultimately resulted in failure to generate accurate predictions of pest population and trajectories (Liebhold, 1994). Two of the most significant challenges, which persist in more recent insect infestation modeling approaches, include lack of system level data available for top-down model parameters i.e. rates of spread, population densities, and enemy population densities, and the difficulty in capturing the complexity in the ecological interactions that generate patterns of spread (Liebhold, 1994).

Like many ecological systems, insect infestation can be described as complex, not because they are simply composed of a large number of interacting individuals, but because the properties and behavior of these individuals which determine the behavior of the system as a whole, vary from individual to individual, change over space and time, and adapt to maintain their individual needs without any knowledge of their population as a whole (Grimm & Railsback, 2005). These individuals are dependent on forest resources and in turn will modify their environment. Depending on their stage in lifecycle, individuals may modify their environment in different ways and all individuals in the system are subject to feedbacks and bifurcation events (Grimm & Railsback, 2005). All of these factors result in a system that demonstrates non-linear behavior, meaning that the systems properties are not just the sum of the properties of the individuals that the system is composed of (Batty & Torrens, 2005; Grimm & Railsback, 2005).

Grimm & Railsback (2005) coined a new term based on these ideas called individual based ecology (IBE). IBE is motivated by the idea that classical theory ecology, still very important in studying ecological systems today, usually ignores the concepts that individuals are heterogeneous and adaptive (Parunak, 1998). Aligned with the underlying fundamental properties of complex systems theory, individual based ecology employs bottom-up modeling approaches to provide a new perspective in understanding how interacting individuals and their unique properties and behavior give rise to the emergent,

non-linear, complex behavior that is difficult to predict using more conventional modeling approaches. For example, in contrast to the linear perspective that insect infestation population size is a result of birth and death rate, IBE considers that adaptation to maximize fitness and ensure survival and reproduction at an individual level may influence growth, reproduction, and death and thus population size (Grimm & Railsback, 2005).

Current modeling approaches to EAB infestation include both mathematical models and spatially-explicit methodologies. Equation-based models of EAB infestation have been developed in order to represent the diffusion rates of EAB spread using ordinary differential equations (ODE) (Barlow et al., 2014), logistic regression (Siegert et al., 2010), and probabilistic modeling (Marshall et al., 2011; Muirhead et al., 2006). In response to the demand for models that consider how dispersal and behavior are influenced by spatial patterns within the landscape, spatially explicit models which use equations to simulate EAB dispersal across a grid of cells was developed for DuPage County, Illinois (Bendor et al, 2006; Bendor & Metcalf, 2006). A geographic information system-based model representing EAB spread in response to theoretical heterogeneous and homogeneous landscape types was developed by Mercader et al. (2010). Additionally, Prasad et al. (2010) developed a hybrid model that is both equation-based and GIS-based to generate EAB infestation in Ohio, Illinois. These models predict patterns of infestation on a large scale based on EAB preferences, but do not represent the individual at all. More importantly, these models do not address concepts of complexity, heterogeneity, non-linearity, and the representation of small scale dynamics between pest and ash tree host.

In order to address this gap in EAB modeling literature, there is a clear need for the development of a modeling approach that can both address and represent the variability, complexity and non-linearity inherent to insect infestation processes through the explicit representation of pest-host dynamics across space and through time. Agent-based modeling (ABM) is a bottom-up modeling approach encouraged by proponents of individual based ecology. The approach is capable of representing real-world, interacting individuals referred to as “agents” (Castle & Crooks, 2006; Andrade, 2010). ABM is used in simulating spatio-temporal phenomena and seeks to demonstrate how the individual behavior between large numbers of agents and their environment within a well-defined

geographic setting will determine the behavior of the system as a whole (Li et al., 2008; Crooks et al., 2008). The motivation to develop ABM theory and methodologies in application to ecological phenomena is driven by the idea that representing discreteness, uniqueness, life cycles, and variability of individuals may reveal information that challenges or furthers theory developed using classical ecological models (Grimm, 1999).

The main objective of this study is to develop a geospatial ABM which uses the representation of the individual in order to capture the complex, spatio-temporal behavior of EAB spread emergent from pest-host dynamics at the microscale. The model aims to fill the gap in existing EAB insect infestation models by addressing the concern that conventional models which do not represent local interactions do not take into consideration non-linearity of the system. In the developed ABM, real-world EAB behavior is represented by autonomous interacting individual beetle agents over space and time. As such, the study uses geospatial datasets to represent the environment that the EAB interacts with and simulates EAB infestation in Oakville, Ontario, Canada, between 2008 and 2009. The proposed geospatial ABM can be used as a tool to generate easy-to-communicate “what-if” scenarios capable of assisting in planning, policy making, and forest management to forecast insect outbreaks.

3.3. Theoretical Background

3.3.1. Agent-Based Modeling and Insect Infestation

ABMs are composed of a number of heterogeneous interacting agents, software routines which are coded to live within their virtual environment and attempt to meet objectives, learn, and adapt their state and behavior in response to other agents and their environment (McLane et al., 2011). An agent’s behavior is programmed using methods of artificial intelligence to govern their decision making (Castle & Crooks, 2006). The virtual environment in which agents operate within can be composed of a geographical space represented with real-world geospatial data. The ABM methodology uses a bottom-up approach to understand how system level properties emerge from the interactions and adaptive behavior of individuals and how the spatial environment influences these individuals.

In the ecological modeling literature, ABM approaches were used in the past to represent complex ecological processes, where the individual makes up the basic unit of the system (Parunak, 1998; Wilson, 1998). Of the earliest ABMs developed were a forest model (Botkin et al, 1972) and a fish cohort growth model (DeAngelis, Cox, and Coutant, 1980), where research objectives could not be met using traditional approaches. The ABM approach has been used in modeling insect infestation propagation such as the mountain pine beetle (Perez & Dragicevic, 2010; Perez & Dragicevic, 2011; Bone et al., 2014), mosquito populations (de Almeida et al., 2010), the potato moth (Rebaudo et al., 2010), the forest tent caterpillar (Babin-Fenske & Anand, 2011), the spruce budworm (Sturvant et al., 2013), and dragonflies (Kaiser, 1979).

Kaiser (1979)'s work was paradigmatic in identifying the usefulness of the ABM approach in contrast to classical modeling approaches unable to represent the individual differences and local interactions (Grimm & Railsback, 2005; Wilson, 1998). It has been argued that in many domains, ABMs give more realistic results than equation-based models (Parunak, 1998). Although Partial Differential Equations (PDE) are capable of representing complex behavior like the ABM approach, the PDE models are too rigid and complicated to be manipulated for "what-if" scenarios (Parunak, 1998). ABM representations of ecological systems are easily manipulated for the direct experimentation to aid in exploring potential changes in the state of systems and management scenarios (Perez & Dragicevic, 2012).

3.3.2. Artificial Intelligence and Decision Theory

Of particular importance to this study is artificial intelligence (AI), an integral part to ABM functionality. AI is defined as a science emerging from research on developing systematic methods for autonomous computer problem solving and decision making (Horvitz et al., 1988).AI techniques have been used in application to ecological models, specifically agent-based models, in order to simulate the behavior and decision making of individuals (Saarenmaa et al., 1988; Folse et al., 1989).

AI methods provide possibilities for automated reasoning and decision making under uncertainty by agents within computer simulations. Common AI decision making

methods in an uncertain environment include preferences and utility theory (Fishburn, 1964), probabilistic Bayesian networks (Cooper, 1990), Markov decision processes (Poole, 1997), reinforcement learning (Frank & Claus, 2006), and in multi-agent decision making, game theory (Simon, 1959). Of particular value to the developed model in this study is the integration of AI and preferences and utility theory.

Preferences are essential for decision making of autonomous agents (Goldsmith & Junker, 2008; Walsh, 2007). The technique uses decision theory, an extension of probability theory that allows for decision making in an uncertain environment where agents may have incomplete information (Horvitz et al., 1988). Decision theory ranks agent preferences, specifically how objects, states, or characteristics are valued over one another, guiding decisions. This preference ordering can be used in the case of individuals with consistent preferences where preferences can either be strict $one > other$ where one is strictly preferred to the other, not strict $one \succcurlyeq other$ where one is mostly preferred to the other, or be indifferent $one \equiv other$ where one is indifferent to the other. The theory also involves a notion of a "lottery", where in an uncertain environment there is more than one possible decision and the final choice may be somewhat random (Debreu, 1954).

3.3.3. EAB Characteristics

EAB Biology and Life Cycle

In order to represent the behavior of the EAB using an ABM, it is important to understand the biological characteristics of EAB with respect to its lifecycle. The EAB life cycle takes place over the span of one year and consists of four stages: (1) active larvae, (2) inactive larvae, (3) pupae, and (4) adulthood. Following emergence from their ash tree hosts in the months of late May through to August, with peak emergence in June, EAB feed on ash tree leaves for about seven days to build up strength before mating. During feeding, female EAB beetles communicate with male EAB beetles through conspecific attraction, where female EAB release the compound macrocyclic lactone that attracts male EAB as mates (Bartelt, 2007). Once mated, female EAB will search for a suitable host and at maturation, will begin to oviposit eggs. Female EAB will deposit their eggs on the surface of the ash tree, either in its crevices or cracks or just under the outer bark of the tree. Female EAB deposit on average 60-90 eggs within their lifetime, either

individually or in groups (Jennings et al., 2014). Male EAB live on average for 13 days and female EAB life on average for 22-25. Eggs hatch in approximately one week into active larvae, the longest stage of the EAB lifecycle. Active larvae bore into the ash and feed on the ash phloem for twenty weeks from mid-June to October, causing a slow death to the tree (Wang et al., 2010). In late October, active larvae cease feeding and bore into the outer sapwood of the tree in preparation for overwintering. The larvae become inactive for roughly twenty weeks during the winter months. During this time, inactive larvae are highly susceptible to predation and environmental factors. The inactive larvae pupate in spring and begin to take the form of an adult beetle.

