

# Sensitivity of a Fuzzy-Constrained Cellular Automata Model of Forest Insect Infestation

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## Abstract

Cellular automata (CA) are discrete systems used for modelling complex spatial dynamic phenomena. The discrete nature of CA enables integration with raster-based geospatial datasets in geographic information systems (GIS), and also can be beneficial when modelling complex ecological processes that evolve over time. However, when modelling forest insect infestations it is difficult to use discrete cell states to represent, for example, the concept of susceptibility of a tree to insect attack. The use of binary or probabilistic approaches for cell states definition is not appropriate because insect disturbances are driven by numerous components of insect-tree relationships that are difficult to understand. Furthermore, uncertain transition zones exist between forest stands of different sizes and different species where a discrete definition of a cell cannot be provided. The objective of this study was to integrate fuzzy set theory with GIS-based CA modelling to model tree mortality patterns caused by insect infestation, and to explore the sensitivity of the model to different spatial properties. This study focused on a case study of lodgepole pine, *Pinus contorta*, mortality patterns caused by infestations of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins. The use of fuzzy set theory addresses the issue of inherent uncertainty of the geospatial data used for studies of forest infestations, while a test of model sensitivity explores the influence of the spatial properties of a fuzzy-constrained CA.

## 1. Introduction

Cellular automata (CA) are spatial dynamic models used for modelling complex systems where local interactions lead to global patterns (White and Engelen 2000). The discrete nature of CA

facilitates the integration with raster-based information in geographic information systems (GIS). CA modelling in GIS has proven especially successful in simulations of urban growth and land use change (White et al. 1993, Xie and Batty 1997, Clarke and Gaydos 1998, Batty et al. 1994, White and Engelen 2000), where discrete landforms occupy various spaces over time. However, the discreteness of CA also hinders its use with complex ecological processes where cell states cannot adequately represent the ecological entities. Such is the case with modelling forest insect infestations where each cell represents the susceptibility of a tree to attack. Two main problems exist that prevent representing a cell as discrete.

The first problem concerns defining a tree's susceptibility to insect attack. It is difficult to use contemporary approaches to this problem, such as defining a tree as either susceptible or not susceptible or deriving the probability of a tree becoming attacked. This is due to the fact that insect disturbances are driven by numerous components of insect-tree relationships that are difficult to understand. Appreciating this relationship is further complicated by the presence of numerous climatic variables such as temperature, wind, humidity and precipitation, which, coupled with the geographic variation of a species' life cycle, produce varying results and incomplete or vague knowledge on insect behaviour (Carroll and Safranyik 2004). Therefore, considering a raster-based representation of a forest landscape, significant uncertainty is present when attempting to assign a discrete binary value or probability value for describing a tree's susceptibility to attack.

The second problem is the inherent uncertainty in classifying raster-based data of forest landscapes in a GIS. Processes such as insect infestations operate at refined spatial and temporal scales. As forests are continuously changing over space and time, the value given to a cell through classification procedures only represents that location for the moment in time when the data was acquired. An apparent consequence of the characteristics of forest raster-based data is that the borders between forest stands cannot be defined with certainty (Lowell 1996). Therefore, uncertain transition zones exist between forest stands of different sizes and different species where a discrete definition of a cell cannot be provided. Furthermore, the often-inappropriate spatial and temporal resolutions of commonly used geospatial data hamper the ability to study and understand the forest infestation process. It is difficult to determine attack patterns with large-scale images collected over a short and inappropriate time periods of an infestation phenomenon that occurs at very small scale (e.g. tree-size) but have consequences on the large forest environments.

The objective of this study was to integrate fuzzy set theory with GIS-based CA modelling to simulate tree mortality patterns caused by insect infestation, and to explore the sensitivity of the model to different spatial properties. More particularly, this study used lodgepole pine, *Pinus contorta*, mortality patterns caused by infestations of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, as an example. Fuzzy sets have successfully been applied to urban growth and land use change CA models (Wu 1998, Liu and Phinn 2001), however it is not yet fully elaborated in the research literature related to the modeling dynamic ecological processes. The use of fuzzy theory addresses the issue of inherent uncertainty of the geospatial data used for studies of forest infestations. In addition, the focus was in applying several tests of model sensitivity to explore the influence of the spatial properties of a fuzzy-constrained CA.

## 2. Background

### 2.1 Fuzzy-Constrained Cellular Automata

White and Engelen (2000) explain CA as five components: (1) a grid of cells that represents a landscape; (2) a finite number of discrete states that represents objects in the landscape, where each cell is represented by a single state; (3) a local area called the neighbourhood where information is gathered to determine the state of each cell at the next instance in time; (4) transition rules that govern the nature of state transition; (5) a number of iterations for which the model is performed. The premise behind CA is that the state of each cell is determined at each iteration by the states of the cells in the neighbourhood and the transition rules that define the influence of those cells.

An appropriate CA-based model of insect-induced tree mortality requires a forest landscape represented by a grid of cells where each cell represents a single susceptible tree in order to simulate the local insect-tree interaction. A susceptible tree is more likely to be attacked if there are a significant number of trees in the neighbourhood that are already attacked because the insects in those trees or their offspring will soon be looking for a new tree to infest. Therefore, discrete cells states would represent 'susceptible' or 'non-susceptible' trees that change to an 'attacked' tree over time based on the transition rules that define how many insects are required in order for a susceptible tree to become attacked. While discrete cell states are commonly employed in CA models of ecological processes where states represent the presence or absence of a species (Jeltsch et al. 1996, Wilson and Nisbet 1997, Grist 1999) or the presence of one species versus another (Dytham 1995, Baltzer et al. 1998, Chen et al. 2002), significant difficulty exists with representing the susceptibility of trees due to the two problems described above.

