Spatial-Temporal Analysis of Mountain Pine Beetle Infestations to Characterize Pattern, Risk, and Spread at the Landscape Level

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Abstract

An understanding of spatial processes is necessary when modelling and predicting mountain pine beetle (*Dendroctonus ponderosae* Hopkins) behaviour. The recent availability of large area, mountain pine beetle data sets enables new approaches to studying spatial processes of infestations. Our goal is to explore observed, landscape level, spatial and spatial-temporal patterns of mountain pine beetle infestations using data collected by the Morice Forest District. A better understanding of mountain pine beetle spatial behaviour will be obtained by: investigating the nature of error and information content of the data and improving data visualization; exploring spatial and spatial-temporal patterns in observed data; comparing observed spatial patterns with modelled expectations to identify areas with unexpected patterns; and exploring the landscape characteristics of areas that are statistically different from our expectation of mountain pine beetle behaviour. We provide an introduction to our project by presenting the objectives, methods, and some preliminary results.

Introduction

The increasing number of spatially explicit mountain pine beetle studies attest to the importance of incorporating spatial processes when modelling or predicting insect activity (e.g., Bentz et al. 1993; Powell and Rose 1997; Logan et al. 1998; Fall et al.2004). Spatial studies of bark beetles can be carried out at many different scales. For example, at a fine scale, the spatial patterns of individual insects within a gallery have been studied (Byers 1984), while at a coarser scale, the spatial pattern of tree mortality within a stand has also been analyzed (Mitchell and Preisler 1991; Preisler and Mitchell 1993). Landscape scale studies have been more limited due to a lack of large area data sets, with most using simulation of mountain pine beetle (*Dendroctonus ponderosae* Hopkins) processes, both spatial and aspatial, to better understand mountain pine beetle behaviour (e.g., Powell et al. 1996; Logan et al. 1998; Riel et al. 2004; Fall et al. 2004).

An influx of monitoring programs, combined with new technology and data acquisition methods, has generated large area, multi-temporal, mountain pine beetle data sets. For instance, point data on

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infestations has been collected for the Morice Forest District (1.5 million ha) since 1995. Using these data, we can explore observed spatial patterns in mountain pine beetle infestations. Pattern-based analysis can be used to better understand the spatial processes associated with mountain pine beetle infestations and may enable refinement of process-based models.

Our research goal is to explore landscape scale, spatial and spatial-temporal patterns in mountain pine beetle infestations by applying spatial statistical analysis tools to infestation data from the Morice Forest District. In this document, we outline our study objectives and provide an introduction to our research by describing research questions and methods, and presenting some preliminary results. We begin this discussion by describing data attributes and characteristics relevant to this study.

Study Area and Data

The Morice Forest District, near Houston, British Columbia (BC) (see Fig. 1), is currently experiencing epidemic numbers of mountain pine beetles. Bordered on the west by the Cascade Mountains and on the south by Tweedsmuir Provincial Park, the topography is gentle in the north and east, and mountainous in the southwest. Covering an area of approximately 1.5 million ha, the Morice Forest District is dominated by lodgepole pine (*Pinus contorta*) and spruce (*Picea*).

While the central and northern portions of the Morice Forest District were infested in the early and mid 1990s, the southern portion was infested later. Since there are many differences in mountain pine beetle activity, the northern, central, and southern areas of Morice are considered separately where appropriate in our analysis.

The Morice Forest District has used aerial surveys to monitor mountain pine beetle infestations since 1995. From helicopters, surveyors identify clusters of dying or infested trees and a global positioning system is used to record the location of the cluster centroids. For each cluster, the number of infested trees is estimated and the species of infestation is recorded. The maximum area associated with a location point is a circle with a radius of 100 m. However, points may represent smaller areas and variations are unknown.