EAB Host Selection

EAB spread is governed by resource availability. EAB are not perfect foragers in that they do not choose the most suitable host every time, but their choice of host is also not entirely random. Instead the choice of host is driven by EAB preferences which make some host trees more attractive than others. Female EAB preferences include following: (1) EAB females prefer to lay their eggs on stressed trees (McCullough et al., 2009), although once EAB population densities build, healthy trees will also be attacked and killed; (2) EAB females prefer to lay their eggs in areas with a higher proportion of ash trees in the stand (Mercader et al., 2011) as adult beetles feed on ash tree leaves; (3) recent studies reveal that EAB preferences for infestation is heavily influenced by interspecific variation among ash tree types. Black ash trees are typically initial targets, green ash and white ash are equally preferred, and all other types are preferred over blue ash (Anulewicz, 2007) and (4) the total number of larvae and the size of the diameter at breast height (DBH) of the tree are correlated (Wang et al., 2009) where female EAB prefer to oviposit on trees larger in size. Therefore, trees of larger size that produce more phloem to sustain EAB galleries have a higher probability of becoming infested (Mercader et al., 2011). Factors that constrain the movement in female EAB include the following: (1) EAB are constrained by tree size in that the ash tree must have a DBH of 5 cm, typical of a tree aged 10 years or more (BenDor et al., 2006) and (2) EAB are constrained by population density, a main driver of EAB spread. The maximum density of EAB adults per tree is approximately $4/m^2$ (BenDor et al., 2006). The maximum density of larvae per tree is approximately $300/m^2$ (BenDor et al., 2006). In general, as carrying capacity decreases, population density increases, and EAB emigration increases.

EAB Dispersal

The EAB spreads through both short-distance and long distance dispersal. Rates of spread for short distance dispersal vary within the literature with recorded rates ranging from 10.6 km per year (Smitley et al., 2008), to 6.5 km per year (Siegert et al., 2008), to 1.37 km per year (Sargent et al., 2010). The disparities between these rates are influenced by the spatial arrangement of the host (Smitley et al., 2008). Regions of homogeneous and ash abundant stands will facilitate colonization and spread much faster than heterogeneous and ash sparse stands. A study by Taylor et al. (2007) found that EAB adults can fly up to the equivalent of 2.8 km/day at speeds greater than 1.5 m/second independent of their environment.

EAB long-distance spread is facilitated by human transportation systems, dispersing EAB to distances farther than they could travel naturally (Muirhead et al., 2006). Long-distance dispersants provide opportunities for new EAB populations to develop ahead of the main invasion front, increasing the rate of infestation. EAB larvae or adults residing within firewood, raw logs, or nursery stock are transported via road vehicles or by air transport. Risk of long distance EAB spread increases in geographic regions characterized by heavily frequented transportation networks, the presence of wood product industries, greater population density, and the presence of campgrounds (Prasad et al., 2010), although instances of long distance spread is diminishing due to increased regulation and public awareness.

3.4. Methods

The geospatial ABM of EAB is described in the following sections using the most relevant components of the Overview, Design concepts, Details (ODD) protocol developed by Grimm et al. (2006; 2010), specifically used for the scientific communication of agent-based models. The model is written in the object-oriented programming language, Java, using Repast Simphony (2014) 2.2., a free and open source Recursive Porous Agent Simulation Toolkit (Repast). Repast Simphony provides a mechanism for modeling complex adaptive systems through the development of ABMs and has a large and growing

community developing a wide range of applications form social, evolutionary, industrial, and ecological simulations (North et al., 2013).

3.4.1. Model Overview and Purpose

The proposed geospatial model is an ABM, composed of a number of autonomous agents interacting among themselves and with their environment. The purpose of the model is to explore how spatial, biological, and temporal characteristics unique to both the ash tree host and the EAB insect as individuals generate emergent patterns of insect infestation which are observed in reality. EAB behavior is programmed based on knowledge collected from the literature and the beetle agents are integrated into the model to interact within a real geospatial environment representing the Town of Oakville, Ontario, Canada. An ABM which can successfully represent EAB behavior in a local spatial context is useful for the generation of “what-if” scenarios, the projection of future infestation trajectories, the application of the model to non-infested communities, and the improvement of forest management and eradication strategies.

3.4.2. Study Area and Data Sets

Urban environments are the most susceptible to EAB infestation, causing extensive economic, social, and ecological damages (Kovacs et al., 2010; Huset, 2013; MacFarlane & Meyer 2005; Poland & McCullough, 2006). The ABM uses the Town of Oakville, Ontario, Canada (43.4500° N, 79.6833° W) as the study site to represent EAB infestation from May 2008 to the end of August 2009 (Figure 3.1).

The Town of Oakville’s urban forest canopy cover averages 29.1% and is composed of 1.9 million trees (Town of Oakville, 2006). The distribution of trees across the landscape is highly influenced by land use type with a low of 6.6% of forest canopy cover in commercial areas and 90.3% forest canopy cover in woodlots (Town of Oakville, 2006). Ash trees make up an approximate 9.6% of Oakville’s urban forest canopy (Town of Oakville, 2006). The epicenter of EAB infestation was first discovered at the North Iroquois Ridge Community in late July, 2008 at 43° 29' 19.0314" N, 79° 42' 2.7678" W (BioForest Technologies Incorporated, 2011).

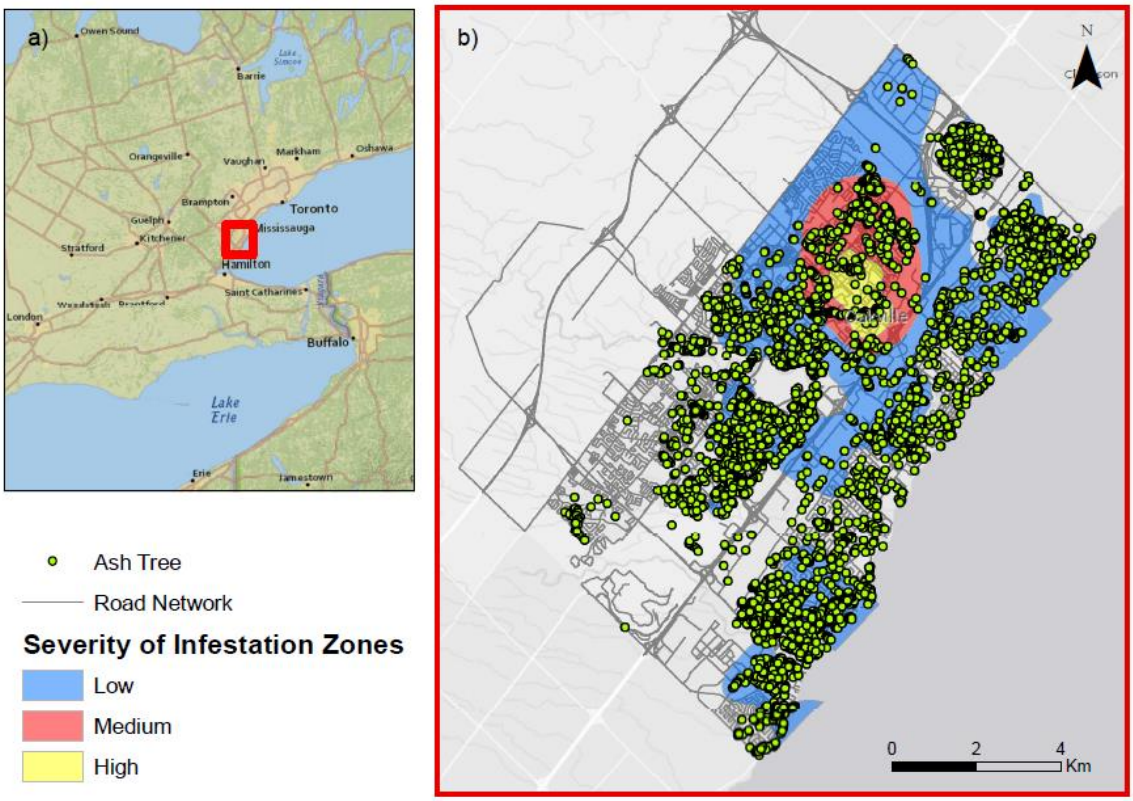

Figure 3.1. Study area, Oakville, located in South Western Ontario (a). A detailed map of the study area that depicts the distribution of all ash trees included in the simulation of EAB infestation (b). The map also depicts the delimitation zones of EAB infestation in 2009 (b) by levels of severity observed in The Town of Oakville obtained from the Oakville's GIS department.

The Town of Oakville has engaged in extensive efforts in EAB tracking, analysis, management, and eradication. As such, the region has acquired and developed data with respect to EAB infestation facilitating model creation, calibration, and validation. The geospatial data used in this study include the following:

(1) GIS data layers containing the tree inventory for the Town of Oakville containing the location and attribute data for all tree species including tree type, tree height, tree diameter at breast height, and crown width. A subset of the tree inventory dataset was extracted containing only the ash tree species of which 35.38 % is white ash (*Fraxinus americana*), 0.23% is black ash (*Fraxinus nigra*), 0.04% is blue ash (*Fraxinus*

quadrangulata), 61.13% is green ash (*Fraxinus pensylvanica)*, and 0.03% is pumpkin ash (*Fraxinus profunda)*. The remaining 4% is of the mountain ash variety (*Sorbus acauparia)*, which are not true ash and as such are not susceptible to EAB infestation and have been removed from the dataset.

(2) GIS vector data layers for the Town of Oakville containing (a) the location of campgrounds extracted from a land use dataset and (b) the city street network.

(3) GIS datasets representing the delimitation of actual EAB infestation by levels of severity which were observed in the Town of Oakville in 2009 (Figure 3.1). The delimitation dataset shows the levels of severity where the calculated standard deviation of EAB density per tree is defined as *high* EAB infestation if the values are ≥1.5 to 2.5, as *medium* infestation if from 0.5 to1.5 and as *low* infestation if ≤- 0.5 to 0.5.

3.4.3. Agents and State Variables

The model structure is composed of (1) beetle agents and (2) tree agents, each located in space with latitudinal and longitudinal coordinates. Beetle agent dynamics include beetle-beetle interactions and beetle-ash tree interactions with healthy trees and infested trees. Beetle agents are programmed to behave as real EAB by incorporating information on EAB biological variation, dispersal, host selection, and lifecycle found within the literature. The ABM only represents female EAB for two reasons: (1) female EAB are the sole agent in infestation patterns and processes (2) although male EAB are involved in EAB reproduction, female EAB attract male EAB to their location for mating. Thus, male beetles do not have any influence on the location of the female EAB and do not need to be represented. Tree agents derive their location and variation from geospatial tree inventory datasets. The description of agent classes, their sub-classes and their associated variables in the model are described in Table 3.1.

Table 3.1. Agent class descriptions and associated variables.