Fuzzy set theory (Zadeh 1965) can be used in cases where uncertainty is present in defining cell states by utilizing expert knowledge on the nature of the complex system under investigation (Robinson 1988). Fuzzy set theory explains that the membership function of an element  $x$  belonging to a fuzzy set  $A$  is represented by  $\mu_A : U \rightarrow [0,1]$ , where  $U$  is the universal set of  $x$ . This explains that the function associates a graded membership with each point  $x$  in  $U$ . Fuzzy sets can be used for defining tree susceptibility by utilizing expert knowledge on the relationship between attacking insects and susceptible trees in order to develop membership functions. Components of this relationship could include the biological characteristics of a tree that are preferred by the insect, or the dispersal patterns of the insect from one tree to another. The membership functions would provide a value between 0 and 1 explaining the susceptibility of a tree based on the nature of these components.

With regards to GIS research, the concepts of fuzzy sets have been employed for defining the spatial and attribute characteristics of geographic objects (Burrough 1992, Wang and Hall 1996), soil classes (Burrough et al. 1992), temporal interpolation (Dragicevic and Marceau 2000), and image classification (Wang 1990, Zhang and Foody 1998) among others. Fuzzy sets have been used for forest research to deal with issues surrounding digitizing objects from thematic maps (Lowell and Gold 1995), identifying forest types (Brown 1998) and identifying individual trees (Brandtberg 2002).

## 2.2 CA Model Sensitivity

CA models produce results that are influenced by spatial properties such as the size of the neighbourhood and study area. However, with the exception of few studies that examined model sensitivity (Kocabas and Dragicevic 2004) and error propagation (Yeh and Li 2005), the effects of spatial properties in CA modelling is largely unexplored (Clarke 2003). The size of the neighbourhood and study area are important when defining cell states with fuzzy sets because trees are represented by graded values of susceptibility. A higher susceptibility value means that fewer insects are required in order to cause significant damage or mortality to the tree. Trees with lower values of susceptibility are relatively more resistant to insect attack, and therefore would require more insects for tree mortality to occur. If the neighbourhood size or the study area size is too small, trees of low susceptibility may not become attacked because there will not exist enough infested trees in the surrounding areas to provide enough insects to overcome the resistance of the tree. Furthermore, the neighbourhood size determines the distance over which MPB will travel; a neighbourhood that is too small or too large will therefore lead to unrealistic dispersal patterns. Also, smaller study areas are more prone to edge effects because they are more likely to exclude infested trees in the adjacent areas not covered by the study area. Therefore, it is important to test the sensitivity of the neighbourhood and study area size in CA models based upon fuzzy set-defined cell states for modelling tree mortality patterns due to insect infestations.

## 3. Methods

The methods for this study are divided into three sections. The first section explains the development of the model input using fuzzy sets, the second section describes the development of the *Tree Mortality Model*, and the third section explains the process of testing the sensitivity of the scale of the study area and the neighbourhood size of the model.

### 3.1 Development of Model Input

A hypothetical study area was used for this study that represents a typical Montane forest of the central interior of British Columbia (see Figure 1). The forest landscape consists of stands of small, medium and large diameter trees that are dominated by lodgepole pine, with relatively smaller proportions of Douglas fir, *Pseudotsuga menziesii*, and white spruce, *Picea glauca*, scattered throughout, as well as stands of the deciduous aspen tree, *Populus tremuloides*. The study area represents an area of 3km x 3km with a spatial resolution of 3m, where each raster cell represents a single tree.

Each tree was represented in the database by its species name and a value indicating its size in diameter at breast height (DBH). The DBH values were assigned based on the stand in which the tree was located. A tree located in a stand of small trees was assigned DBH between 15cm and 32cm; a tree in a stand of medium sized trees was assigned a value between 22cm and 42cm; a tree in a stand of large trees was assigned a value between 27cm and 52cm. These tree size classes were determined from the analysis of ground truth data from a previous study on MPB outbreaks in British Columbia (Roberts et al. 2003). Groups of lodgepole pine were selected to be attacked by MPB in the current year (i.e.  $T_i$ ), which are indicated in Figure 1. These killed trees acted as the seed trees from which MPB disperse and search for new host trees to attack.

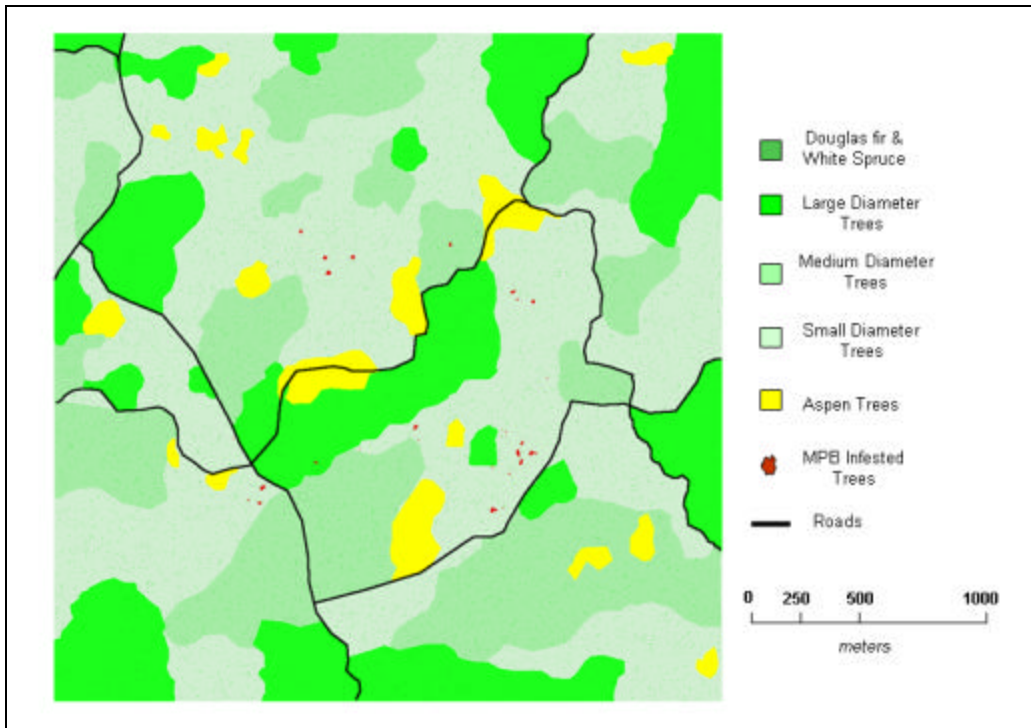


Figure 1. Hypothetical data of forest landscape.