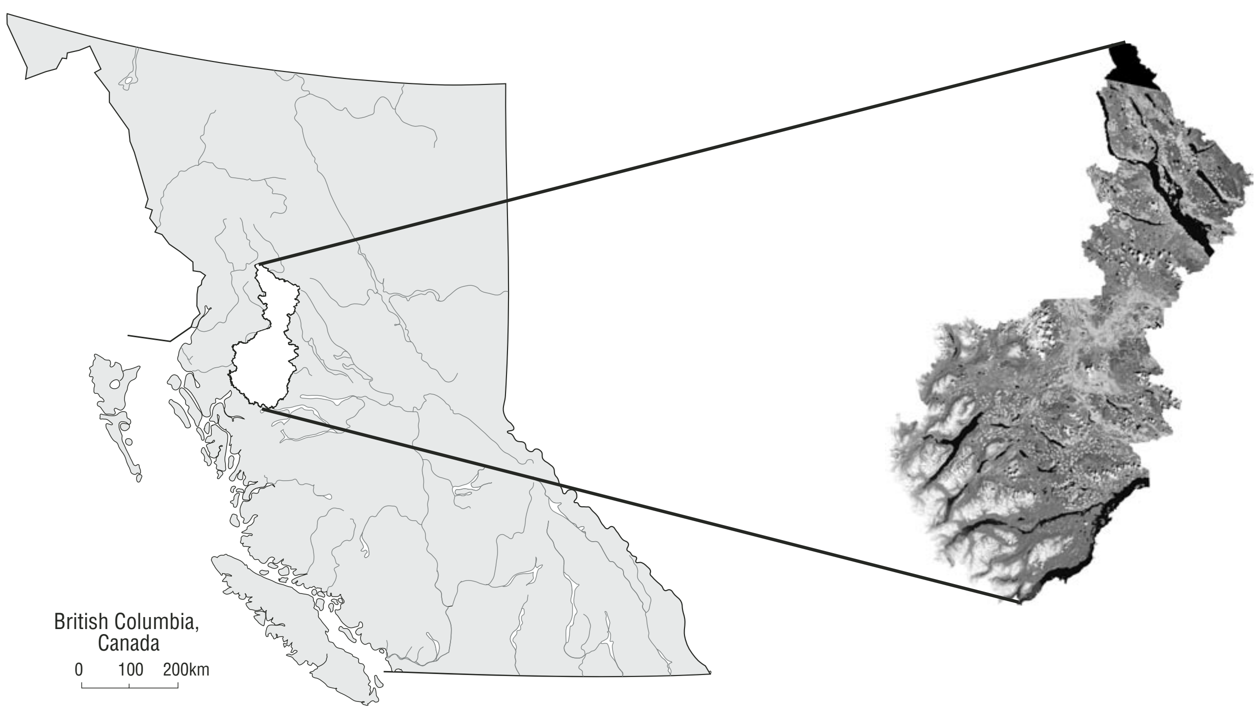


Figure 1. The Morice Forest District is centered in Houston, BC, Canada.

Field data associated with aerial surveys are available from 1999 to 2002. For 2001 and 2002, field visits were made for approximately 75% of aerial survey locations. However, field data from 1999 and 2000 are sparse. During field data collection, ground crews locate the infestation clusters that were recorded during aerial surveys and determine the cause of lodgepole pine mortality. If there are trees killed by mountain pine beetles, crews record the number of green trees currently under attack, the number of trees attacked the previous year, the number of trees attacked two years previously, and the number of trees attacked which are now grey. Later, field sites may be treated in an effort to reduce the impact of the mountain pine beetle, in which case the type of treatment is recorded.

Research Objectives

Our research objectives are grouped into four categories. The first category is the improvement of our understanding of the data by quantifying the information content of point-based, aerial surveys of mountain pine beetle infestations and demonstrating appropriate techniques for visualizing infestation data while considering data uncertainty. The second category is exploratory spatial analysis, including investigations of spatial and spatial-temporal trends in landscape level, mountain pine beetle activity. The third category involves the comparison of observed mountain pine beetle data to expectations conditioned on forest risk. Here we consider how to incorporate data uncertainty when generating a model of forest risk and we use statistical comparison of observed and modelled spatial patterns to identify interesting areas (hot spots) where unexpected patterns occur. The fourth category involves investigation of these hot spots. By analyzing the physical characteristics of areas underlying hot spots, relationships between site conditions and mountain pine beetle infestations can be determined. Such relationships will allow us to better understand model output and may be useful in identifying spatial parameters important for generating mountain pine beetle models.