AGENTS (SUPER CLASS)	DESCRIPTION	SUB-CLASSES	VARIABLES
BEETLE AGENT	Each beetle agent represents a single female adult EAB beetle insect.	Adulthood is the only stage during the lifecycle where beetle interactions take place outside of the tree, therefore there are no subclasses.	Location ID Fertile or not fertile status Maximum number of offspring that can be produced Total offspring that have been produced Age
TREE AGENT	Each tree agent represents a single ash tree within the geospatial environment.	General Tree Agent: The General Tree Agent is used as the basis for all interactions with each beetle agent. All calculations occur at the General Tree Agent level. This is because, once the tree is infested, infestation may continue.	The variables which make up the tree determine the susceptibility of the tree to EAB infestation. Tree susceptibility is determined by tree size, age, carrying capacity, distance from beetle emergence, and tree type. Location ID Type Diameter at breast height Height Surface Area Adult carrying capacity Larval carrying capacity Number of adult EAB individuals Number of larvae individuals Infested or not infested status
		Infested Tree Agent: The Infested Tree agent is used for visualization and quantification of infestation.	Location ID Age

3.4.4. Process Overview and Scheduling

The ABM represents EAB behavior through the succession of a number of sub-models, integrated to represent both EAB processes and ash tree processes over time. The developed EAB ABM simulation represents EAB infestation for two seasons, from May 2008 when the EAB was first thought to have infested the region, to August 2009.

The execution of each sub-model is determined by the EAB lifecycle, meaning a beetle agent's age acts as a signal for a specific sub-model to begin running. The female EAB lifecycle is short, surviving an average of 25 days. Since female adulthood is the stage where emergent patterns of infestation are generated, every iteration of the model represents one day for a total of twenty-five iterations per season. Winter season occurs in one iteration, as EAB are not in active form. EAB undergo all sub-model processes each season simultaneously.

The beetle and ash tree temporal resolution processes are described in Figure 3.2 and the conceptual overview of the processes which determines beetle agent behavior can be seen in Figure 3.3. At the beginning of the season (T_0), adult female beetle agents emerge, disperse locally in search of food, become fertile once they reach maturity (T_7), and infest ash trees (T_{10}). The decision on which host to infest is based on EAB preferences for host selection identified within the literature and defined in the simulation using decision theory preference ordering (Horvitz et al., 1988). It is important to note that EAB will not always make the perfect choice of host (Mercader et al., 2010), and thus their choice of host also incorporates an element of randomness or lottery. Once adult EAB reach the appropriate age (T_{25}), they die, and in the next season, their offspring emerge from the trees (T_{27}), starting the processes from the beginning. EAB long distance dispersal occurs randomly, where satellite populations may develop along major transportation networks or near campgrounds in the south-west region of Oakville, as these trees are most susceptible to long distance dispersal patterns of infestation.

The ash tree agent life cycle is influenced by EAB interactions where ash trees move from a healthy ash stage to an infested ash stage. Because the simulation takes place with a temporal resolution of under two years, ash tree death does not occur in this ABM model.

Each completed simulation, where the model is executed from its initial state in May 2008 (T_1) and finishes in August 2000 (T_{52}), is referred to as a run. Due to randomness in the model, the model has been executed from T_1 to T_{52} 50 times. All 50 simulation outcomes are overlaid to determine the convergence of the overall simulation results and to derive statistical measures such as average number of larvae and average

number of times the tree was infested. The model produces a set of simulation outcomes that can be plotted as maps of the ash trees and the EAB beetle individuals. The simulation output map contains information related to which trees are infested, the severity of infestation, how many larvae are feeding off the tree, and the location of the EAB beetles at that particular time step. The spatial output of particular value is the state of the urban forest at the end of a season at T_{52}, when all beetles have completed their reproductive stage and are about to complete their lifecycle. This dataset provides a good indication of EAB density, not only indicated by the location of the EAB themselves, but also by the number of larvae in the trees. The more larvae, the more times the EAB female adults have visited the tree.

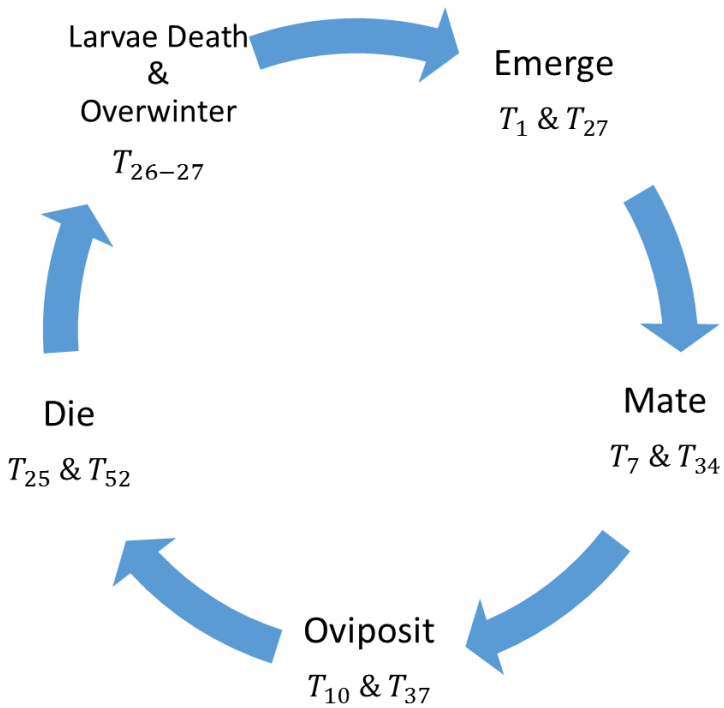

Figure 3.2. Temporal resolution of the model describing the iterations at which each stage in the lifecycle is executed. Each iteration in the model is equal to one day within a beetle agent's lifecycle.

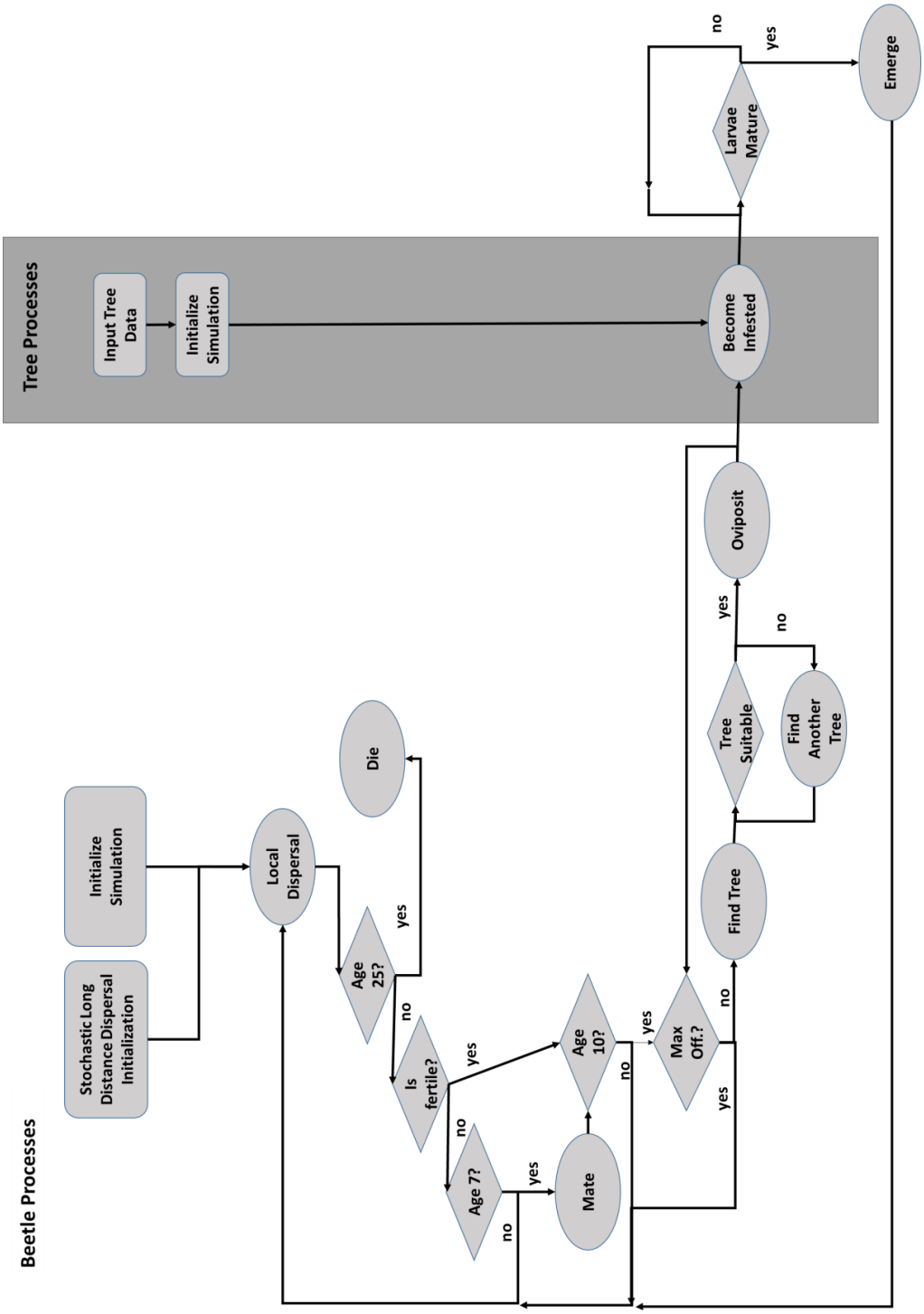

Figure 3.3. **Conceptual diagram of the developed EAB-ABM. Inputs and initial states are represented by squares; determinants to execute sub-models are represented by diamonds, and sub-models are represented by circles.**

3.4.5. Design Concepts

ODD protocol requires the explicit demonstration of the developed ABM design concepts. The concepts of emergence, adaptation, fitness, sensing, interactions, stochasticity, and observation are considered in the developed model as follows:

Emergence: From the local interactions between the individual beetle agents and its ash tree host, the ABM generates emergent spatial patterns of infestation, beetle densities, and larval densities;

Adaptation: Beetle agents adapt their host selection behavior in response to their local spatial and temporal states i.e. larval density;

Fitness: Each beetle agent is explicitly fitness-seeking. Their main objective is to find the best host for egg oviposition. The fitness of the EAB depends on how effectively it makes choices in an uncertain and varying environment;

Sensing: Every beetle agent can sense its immediate environment composed of a number of ash tree hosts with varying characteristics. The decision on which host to infest is a function of the beetle agents state and their knowledge of their surroundings. This information is supplied by the beetle agent's neighborhood;

Interactions: The main interactions take place between beetles and ash trees where beetle agents feed from the ash trees, infest ash trees, and ash trees sustain larvae until emergence.