The study area was analyzed in order to determine the susceptibility of each lodgepole pine tree to MPB attack. Four main tree characteristics were identified that provided information on susceptibility. The first characteristic was *tree size*, as larger diameter lodgepole pine are more susceptible to attack because they are not as strong as smaller and younger trees at defending themselves (Shore and Safranyik 1992, Hinmarch and Reid 2001). The second characteristic was *species diversity*, because a lodgepole pine located in a pure lodgepole pine stand is more susceptible than if it were to be located in a stand mixed with Douglas fir, white spruce and aspen (Amman and Baker 1972, Thomson 1991, Shore and Safranyik 1992). The *species diversity* value for a tree was defined by the proportion of lodgepole pine trees in the stand in which the tree was located. The third characteristic was *distance to attacked trees*, where lodgepole pine that are closer to previously attacked trees are more susceptible to attack (Shore and Safranyik 1992). The fourth characteristic was the *distance to deciduous stands*, as the susceptibility of lodgepole pine increase with distance from stands of deciduous trees. This final characteristic was determined from a previous analysis based on remote sensing imagery of MPB attacked trees (Bone et al. 2005a). Each tree was thus represented with a value for each of the four characteristics.

The next step was to use expert knowledge to develop membership functions that explain how each characteristic relates to susceptibility (Bone et al. 2005a). The fuzzy membership function for each characteristic is shown in Figure 2. Each tree received four values between 0 and 1 after the fuzzification procedure representing its membership to the set of *large lodgepole pine trees*  $\mu(LT)$ , the set of trees *located in pure lodgepole pine stands*  $\mu(LP)$ , the set of trees *close to*

previously attacked trees  $\mu(AT)$ , and the set of trees far from deciduous stands  $\mu(DS)$ . The values ranged from 0 for unsusceptible lodgepole pine to 1 for highly susceptible lodgepole pine (the value 0 was also assigned to non-lodgepole pine trees and to objects such as roads and open spaces). These four values were combined using a multiplicative fuzzy operator that calculates the product of all four values, which resulted in each tree represented by a single value for membership to susceptible trees  $\mu(Su)$ . A multiplicative operator was selected over traditional AND or OR operators because these latter two would only reflect the best and worst case scenario of susceptibility, respectively, and would not account for the other variables. The value for  $\mu(Su)$  was calculated by

$$\mathbf{n}(Su) = \mathbf{n}(LT) \times \mathbf{n}(LP) \times \mathbf{n}(DS) \times \mathbf{n}(AT). \quad (1)$$

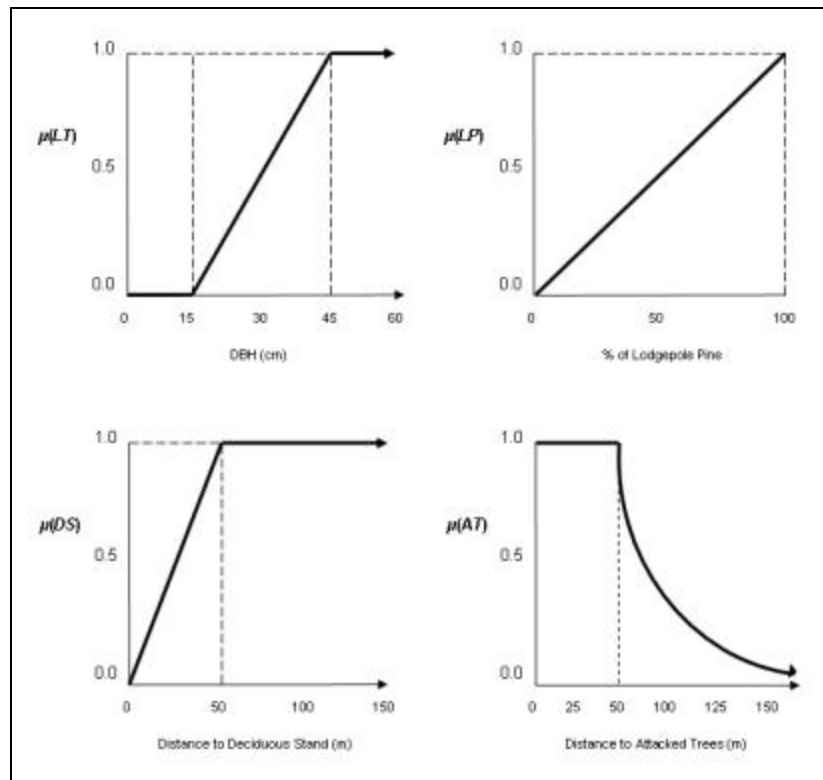


Figure 2. Fuzzy membership functions for (clockwise starting from top-left) large trees  $\mu(LT)$ , trees located in pure lodgepole pine stands  $\mu(LP)$ , trees close to previously attacked trees  $\mu(AT)$ , and trees far from deciduous stands  $\mu(DS)$ .

The final stage of the model input was to create fuzzy transition zones between stands in order to represent the intermediate nature of forest stands (i.e. the second problem with defining discrete cell states discussed above). This was accomplished by implementing a 10m buffer on either side of the boundaries between forest stands. Each tree in this fuzzy transition zone received a

susceptibility value  $\mu(Su)$  based on the distance to the nearest tree in the adjacent stand and the susceptibility value  $\mu(Su)$  of that tree. The  $\mu(Su)$  value for a tree in the fuzzy transition zone was calculated by

$$m(Su) = \text{MAX} \left\{ \left[ m(Su_i) \frac{1}{D_i} \right], \left[ m(Su_j) \frac{1}{D_j} \right] \right\} \quad (2)$$

where  $\mu(Su_i)$  and  $\mu(Su_j)$  are the susceptibility values of the nearest cell in adjacent stands  $i$  and  $j$ , respectively, and  $D$  is the distance to those nearest cells. Each cell in the fuzzy zone had two values as it was a member of two stands; therefore, the maximum value was obtained in order to represent the higher level of susceptibility. The final result was the input for the *Tree Mortality Model*.