Randomness: The random behavior of beetle agent is introduced by some stochastic elements, however the randomness lies between real thresholds identified within the literature, addressed in detail in section 3.7 in the description of the geospatial ABM sub-models. In order to adequately capture this behavior, stochastic elements are introduced as follows: (1) defining initial agent state variables (Table 3.1) such as the maximum number of offspring that the beetle agents will produce during its lifetime; (2) in the host selection algorithm where choice of which ash tree to infest is made; (3) the maximum distance a beetle may travel each iteration; (4) the instance and location for the

development of satellite populations which develop ahead of the main invasion front as a result of long distance dispersal. The development of satellite populations are more likely to occur along road networks where insect hitchhiking may occur or near camping zones where firewood may be transported into the environment; (5) the number of eggs oviposit on each tree during the female beetles reproductive stage; and (6) the number of larvae which die over the winter;

*Observatio*n: At each time step of the model, data is collected on number of agents, number of larvae, number of trees infested, and number of dead trees to allow for the validation of the model outputs.

3.4.6. Initialization

The model is initialized for the time T_0 in May 2008 where a random number of EAB adults emerge from an infested stand containing four ash trees located at the epicenter of EAB infestation in the Town of Oakville. Although the number of beetle agents is random with each initialization, it falls within a maximum threshold proportional to the DBH of the ash tree based on the ash trees carrying capacity. This value is reduced by 50% to only represent female EAB. For example, on average, 40 adult EAB may emerge from one tree. The urban forest stand used for the initial location of infestation is scheduled to begin at the same location for every run; however number of beetles and the state variables of the beetle agents such as the number of offspring they are capable of reproducing varies randomly with each simulation. There are 6128 ash tree agents in the simulation.

3.4.7. Sub-Models

Beetle Processes

Aging - The aging sub-model tracks the age of the adult beetle in days following emergence. Age increases by one with every iteration and is expressed as:

$$na_{T_{n+1}} = T_n + 1 \qquad (3\text{-}1)$$

where age na at the next iteration T_{n+1} is the iteration number T_n increased by one.

Long-Distance Dispersal – Taylor et al. (2004) indicates that long distance dispersal occurs in 1% of the EAB population. Mechanisms of long distance dispersal include insect hitchhiking and human-assisted movement of larvae in infested firewood or wood products. Long distance is implemented by measuring susceptibility to long distance infestation based on their distance from highways and campgrounds where trees closer to both highways and campgrounds are more susceptible. There is a 30% chance of successful establishment of new satellite colonies due these mechanisms facilitating long distance dispersal, determined through sensitivity testing. A random number generator returns a number from 1-100. If the value is between 1 and 30, the satellite colony will become successfully established.

Short-Distance Dispersal – Short distance dispersal takes place at every time step as EAB change in location l to search for food or to find a host for larval galleries. EAB dispersal rates recorded in the literature vary as they are subject to landscape homogeneity and host availability. Beetle agents in the ABM are thus programmed with flight capabilities independent of their environment with a daily flight radius of 2.8 km per day based on Taylor et al. (2008). Once placed in their geospatial environment which is characterized by varying spatial arrangements of host trees, the rate of infestation will be influenced by their surrounding landscape and the resources available to each individual beetle agent. Trees nearest to the beetle agent have a higher probability of becoming infested first. The model contains a host selection algorithm which retrieves the trees within the daily flight distance and evaluates the tree as a host based on beetle agent preferences. Trees which are strictly not suitable will not be chosen as a host. Trees which have characteristics preferable to EAB infestation will have a greater probability of being chosen as a host. Ash trees are compared, and once chosen, the beetle agent disperses to the chosen host tree. The host selection algorithm is only used for choosing a host for offspring. Beetle agents may disperse to any tree within their daily flight radius to feed. Short distance dispersal can be expressed as:

$$N_{lb} = \pi 2.8^2 \qquad (3\text{-}2)$$

$$at = l_a \in N_{lb} \qquad (3\text{-}3)$$

where the search neighborhood *N* of the beetle *b* at location *l* is a circular area with a radius of 2.8 km. The ash tree is a potential target (*at*) if the ash tree *a* with the location *l* is within the neighborhood of the beetle.

The host selection algorithm was expressed using preference ordering theory, a part of decision theory, where ash trees within the neighborhood are selected on based on the individual's preference for location, stress, size, and type.

$$d_{bi}^{at} < d_{bi}^{tn} \succcurlyeq d_{bi}^{at} > d_{bi}^{tn} \tag{3-4}$$

$$st_{at} > st_n \succcurlyeq st_{at} < st_n \tag{3-5}$$

$$si_{at} > si_n \succcurlyeq si_{at} < si_n \tag{3-6}$$

$$ty_1 \succcurlyeq ty_2 \equiv ty_3 \succcurlyeq ty_n \succcurlyeq ty_5 \tag{3-7}$$

$$ty \succcurlyeq si \succcurlyeq \mathrm{d} \succcurlyeq \mathrm{st} \tag{3-8}$$

Equation 3-4 describes the preference ordering for location where the distance between beetle *b* and the target ash *at* is smaller than the distance between beetle b and another ash *tn*. In other words, if the target ash is closer, it is more preferred. Equation 3-5 describes the preference of ordering for stress where the stress of the target ash is greater than the stress of another ash, is more preferred. Stress occurs when an ash tree is under attack or dying. The dying tree releases a chemical signal that subsequently attracts more EAB individuals to deposit their eggs (McCullough et al., 2009). Equation 3-6 describes the preference of ordering for size where the size of the target ash is greater than the size of another ash is more preferred. Equation 3-7 describes the preference of ash of type 1: black ash to be preferred over type 2: white ash. Type 2: white ash and type 3: green ash are equally preferred, and all types of ash are preferred over type 5: blue ash. Lastly, equation 3-8 describes the relation between these four preferences in that the type of tree is preferred over the size, size is preferred over distance, and distance is preferred over stress. This was determined using sensitivity analysis.

Mate – After one week of feeding and maturation at T_7, the female beetle agent becomes fertile, due to mating with their male counterparts. This is not explicitly represented as mating does not change the location of the female. Female EAB produce on average up to 100 offspring in their lifetime and as such female beetle agents are randomly assigned a maximum number of offspring between 60 and 100. The mating sub-model can be expressed as:

$$ot_b = random(60,100) \qquad (3\text{-}9)$$

where the offspring total (*ot*) of beetle *b* is a random value between 60 and 100 (Bendor et al., 2006).

Oviposit - At T_{10}, once the mating process has taken place and the female beetle agent has reached maturation, the "infest" sub-model is scheduled, signaling the female beetle agent to decide on a tree suitable for infestation. Female beetles find a host using the host selection algorithm, move to its location and oviposit a random number of eggs on the tree. Eggs may be laid individually or in groups. If the maximum number of offspring have not been produced, the female beetle agent will choose another suitable host at the next iteration, and the process continues until her maximum number of offspring have been produced. The oviposit sub-model can be expressed as:

$$op_{Tn+1} = random(0, ot_b - op_{Tn}) \qquad (3\text{-}10)$$

where the offspring produced (*op*) at the next iteration (Tn_{+1}) is a random value between 0 and the offspring total (ot_b) minus the number of offspring that have already been produced (op_{Tn}).

Die - Female beetle agents die at age 25 days. This sub-model can be expressed as:

$$nb_{T25} = 0 \qquad (3\text{-}11)$$

where the number of beetles *nb* at iteration 25 is 0.

Emerge - Over the winter, a random percentage of larvae per tree die as a result of carrying capacity and predation. Following BenDor et al. (2006)'s assumption, larval death

increases as carrying capacity decreases, however, EAB larval death has not been studied in depth. Following the winter months and subsequent death of the larvae due to environment and predation, the remaining larvae develop into female beetle agents, which make up on average 50 percent of the total remaining larval population, and emerge from the infested ash trees (Lyons, 2011). The process can be expressed as:

$$nl_{ai_{T26}} = nl_{ai_{T25}} - (nl_{ai_{T25}} * \frac{1}{si_{ai}}) \qquad (3\text{-}12)$$

$$nb_{T28} = \sum nl_{ai_{T26}} * 0.5 \qquad (3\text{-}13)$$

where in equation 3-12 the number of larvae (nl) in tree ai at T_{26} is equal to the number of larvae in tree ai at T_{25} minus the number of larvae at T_{25} multiplied by 1 over the size of tree ai. This equation makes the death rate of the EAB larvae proportional to the tree size, where larger trees with greater carrying capacity will have less larval death over the winter (BenDor et al., 2006).

Equation 3-13 states that the number of beetles (nb) at T_{28} is equal to sum of the number of larvae of each tree reduced by 50% to represent the female population only (Lyons, 2011).

Tree Processes

Become Infested – Ash trees become infested once an adult beetle agent has chosen it as a host and laid their eggs on the tree to become larvae. The process of an ash tree becoming infested can be expressed by:

$$nl_{ai>1} \rightarrow ainf \qquad (3\text{-}14)$$

where an ash tree is infested $ainf$ if the number of larvae of a particular tree ai is greater than 1.

3.4.8. Model Calibration

Model parameters that were adjusted during internal calibration to determine the initial state of the model include the following: (1) larval death rates or the percentage of larvae that survive during the winter, a threshold that is not determined within the literature; (2) the number of long distance dispersal instances; and (3) preference ordering of criteria which determine the probability of an ash tree for infestation.

Sensitivity analysis was conducted to determine the influence of changes in these parameters. Sensitivity analysis was performed for calibration of parameters 1 and 2 by testing the use of different values and finding the value that produced behavior closest to the real world observation data of EAB propagation. The calibrations of these parameters were guided by the literature. For example, Taylor et al. (2004) determined that only 1% of EAB population will be transported by mechanisms of long distance dispersal. Sensitivity analysis determined it was not realistic for this to occur every season in the ABM simulation as satellite colony developments experienced far too severe levels of infestation in comparison to observation. Reasons explaining this may be that the conditions under which a satellite population will survive to become successfully established are circumstantial. If the long distance dispersal is a product of moving infested firewood, the likelihood that a population will become established is dependent on the survival of the larvae within the firewood. If the long distance dispersal is a mechanism of beetle hitchhiking, the beetle must survive, be of female gender, and must have mated in order to lay their eggs in the new environment. As such, each year of the simulation, a number between 1 and 100 is generated randomly. It was decided through sensitivity testing, that if the number is between 1 and 30, the satellite population will become established successfully. Otherwise, the satellite population will not become established.

Preference ordering was tested by rearranging the order of EAB preferences for trees of a specific location, stress, size, and type. Preferences allow the beetle to compare between trees within their environment. A list of trees is generated specific to the individual, where trees are ordered from the most preferred tree to the least preferred tree at each time step. The beetle randomly chooses from the top 10 most preferred trees. The order of preferences is difficult to determine since the list of trees can be dramatically

different with each combination of preferences. The correct combination was determined by evaluating the behavior of the beetle agents with each combination. For example, if tree stress is given a higher preference, beetles will tend to attack trees which are only already infested, and the infestation propagation does not take place. An additional example of the importance of the combination of preferences can be found when distance is given less of a priority. If tree stress is prioritized over tree distance, the patterns resulting from the idea that trees nearest to the EAB beetle have a higher probability of becoming infested first (Smitley et al., 2008; Huset, 2013) become much less prevalent.

3.5. GIS-ABM Results

Figure 3.4 presents one full model run representing the propagation of EAB infestation through the Town of Oakville, Ontario from 2008 to 2009 at T_{10} (Figure 3.4a), T_{25} (Figure 3.4b), T_{37} (Figure 3.4c), and T_{52} (Figure 3.4d). Each iteration T_n represents one day of the EAB lifecycle in reality.

Due to the stochastic elements integrated into the simulation, each run generated slightly different patterns of infestation. Figure 3.5a is a map representing average EAB infestation obtained from the combined 50 model runs. The combined results were classified into *low, medium, and high* levels of infestation, as previously defined where ≥1.5 to 2.5 of the standard deviation of EAB density per tree is defined as high EAB infestation, 0.5 to1.5 of the standard deviation of EAB density per tree is defined as medium infestation, and≤ −0.5 to 0.5 of the standard deviation of EAB density per tree is defined as low infestation. The real-world observation data with reference to the delimitation of infestation is also classified into low, medium and high levels of infestation using the same metric in the Town of Oakville in 2009 and has been presented in Figure 3.5b.

The capability of the EAB ABM in representing realistic EAB behavior and propagation was determined by examining simulation outputs representing infestation in 2009 in comparison to real world observation data representing spatial and temporal patterns of infestation for the Town of Oakville in 2009. Validation included the following measures where the simulation results were compared to Oakville's datasets with respect

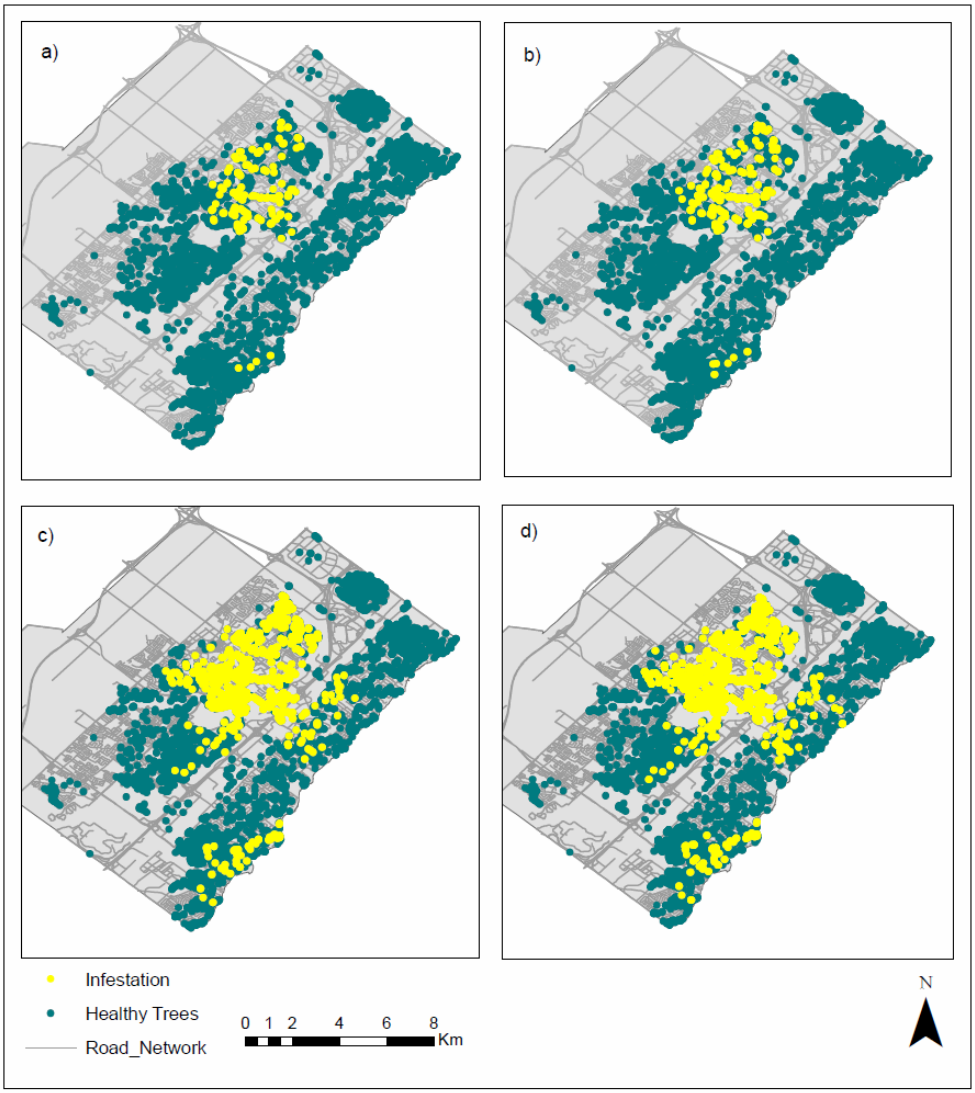

Figure 3.4. **Maps depicting EAB propagation across the Oakville for one full model run from 2008 to 2009 at T_{10} (a), T_{25} (b), T_{37} (c), and T_{52} (d).**

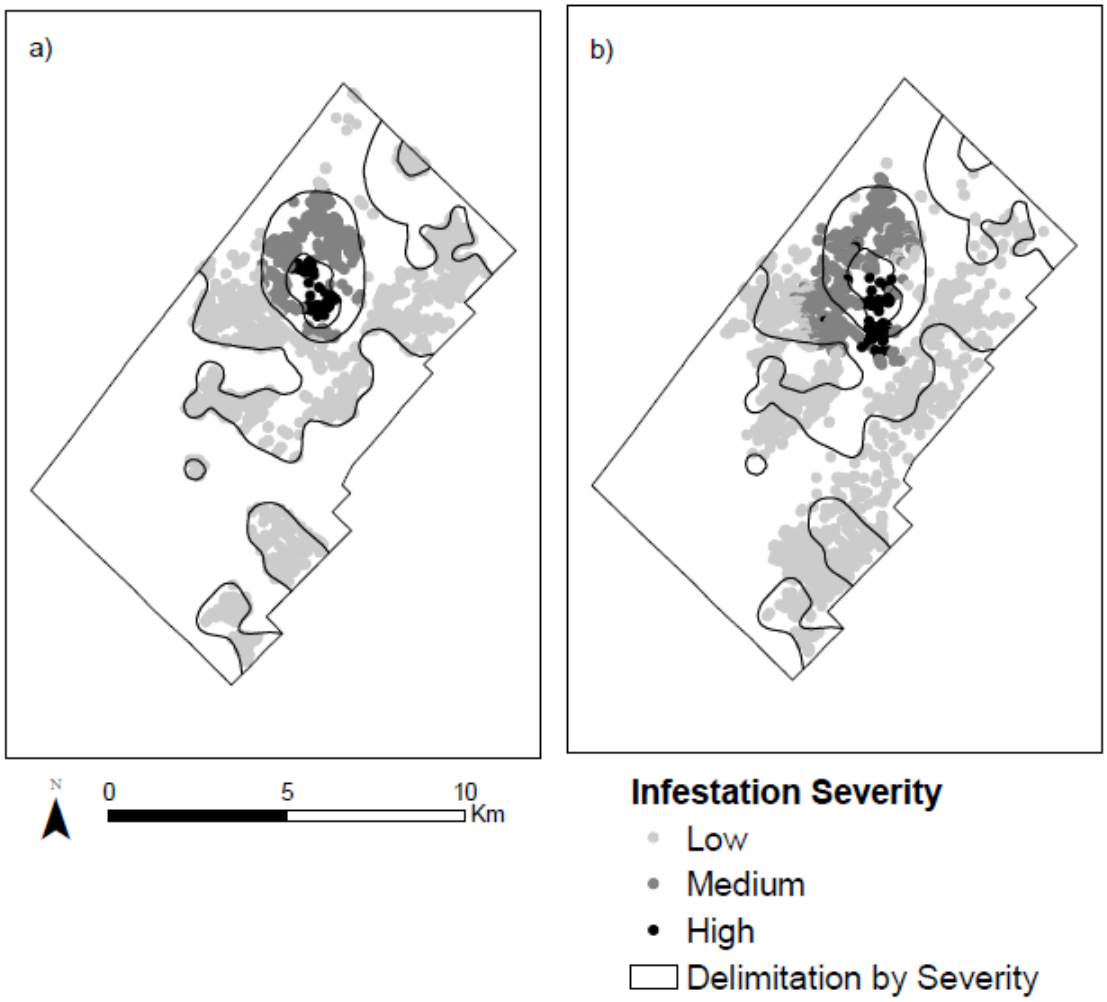

Figure 3.5 **Maps representing the delimitation of low, medium, and high EAB infestation for Oakville, Ontario in 2009 and for (a) the real data of and (b) the combined 50 model runs.**