### 3.2 Tree Mortality Model

The *Tree Mortality Model* emulates the annual pattern of trees killed by MPB (Bone et al. 2005b). The model is composed of three sub-models. The first two – the *Initial Attack Sub-Model* and the *Spot Growth Sub-Model* – are governed by CA, while the third sub-model, termed the *Mortality Sub-Model*, controls MPB population levels.

#### 3.2.1 Initial Attack Sub-Model

MPB leave their currently infested trees in late July to early August in search of a new tree to attack. Females first emerge and fly varying distances in search of a new host tree. Once a new host has been selected, the female bores through the bark and releases a chemical compound that attracts male beetles to the same tree. The tree's defensive mechanisms are overcome once a sufficient number of MPB have attacked the tree (Powell et al. 1998); fewer beetles are required for killing trees that are more susceptible. This initial attack on susceptible trees was modelled using a CA with a large landscape-scale neighbourhood in order to allow the beetles to fly from one stand to another when in search of a new host. The transition rules for this sub-model were defined by an allometric function that explains the relationship between the susceptible value  $\mu(Su)$  of a tree and the number of beetles in the neighbourhood required to kill the tree. These rules, illustrated in Figure 3, explain that a tree with a given level of susceptibility  $\mu(Su)$  will be killed if a specified number of MPB are located in the neighbourhood. The *Initial Attack Sub-Model* is complete once the CA has been performed for a single iteration, which is equivalent to the time span of one week.

#### 3.2.2 Spot Growth Sub-Model

At the completion of the *Initial Attack Sub-Model*, the number of beetles on each tree thus far attacked has reached capacity. At this point, the beetles boring into the tree begin to release an anti-aggregation chemical compound that sends a signal to beetles still flying toward the tree that no more beetles are required to kill the tree (Huber and Borden 2001). The anti-aggregation compound redirects beetles to nearby trees which they begin to attack in attempt to kill. This creates what is termed as 'spot growth' (Carroll and Safranyik 2004), where trees are attacked in clusters. Spot growth was modelled using a CA with a smaller local neighbourhood in order to

ensure local clusters of trees were attacked. This sub-model also used an allometric function to define the transition rules. *The Spot Growth Sub-Model* was completed after the CA had been performed for two iterations – each iteration again representing one week.

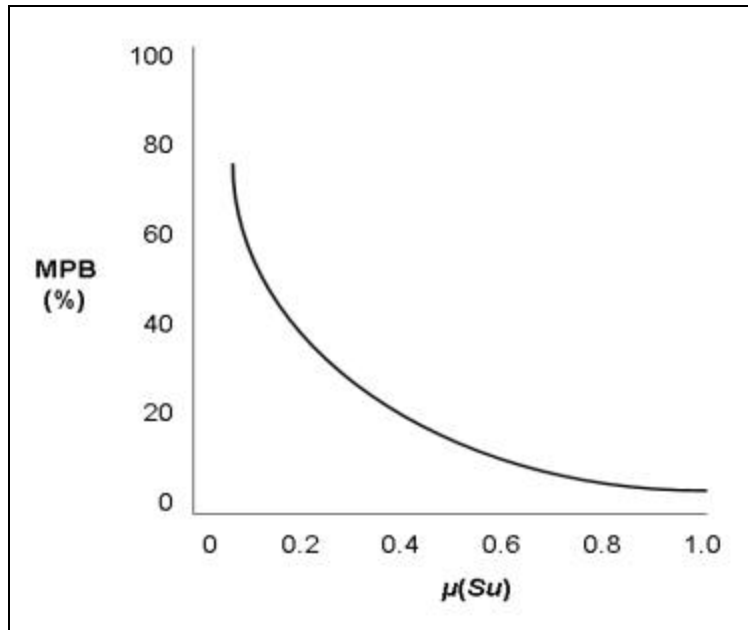


Figure 3. The CA transition rules are governed by an allometric function explaining the percentage of MPB infested trees required in the neighbourhood in order for a tree of a given susceptibility  $\mu(Su)$  to become attacked.

### 3.2.3 Mortality Sub-Model

MPB experience high levels of mortality each winter when cold temperatures have detrimental effects on the developing stages of the beetles. During outbreaks, it is common to have a mortality level of 80% due to cold temperatures. Winter mortality was simulated by having 80% of the attacked trees void of MPB. This resulted in having 80% less trees as sources of MPB for the following year's attack, but the trees from which the beetles were removed were still considered dead. The completion of the *Mortality Sub-Model* produced the pattern of trees killed by MPB after one year. This also represents the completion of one cycle of the *Tree Mortality Model*, which is the equivalent to one life cycle of the MPB. Therefore, the *Tree Mortality Model* was performed for five cycles in order to represent a five-year period of MPB-induced tree mortality.

### 3.3 Sensitivity Analysis

The sensitivity of the *Tree Mortality Model* was tested based on the size of the neighbourhood of the *Initial Attack Sub-Model* and the scale of the study area. The initial neighbourhood size was 500 x 500 cells, which facilitated MPB dispersal across the landscape. The neighbourhood size was changed to 400 x 400, 300 x 300 and 200 x 200 cells in order to determine the effects of the



variable neighbourhood on MPB-induced patterns of tree mortality. Neighbourhood size was tested using the entire study area and performing the *Tree Mortality Model* for five cycles for each neighbourhood size.