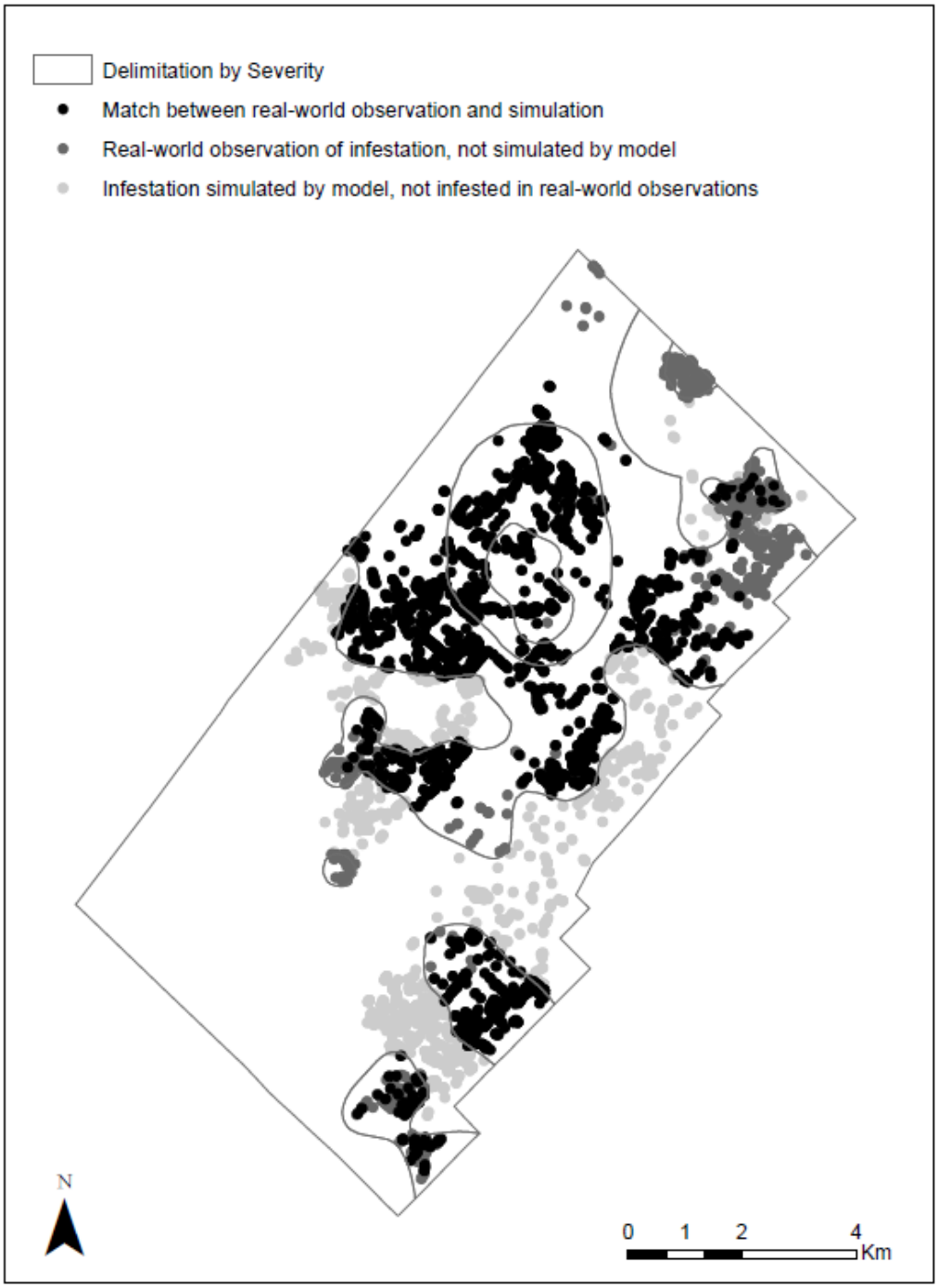

Figure 3.6. Map representing the match between the real world dataset and the simulation output in 2009.

to the following: (1) a spatial agreement on trees infested and not infested in 2009. This metric compares *the state (infested or not infested) of each ash tree from the simulation output for August 2009* with *the state (infested or not infested) of its corresponding tree with the same latitudinal and longitudinal coordinates from the real-world observation data from Oakville in 2009*; (2) a spatial agreement on severity of infestation in 2009. This metric compares *the state (severity of infestation – high, medium, low, or not infested) of each ash tree from the simulation output for August 2009* with the *state (severity of infestation – high, medium, low, or not infested) of its corresponding tree with the same latitudinal and longitudinal coordinates from the real-world observation data from Oakville in 2009*; (3) a proportional agreement (non-spatial) on severity of infestation in 2009; a metric that *compares* the proportion of the trees from the simulation output from August 2009 which have either high, medium or low severity of infestation with the proportion of the trees from the real-world observational data (4) the agreement of the extent and rate of infestation from 2008-2009. This metric compares the distance of EAB propagation from the epicenter of EAB infestation in 2008 to trees infested in 2009 in the simulation with the distance of observed EAB propagation from the epicenter of EAB infestation in 2008 to trees infested in 2009 in Oakville. The results of the analysis of the model outputs using these metrics are described in detail as follows:

(1) The real-world dataset indicates that there was 3652 ash trees infested in the Town of Oakville by 2009. The EAB ABM infested 2589 of those trees which can be represented with a 71% accuracy (Figure 3.6). A map of the spatial agreement of regions infested (Figure 3.6) provides a visual representation of the regions with the largest discrepancies between the simulation output and the real-world dataset. The map provide the location of trees that were infested in the simulation, but not in reality (Figure 3.6, light grey), the location of trees that were infested in reality, but not in the simulation (Figure 3.6, medium grey), and the location of trees where the simulation matched the real-world data (Figure 3.6, black). Analysis of model inaccuracies revealed that the majority of instances where the model simulated infestation of trees that are not infested in reality only occurred in 1 of the 50 runs, less than 2% on average.

(2) A confusion matrix (Table 3.2) was generated in order to better understand the spatial agreement of the levels of severity of infestation between the simulation output and

the real-world observation data for Oakville. As stated, ≥1.5 to 2.5 of the standard deviation of EAB density per tree is defined as high EAB infestation, 0.5 to1.5 of the standard deviation of EAB density per tree is defined as medium infestation, and ≤-0.5 to 0.5 of the standard deviation of EAB density per tree is defined as low infestation. According to the confusion matrix, a total of the 3605 trees were classified with the correct severity of infestation out of 6128 ash trees, giving the simulation a 58% overall accuracy in predicting location of severity of infestation.

Table 3.2. Confusion matrix of severity of infestation where *real world severity of infestation (top)* is compared *to simulated severity of infestation (left).*

SIMULATED \ REAL	NOT INFESTED	LOW INFESTATION	MEDIUM INFESTATION	HIGH INFESTATION
NOT INFESTED	1466	1009	42	0
LOW INFESTATION	1045	1449	310	31
MEDIUM INFESTATION	3	34	641	35
HIGH INFESTATION	1	1	39	49

(3) Proportionally, the EAB ABM simulates the different levels of severity of infestation close to reality and they are presented in Figure 3.7.

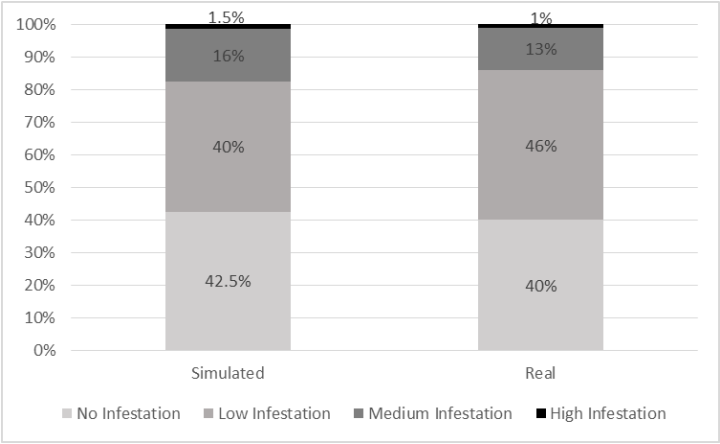

Figure 3.7. Proportional representation of severity of infestation.

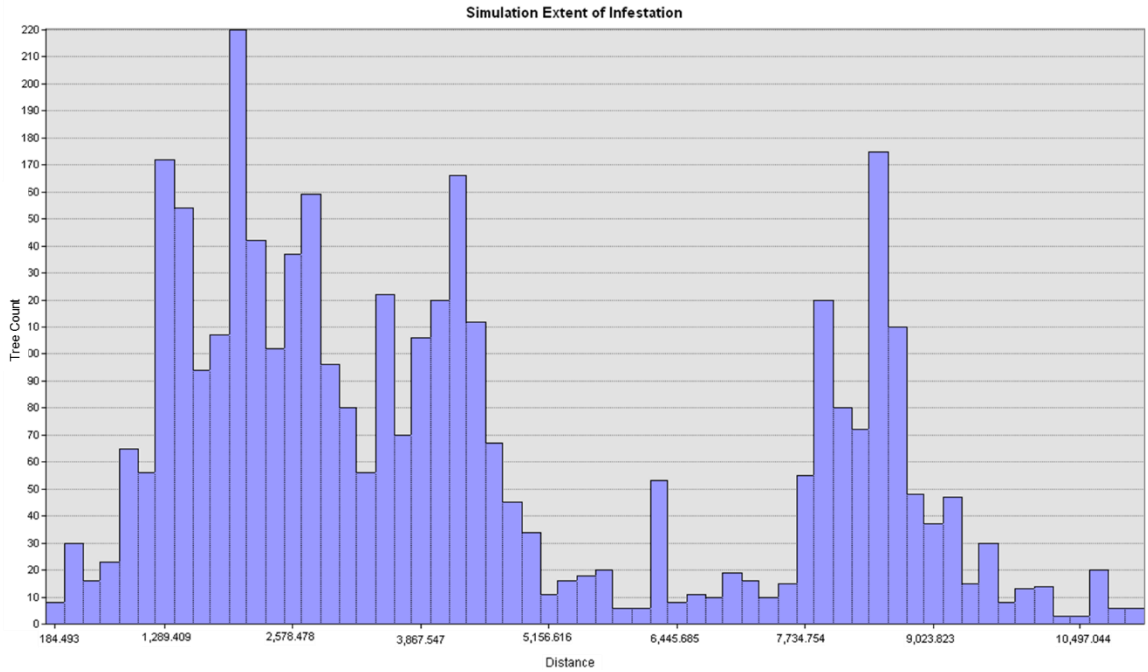

Figure 3.8. Distance in meters between the initial point of infestation in 2008 to trees infested in the simulation in 2009.