The model was then performed on the central area of the forest landscape in order to test the sensitivity of the scale of the study area. The central area was defined by dividing the original landscape into nine equal-sized quadrats and using the central quadrat (Figure 4). Only the MPB infested trees located in the centre quadrat were used for this test, as the infested trees located outside the centre quadrat were eliminated. The *Tree Mortality Model* was performed for five cycles, and the results were compared to the tree mortality patterns over the same area when the entire study area was used for the model. A neighbourhood of 500 x 500 cells was used for this test.

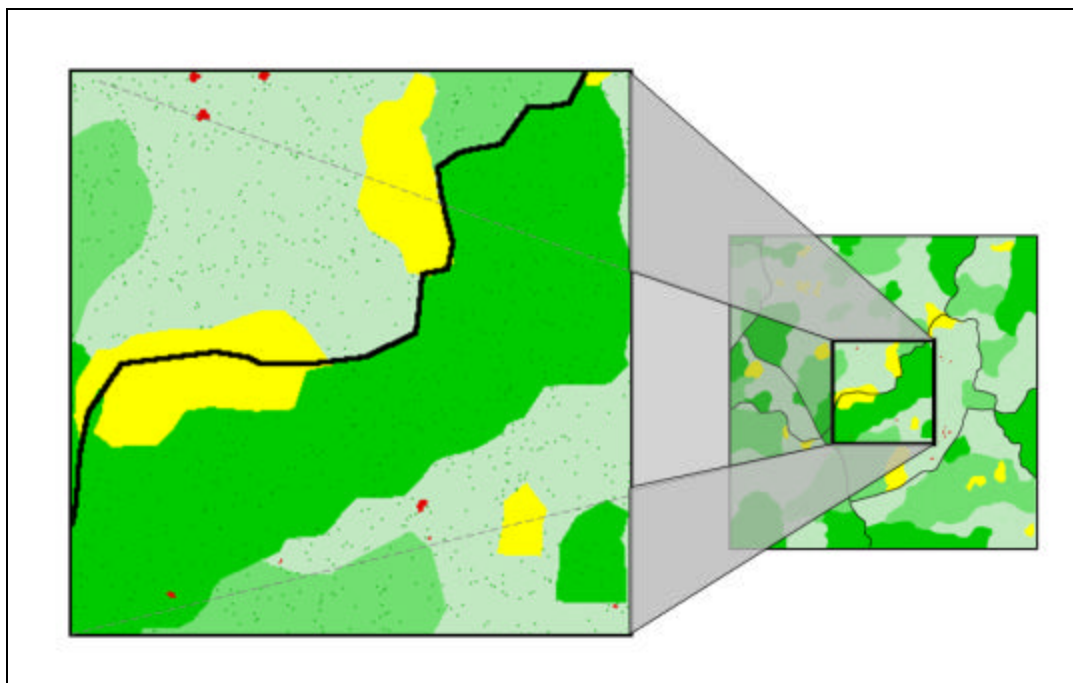


Figure 4. The central area (left) of the study area (right) used to test the sensitivity of the model to the size of the study area.

#### 4. Results

The result of the model input development is shown in Figure 5. The result is a forest landscape represented by values  $\mu(Su)$  between 0 and 1 indicating each tree's susceptibility to MPB attack. The value 0 refers to lodgepole pine that exhibit no susceptibility and also to objects other than lodgepole pine such as Douglas fir, white spruce and aspen trees, open areas and roads. Values closer to 1 represent higher levels of susceptibility, which are indicated in Figure 5 with a lighter shade.

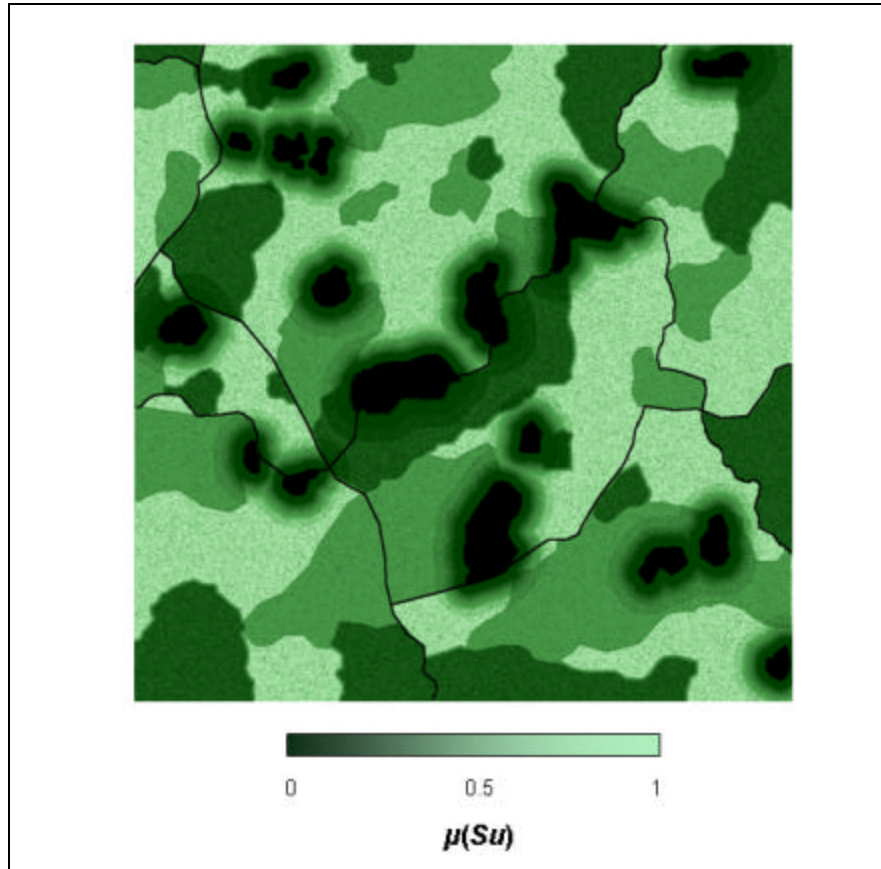


Figure 5. *Tree Mortality Model* input derived from fuzzy sets. Darker shade indicates lower susceptibility ( $\mu(Su)$  values close to 0) and lighter shade indicates higher susceptibility ( $\mu(Su)$  values close to 1).

The results for the *Tree Mortality Model* using the original study area for testing the four different neighbourhood sizes are shown in Figure 6. Each model was performed for five cycles representing the tree mortality from the end of the first year ( $T_{i+1}$ ) to the end of the fifth year ( $T_{i+5}$ ). The results from the sensitivity analysis of the scale of the study area are presented in Figure 7 where the tree mortality patterns are shown for the central area of the study area.

A numeric analysis of the number of trees killed is also provided for the different neighbourhoods (Figure 8) and for the different size study areas (Figure 9). These two graphs illustrate how using different neighbourhoods or study area sizes affects the overall number of trees killed for each cycle of the model.

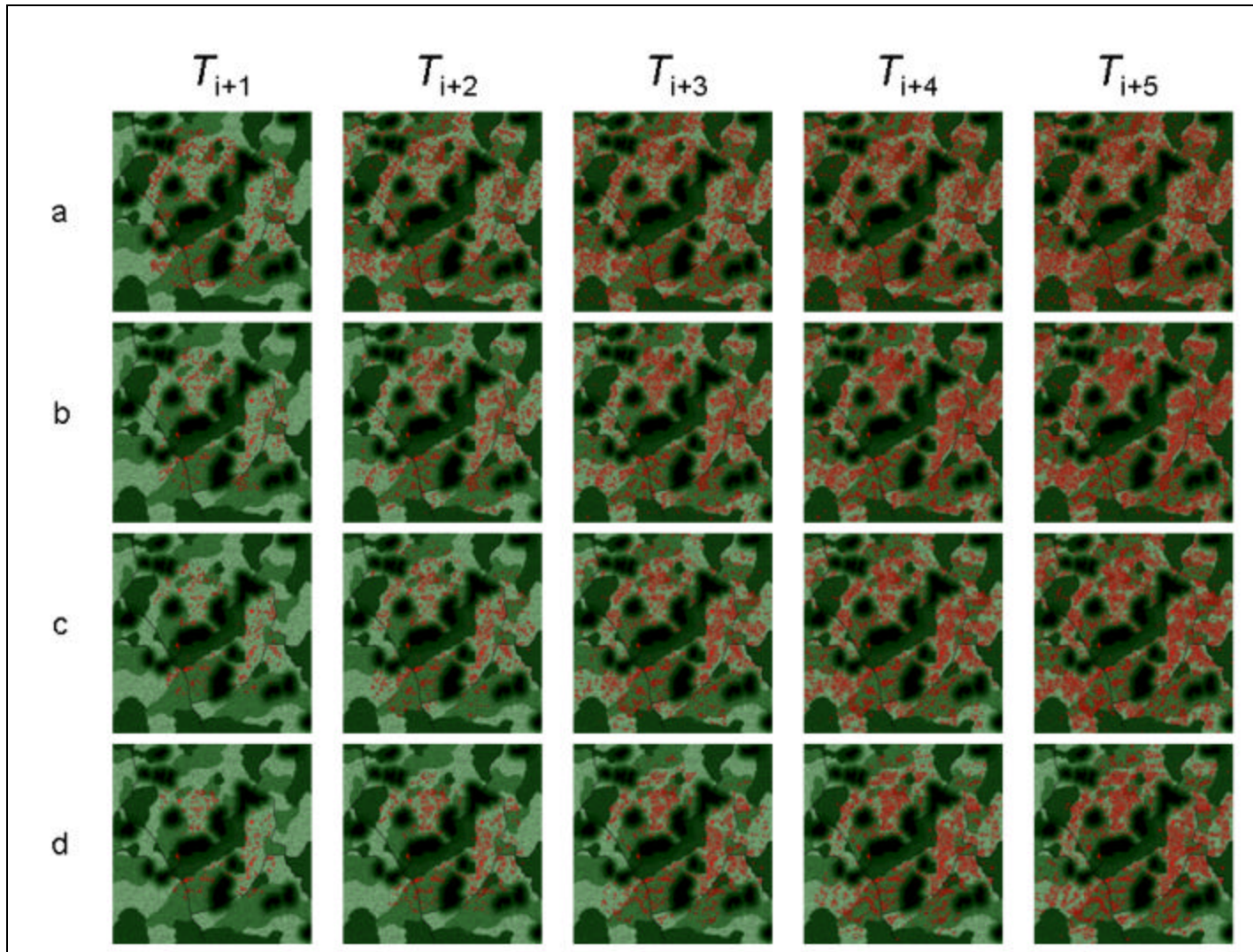


Figure 6. Five-year simulation of MPB-induced tree mortality patterns using a (a) 500 x 500 neighbourhood, (b) 400 x 400 neighbourhood, (c) 300 x 300 neighbourhood, (d) 200 x 200 neighbourhood.