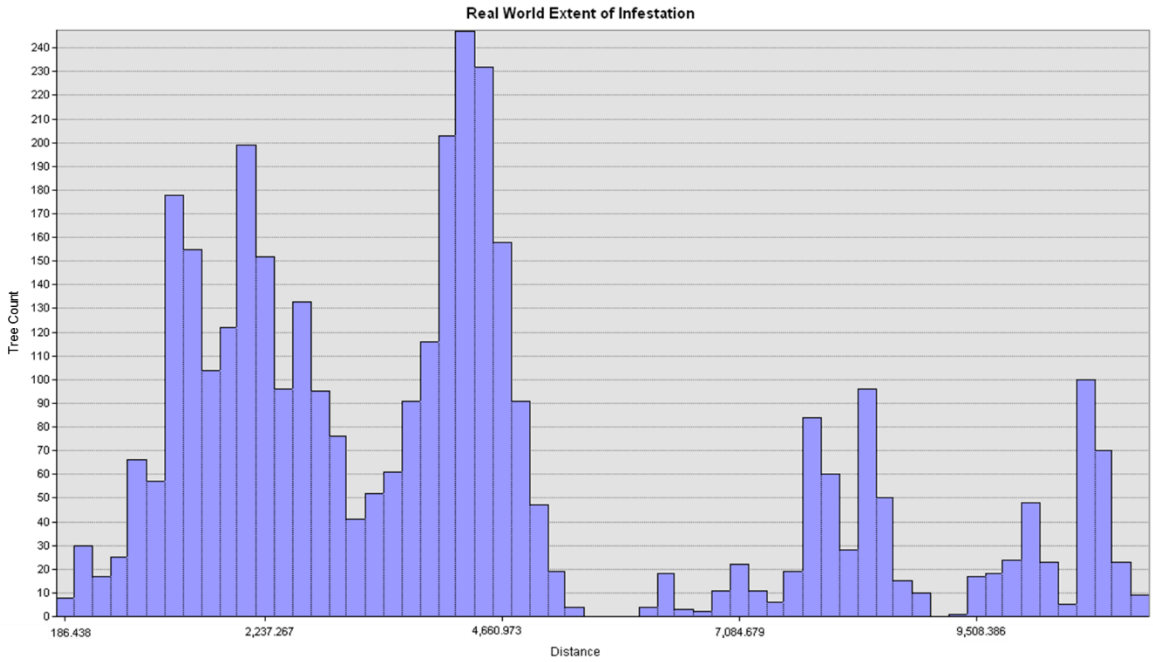

Figure 3.9. Distance in meters between the initial point of infestation in 2008 to trees which were actually infested in the real world in 2009.

(4) The spatial extent of the infestation is represented using a histogram where the distance between the epicenter in 2008 and all infested trees in 2009 in the simulation are represented in Figure 3.8 and the distance between the epicenter in 2008 to infested trees in 2009 in the real world are represented as a histogram in Figure 3.9. The average distance from the epicenter of infestation in 2008 to the delimitation of infestation in 2009 for the real world dataset is 4196.17 m with a maximum distance of 11186.33 m. In high agreement, the average distance from the epicenter of infestation in 2008 and the delimitation of infestation in 2009 for the simulation is 4238.77 m with a maximum distance of 11049.50 m. Plotting this data as a histogram clearly depicts both short and long distance dispersal. Short distance dispersal is represented along the first half of the x-axis beginning with a distance of 0 m from initial infestation to a distance of roughly 5500 m from initial infestation. Long distance dispersal distances are plotted in remainder of the x-axis in the histogram.

3.6. Discussion

The obtained results suggest that the proposed agent-based model and the chosen methodology adequately represent emergent patterns of EAB invasive species insect infestation through the explicit representation of the local, heterogeneous, individual-based interactions at the micro scale. The simulation provides an overall accuracy of 71% in determining the location of infestation and 58% in determining the severity of infestation in Oakville, Ontario.

Long distance dispersal in the model is a random process where location is chosen based on probability as a result of distance from highways and campgrounds. Long distance dispersal in the EAB-ABM simulation occurs in the south-west corner of the study area only (Figure 3.10 A). This location is an attractive choice for long distance dispersal as there is both a highway and a campground here. The simulation over-estimates the infestation in this region, where the number of trees infested is considerably higher than in the real world infestation dataset. The model simulates infestation in this location in about 30% of the simulation runs, contributing to the high frequency of infestation or tree count represented by the y-axis in the histograms. In contrast, the real-world Oakville delimitation dataset shows a number of regions impacted by long distance dispersal, not

just one. In reality, it appears three satellite populations are developed by 2009 (Figure 3.10). Infestation of these regions was under-represented in the simulation. Therefore, it can be concluded that the accuracy of the EAB ABM could be improved by improving long distance dispersal in the simulation or by testing the influence of other factors such as wind and temperature.

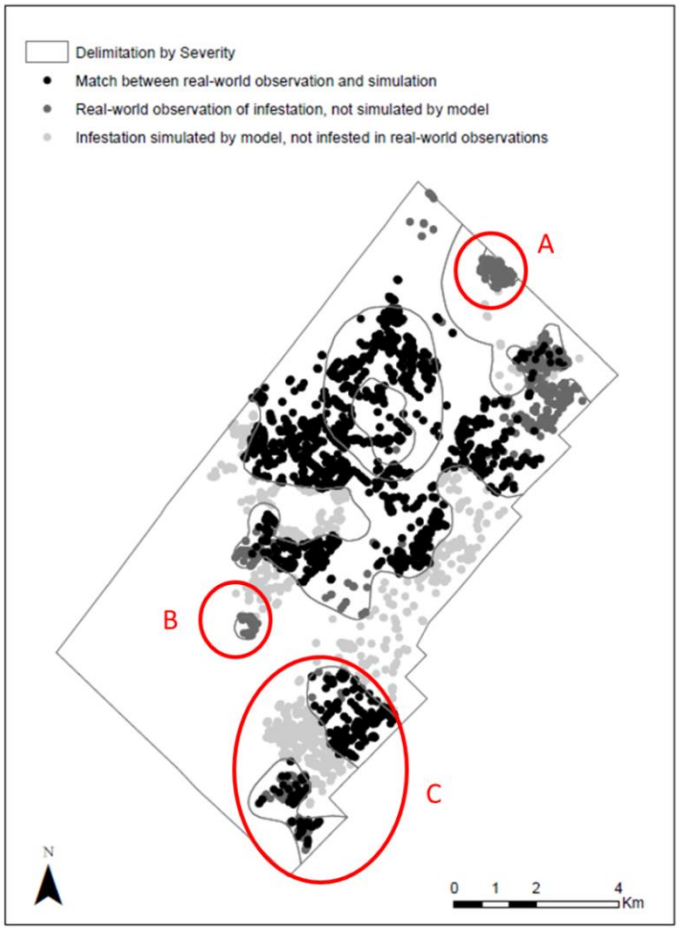

Figure 3.10. Potential regions of long distance dispersal. The contour lines represent the delimitation of severity of infestation.

Accuracy in determining the location of different levels of infestation severity was relatively low at 58%. The largest discrepancy between the simulation and the real-world data lies between regions of low infestation and regions not infested, where 1045 ash trees were misclassified as not infested when they should have been classified as low

infestation and 1009 trees were misclassified as low infestation when they should have been classified as not infested. As mentioned previously, there are however a number of trees that were infested and thus classified as low infestation less than 2% of the time (once in fifty runs of the simulation) and can be considered infrequent. The removal of these outliers would increase the accuracy of the simulation to 65% in predicting the location of severity of infestation. In addition, it could be assumed that these trees are at high risk to infestation in future time steps.

Visual observation shows that the spatial patterns of the severity of infestation is shifted slightly in a south-west direction (Figure 3.5), which may explain the difference of agreement for severity of infestation between the simulation output and the real-world observational data for Oakville. This is most likely caused by clusters of trees, where the distances between ash trees are small in the north-west part of the study area. Since distance is a key factor in the host-selection algorithm, specifically where beetle agents have a preference for travelling shorter distances, the simulated spread tends moves towards the clustered trees in a south-west direction for a majority of the model runs. The inclusion of wind as a factor in the ABM model may improve this as Ontario wind moves predominantly in a north-east direction and may shift the infestation back to match closer to reality.

The EAB-ABM simulated the level of severity by proportion of the landscape accurately where, for example, the proportion of the landscape with high infestation is the same for both the simulation and the real-world datasets. The EAB-ABM was also successful in simulating the extent of the infestation after two years which is presented in the histograms (Figure 3.8 and Figure 3.9).

The developed model indicates that representing the local small scale interactions between heterogeneous individuals can generate the simulation of patterns of EAB infestation that are close to reality and provides insight to the phenomenon that some conventional models are not able to provide. Firstly, the EAB ABM gives some indication as to why the recorded rates of infestation within the literature may vary considerably. Landscape structure and resource availability in the surrounding environment of the individual EAB beetle plays a major role in host selection, subsequently generating

aggregate patterns of insect infestation. This is evident in the model as regions where host resources are clustered and homogeneous tend to become infested first. Thus, it may be beneficial not to impose the rate of infestation when designing the model using studies that determine rates within landscapes of a different structure, composition and availability of host.

The model also allows for the observation and identification of potential underlying individual biological drivers of the rate of spread and patterns of infestation, which may not be easily observed in reality. As female beetles are responsible for the generation of infestation propagation across the landscape, the feeding habits of EAB female beetles may have a significant influence on the rate of spread. For example, female EAB which fly further from their point of emergence during the feeding stage of the lifecycle will not only draw male EAB out to further distances, but will also then oviposit at further distances, increasing the rate of infestation. In addition, the number of eggs which are laid on each tree during the oviposition stage of the lifecycle will also influence rate of infestation. Female EAB who lay fewer eggs on trees will increase the rate of infestation as they infest more trees. These random elements in the model permits the emergent behaviour of the observed complex beetle aggregations. The only parameters which are imposed are limitations to distance travelled and the total number of eggs a female may produce, as identified within the literature. As an alternative to imposing top-down rates of infestation, dispersal was generated from the bottom-up, influenced by the EABs immediate environment, life cycle, and biological heterogeneity, all of which are unique to that individual.