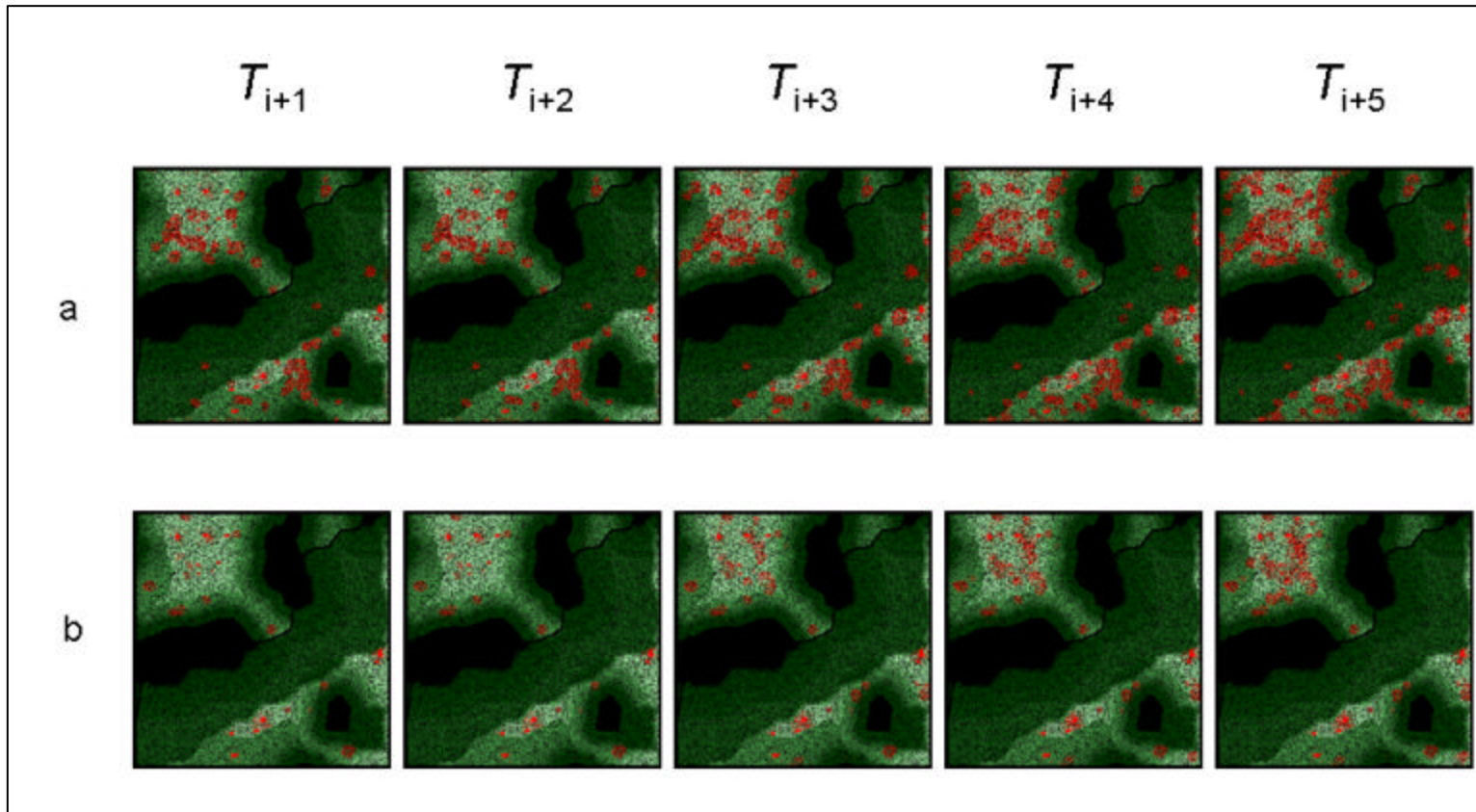


Figure 7. Five-year simulation of MPB-induced tree mortality for the central region using (a) the entire study area as the input for the model, and (b) using only the central quadrat as the input for the model.

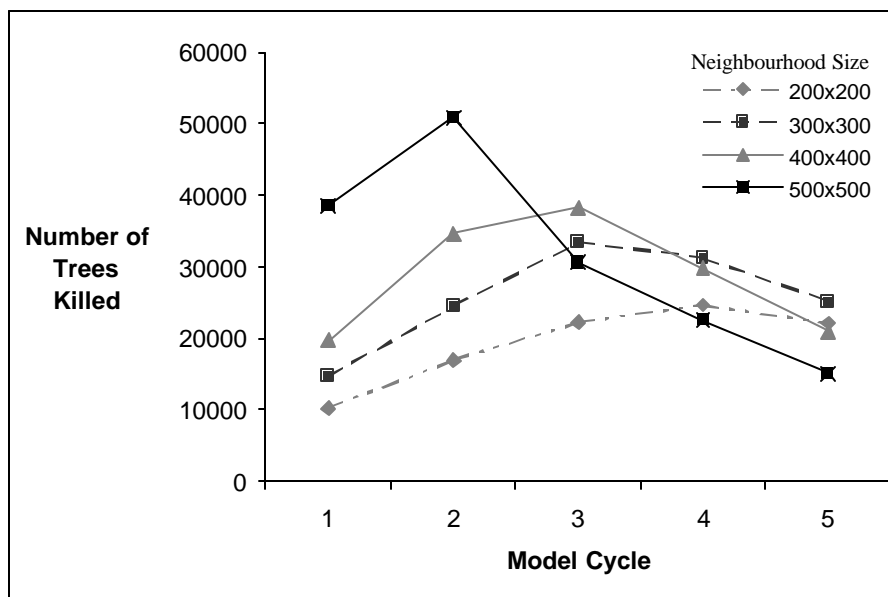


Figure 8. Number of trees killed at each cycle of the model for each neighbourhood size.

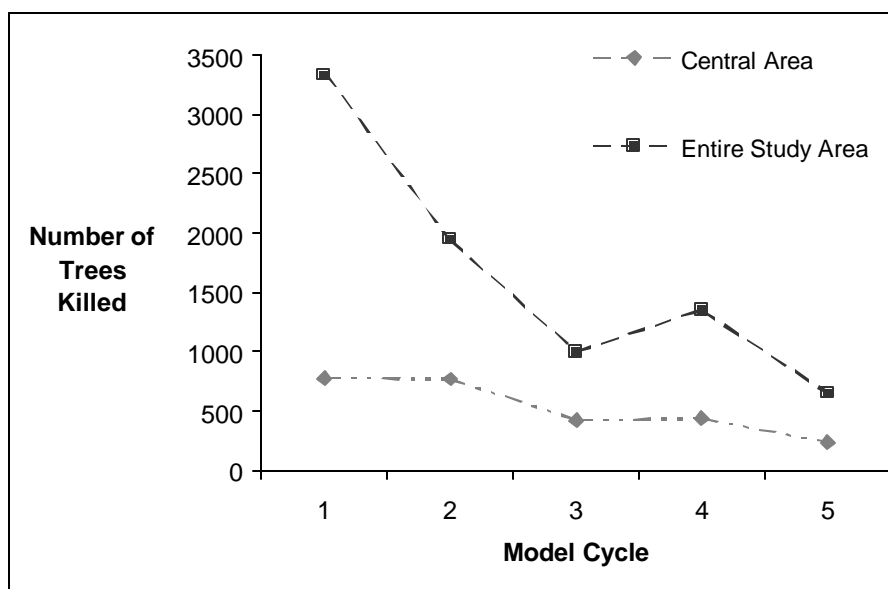


Figure 9. Number of trees killed at each cycle of the model for different size study areas.

## 5. Discussion

The results from the analysis of the *Tree Mortality Model* indicate that the model is significantly sensitive to the choice of the size of both the neighbourhood and study area. A visual and numeric analysis of the images from the five-year simulations of MPB-induced tree mortality patterns reveals several findings.

First, the results presented in Figure 6 clearly illustrate that smaller neighbourhoods result in less overall trees attacked during the first two cycles, which is confirmed by the information from Figure 8. The decrease in the number of attacked trees was due to two reasons. The first reason is that smaller neighbourhoods restrict the distance over which MPB will disperse through the forest. Large neighbourhoods include more trees, therefore highly susceptible trees that are relatively far from currently infested trees can still become attacked. Spot growth then commences once the distance trees are attacked, which creates new areas of infested trees. Smaller neighbourhoods limit dispersal and therefore result in more localized infestations that require more cycles in order to spread significant distances.

The second reason for fewer attacked trees when using a smaller neighbourhood for the first two cycles was because trees of low susceptibility were seldom attacked. The results show that low susceptible trees were not attacked until at least the third cycle for the simulations using the neighbourhood with 300 x 300 cells, and not until the fourth cycle for the 200 x 200 cells neighbourhood (excluding the trees that were already attacked at initial time  $T_i$ ). However, low susceptible trees were attacked in the first cycle when using the 500 x 500 cells neighbourhood. This difference is due to the fact that smaller neighbourhoods do not cover a large enough area for a sufficient amount of infested trees to be considered in order for low susceptibility trees to be attacked. This leads to few low susceptible trees attacked, and a large number of high susceptible trees to become attacked in a dense area when using the smaller neighbourhoods. Conversely, the results using the neighbourhood with 500 x 500 cells exhibit a more dispersed pattern of tree mortality as insect attack was more spread out due to high numbers of insects in the neighbourhood that allowed for mortality of both high and low susceptible trees.

Figure 8 also shows that after the second cycle tree mortality for the 500 x 500 and 400 x 400 cells neighbourhood decreases considerably for the remaining three cycles to the point where it is less than the tree mortality for the neighbourhood with 200 x 200 cells. This occurred because a significant number of trees were killed in the first two cycles using the larger neighbourhoods, which left fewer trees to attack in the remaining cycles. Whereas tree mortality occurred more slowly using the 200 x 200 neighbourhood, which allowed for more trees to be killed in the last cycle.

Similar observations were made when examining the results from testing model sensitivity using different study area sizes as presented in Figure 7. That is, the smaller study area received significantly less attacked trees for the central area than did the model using the entire study area. This is due to the fact that the smaller study area was not able to acknowledge MPB-infested trees in the areas adjacent to the boundaries of the study area. Therefore, there were significantly fewer infested trees in the neighbourhood of each tree, which resulted in small amounts of attacked trees in areas of high and medium susceptibility, and no attacked trees in areas of low susceptibility. Conversely, the results from using the entire study area demonstrate high

incidences of attacked trees in all areas because all the currently attacked trees were taken into consideration. Although tree mortality for the entire study area decreased significantly over the five cycles as shown in Figure 9, it still remained higher than tree mortality for the smaller study area.

It is important to consider the behaviour of MPB when deciding which is the appropriate neighbourhood and study area size due to the significant difference in patterns resulting from the CA model simulations. Safranyik et al. (1999) state that MPB disperse varying distances to attack highly susceptible trees first and more frequently than low susceptible trees. Less susceptible trees become attacked as MPB population increases as large areas became infested. Therefore, a larger neighbourhood (i.e. a 500 x 500 cells or 400 x 400 cells neighbourhood) and study area size is more appropriate as MPB disperse both near and far distances oppose to the smaller neighbourhood and study area simulations where MPB mostly dispersed in nearby areas. Furthermore, the CA model that uses larger neighbourhood and study area sizes also ensure that MPB attacked less susceptible trees once a sufficient amount of high susceptible trees were attacked and MPB population increased. However, the neighbourhood with 400 x 400 cells is more appropriate than the 500 x 500 cell-neighbourhood because the simulated patterns indicated too many low susceptibility tree may been attacked using the latter, which corresponds to the logic derived from Safranyik et al. (1999).

The importance of this study is that the parameters selected for CA modelling can significantly influence the results of the model. Parameters such as the neighbourhood have to be carefully selected in order to adequately represent the modelled phenomenon. The neighbourhood size was considered the most sensitive of the five CA components at the onset of this study because the use of graded susceptibility values  $\mu(Su)$  increased the importance of the number of attacked trees that were considered to be in the local area; therefore the neighbourhood size was tested and conclusions were drawn. However, this study can be extended to test the sensitivity to other components such as the size of the cells in the raster grid, the number of cell states, the types of transition rules or the number of iterations for which the model is performed. Furthermore, the choice of the size of the study area is important for CA modelling as small study areas can exclude important information that can cause major variations in the simulation results. Conversely, the use of study areas that are too large may provide redundant information while the geospatial data collection at high resolutions may be costly. Overall, these points stress the need for careful consideration when developing dynamic models for simulating complex spatial systems.

## **Acknowledgements**

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