3.7. Conclusion

The proposed geosimulation model composed of a GIS-based ABM based on complex systems theory provides an approach for capturing the spatio-temporal dynamics of insect infestation. The obtained simulation results indicate that the developed model effectively represents some of the local dynamics between the EAB and ash tree host and generates emergent patterns of infestation over a two year period. The model allows for the characterization of underlying local processes which may influence EAB patterns of

infestation and rate of spread and in addition, offer an approach that avoids imposing system level observables through a bottom-up representation of the system.

Like all modeling approaches, ABMs in the context of individual based ecology, have their own limitations as described thoroughly by Grimm & Railsback (2005). The models, in their quest to acknowledge complexity, can as a result, be time consuming and difficult to develop. ABMs often do not use the common scientific language of mathematics and may contain processes that cannot be described mathematically making them difficult to communicate. In addition, error and uncertainty at every stage will propagate throughout the model threatening the models usefulness and testability.

The limitation of this EAB-ABM which contributes to the highest level of spatial disagreement between the geosimulation and the real world dataset is a result of the challenge in representing long distance dispersal. The model can be enhanced by improving the representation mechanisms of long distance dispersal. Additional limitations include computational challenges. Due to the availability of data for the Town of Oakville, the model was originally planned to simulate EAB insect infestation to the year 2012, however as EAB population increases exponentially, the computational efficiency was affected during the decision making process of each individual and simulation time became unacceptable. This is a common issue in ABM, as to add dynamics to a model, calculations are applied to every individual, and thus computation performance often becomes an issue (DeAngelis & Mooij, 2005).

Complex phenomena such as insect infestation commonly lack observational data for improved model validation. One of the main limitations of the Oakville dataset was the lack of heterogeneity among infestation severity levels, where the dataset represented only three discrete levels of severity. It would have been useful to see the within level heterogeneity. Additional geospatial datasets such as EAB density levels would have been useful to improve model calibration and validation. It is important to note, however, that complex systems modeling methods are designed for dealing with data scarcity and as such are valuable in modeling these types of phenomenon.

The integrated GIS-based ABM provides the potential to explore what-if scenarios such as testing newly implemented eradication strategies such as biological eradication

and control measures such as the use of the stingless wasp, a natural EAB predator. Additional what-if scenarios could include investigating the influence of wind and temperature in order to see the impact of these factors on a local scale. This model demonstrates the potential to use the developed model as a tool to assist decision makers in evaluating current and potential eradication strategies and fill knowledge gaps with respect to spatio-temporal dynamics of EAB spread, aiding in future forest management.

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Chapter 4.

Conclusions

4.1. Synthesis of Research

The focus of this thesis research is the exploration of complex system modeling methods capable of capturing the behavior of invasive forest insect infestation using the emerald ash borer (EAB) as a case study. The research contributes to the existing modelling community by providing a toolset that addresses how large scale patterns of insect infestation are a result of complex, non-linear, individually driven processes within a changing spatial environment.

The objectives of this research have been achieved through the development of two bottom-up modeling approaches to capture the spatial and temporal patterns of EAB infestation. The approaches include, first, the development of a GIS-based CA model to capture patterns of insect infestation across the regional scale. Although the bottom-up CA model generates large scale patterns of infestation by representing local dynamics between the ash tree and the EAB, the simulation of these dynamics at each time step was limited to the size of the neighborhood. The improvement of EAB mobility within the geospatial environment aids in better representing both short distance and long distance dispersal patterns of EAB infestation. As such, a second bottom-up approach, specifically a GIS-based ABM, was developed that explicitly represents the small scale dynamics between heterogeneous, autonomous individuals from which larger scale patterns and processes emerge. The EAB individuals are free to move independently within their environment and their interactions are not restricted to the neighborhood.

The development of the CA model was motivated through exploring a new modeling approach to the EAB infestation problem that addresses the complexities of insect infestation. The developed model simulates the relationship between EAB and ash trees of varying and changing susceptibility and generates large scale patterns of infestation across three different landscapes. The model provides a novel way to estimate the susceptibility of ash trees to EAB infestation across space and through time and the

results indicate that the urban environment may be of the greatest risk to loss and change of the urban forest.

The development of the ABM model addresses the lack of acknowledgement in more traditional insect infestation modeling sciences of the importance of the adaptive individual in influencing emergent spatial and temporal patterns on the system as a whole and seeks to address complexity in insect infestation. The ABM also presents a novel host selection algorithm developed using artificial intelligence and complexity theory in order to represent decision making by the individual EAB beetles. The results indicate that the rate of infestation is heavily influenced by the individual and environmental variation and the dynamics between them at the local scale which can be used to explain why infestation rates vary in the literature.

4.2. Future Directions

Effective forest management decision-making requires the integration of information into the decision making process (Power, 1988). Complex spatial problems often have conflicting objectives and various options for solutions, impacting the effectiveness of decision-making (Densham, 1991). Integrating information into the decision making process, specifically spatial information via spatial modeling and analysis, is referred to as spatial decision support systems (SDSS). In the context of pest management, SDSS can be used to better understand how spatial characteristics of insect and host interactions are influenced by other factors (Power, 1998). Integrating a spatial component into pest management can help improve survey design, insect infestation detection and mapping of infestations, risk identification, quarantine and eradication services, analysis of relationships between biophysical factors and pest infestations, estimations of pest-caused forest depletions due to forest loss, prediction of infestation and their impact, and the research and interpretation of biological and chemical control programs (Power, 1998). This information is of great value to forestry services in order to meet its information needs for analysis of pest management in all forest insect infestation contexts.

Unlike some conventional mathematical models, geographic automata systems, CA and ABM modeling approaches are flexible, with parameters that can be easily manipulated for different purposes. This flexibility provides the opportunity for development of “what-if” scenarios, particularly in testing eradication options for the species. Potential scenario development for the CA and ABM could include the evaluation of the effectiveness of chemical eradication, specifically how the spatial administration of chemical eradication affects the spatial patterns of susceptibility of the trees and in turn effects the propagation of EAB due to changing availability of the ash tree host. In addition, “what-if” scenarios could be used to understand how changing the structure of the forest landscape, i.e. strategic removal of ash trees, will affect the propagation of EAB. All of these scenarios would be useful for testing eradication strategies before they are implemented to avoid negative economic and ecological consequences associated in using inefficient eradication strategies.

The type of models proposed in this study, capable to forecast future projections or perform more complex scenario based simulations requires great computational efficiency in order to process all calculations. For example, each individual EAB makes a decision based on their unique situation at each time step. As the EAB becomes established and populations increase exponentially, the numbers of decisions that must be calculated also increase exponentially and the run-time of the program slows considerably. As such, future work can include production of more robust and efficient software code that will be executed using parallel processors to enable shorter processing time. This would facilitate the simulations to achieve multiple years of forecasted insect infestation.

Due to the bottom-up nature of the models, the CA and the ABM can be applied to other study areas in Canada which are not yet infested in order to project future regions of infestation, identify regions of the greatest risk, and aid in urban and rural forest protection. However, in order to do so, the model would need to undergo proper verification, sensitivity analysis, calibration, and validation, which may provide challenging for non-experts. As such, it may be useful for the development of a tool with a user friendly interface which would enable decision makers or managers without extensive computation background to engage in the exploration of spatio-temporal dynamics of infestation. The

flexibility in the input of model parameters would enable the model to simulate infestation specific to the study site and allow for the testing of scenarios.

Despite advantages of CA and ABM as methods for modeling complex systems, the validation of model outputs which are capturing complex non-linear behavior is of increasing concern, specifically with respect to what these types of models can achieve and how they should be evaluated (Batty and Torrens, 2005; White and Engelen, 2000; Crooks et al, 2008). Model testing can be accomplished using a variety of approaches including sensitivity analysis to examine the level of influence each element has on a system, by comparing different model's results with one another, or more commonly in ABM, using validation, where spatial outputs of a model is compared with real world geospatial datasets at the same time (Rykiel, 1996). The technique used in chapter 3 of the thesis for validation has limitations in a bottom-up complex systems context and have the potential to be expanded.

As stated, the outcome of the model depends on local interactions between the phenomenon being modeled and its environment. Uncertainties about future environmental conditions such as climate change impacts or future landscape change can have major impacts on model abilities to forecast the phenomenon. Even if a model is perfectly valid from time t to time $t+20$, the model may be inadequate to simulate any further in time based on the complexities of the phenomenon and the environment i.e. feedback mechanisms, thresholds and bifurcations (Bone et al., 2014). Thus, further exploration of full model testing procedures in the context of complex systems modeling is challenging endeavour, but very useful as the proposed modeling approaches can be transposed on different datasets and study sites, and once fully tested used as spatial decision support.

The presented thesis research provides a novel perspective in the representation of EAB insect infestation patterns and processes through the employment of bottom-up complex systems modeling mechanisms. It is important to note that the models are representations or abstractions of reality. The representation of complex ecological systems such as insect infestation with the addition of uncertainty poses many challenges. The GIS-CA and GIS-ABM approach helps to narrow the gap in modeling the EAB using

bottom-up approach and addressing concepts of emergence, adaptive individuals, and non-linear behavior characteristic of complex systems. The approaches developed in this thesis address only a small set of possibilities available for the representation of complex ecological systems.

4.3. Thesis Contributions

The methods developed in this research aim to contribute to literature related to GIScience, geospatial and ecological modeling of complex and dynamic geospatial systems. Specifically, the methods and results contribute to research pertaining to the integration of GIS and geospatial data with complex systems modeling methodologies such as cellular automata and agent based models of dynamic ecological systems such as insect infestation modeling at various spatial scales. In addition, the integration of techniques for model enhancement such as the use of elements of multi-criteria evaluation and artificial intelligence contribute to the decision making processes within these models to represent autonomous entities such as invasive forest insects.

The developed methodologies proposed in this thesis also contribute specifically to insect infestation modeling, providing a new perspective and toolset that addresses the complexity in spatial and temporal components of insect infestation that existing EAB models cannot. In addition, these models bring to light the concerns that conventional modeling methodologies, many which use top down approaches, ignore the individual and the inherent variation in that individual (Grimm & Railsback, 2005; Paruak et al., 1998). The developed methodologies are particularly useful for dealing with uncertainty and data scarcity by using a bottom-up approach to generate system level observables such as patterns and rates of infestation. This is a particularly valuable aspect of complex systems modeling methodologies that makes these models important for policy-makers, decision-makers, and forest managers as observation data is not often available for such complex phenomena.

4.4. References

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