Understanding the Data

As with all large area data sets, aerial surveys are prone to uncertainty. Therefore, when undertaking spatial analysis, a thorough investigation of data accuracy and information content is necessary to ensure confidence in results. Our comparisons of field and aerial data show that aerial data are useful for mapping the location and magnitude of infestations that occurred more than one year previously. In aerial point data, the majority of attribute values are small, as is the error associated with most individual survey locations. The cumulative impact of error, however, is considerable, as only 28% of survey points have the correct attributes. Although both errors of omission and commission occur, commission errors account for almost twice the uncertainty, and overall the distribution of errors approximates a gamma distribution.

The information available from point-based, aerial surveys is often difficult to visualize. Since aerial surveys are used to monitor large areas, data sets tend to be sizeable and difficult to represent. Simple cartographic techniques generally provide insufficient improvements (Fig. 2) and visualization is complicated by data uncertainty. Data visualization can be improved by converting point data to surfaces using kernel density estimators. As well, using a Monte Carlo approach and estimates of attribute error, kernel density estimators can be used to incorporate uncertainty into data visualization.

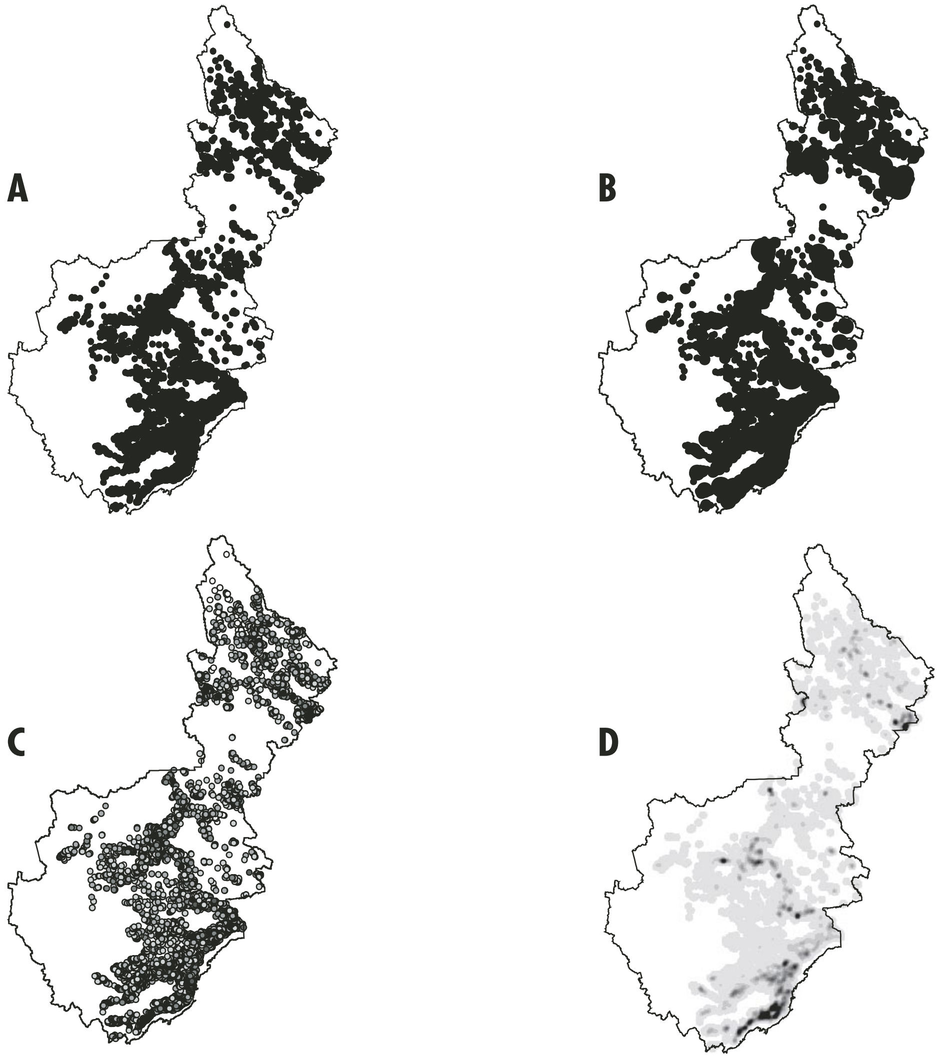


Figure 2. Comparison of data visualization techniques: A) Aerial survey points with no enhancements. B) Aerial survey point attributes represented as proportional symbols. C) Aerial survey point attributes represented as proportional colours. D) Aerial survey point attributes represented using a kernel density estimator. (darker locations have higher infestation).

For details on kernel density estimators we refer the reader to Silverman (1986) and Bailey and Gatrell (1995). Essentially, kernel density estimators can be used to visualize the intensity of events over space. Conceptually, the intensity $\lambda(z)$ at a particular location $\boldsymbol{z}$ in a study area A can be estimated by the naïve kernel density estimator

$$\hat{\lambda}(z) = \frac{\text{the number of events in a disk centred on } z}{\text{area of the disk}}$$

A more precise estimate, $\hat{\lambda}_\tau(\boldsymbol{z})$ is defined by

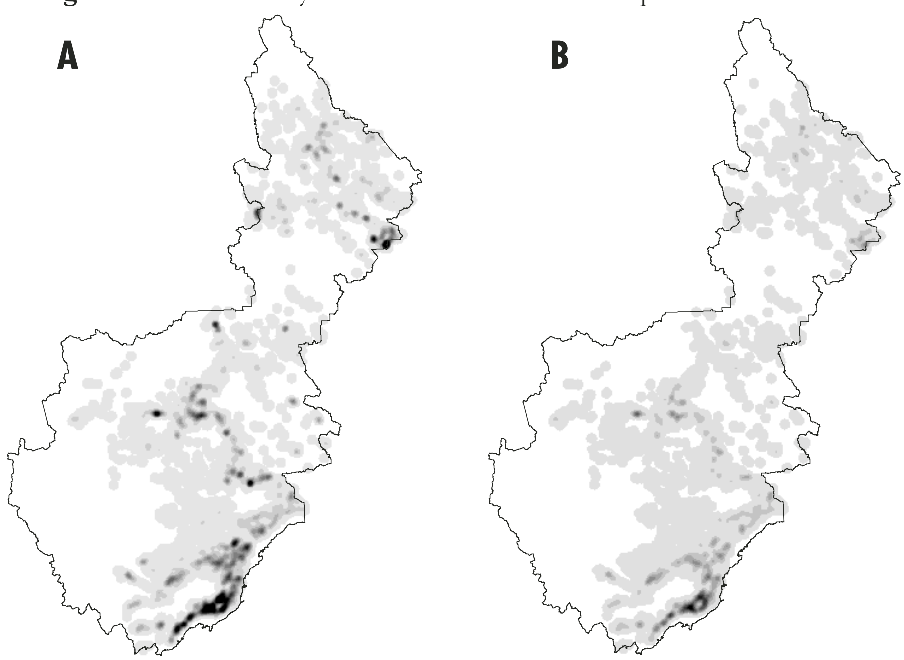
$$\hat{\lambda}_\tau(z) = \frac{1}{p_\tau(z)}\left\{\sum_{i=1}^{n}\frac{1}{\tau^2}k\left(\frac{(z-z_i)}{\tau}\right)y_i\right\} \quad z \in A$$

where $\boldsymbol{z}$ and A are defined as above, τ is the radius of a disk centered on $\boldsymbol{z}$, $k(\ )$ is the kernel or a probability density function which is symmetric around about the origin, $\boldsymbol{z}_i$ ($i = 1, \ldots, n$), are locations of

n observed events, and y_i is the attribute value at $\boldsymbol{z}_i$. The term $p_\tau(z) = \int_A k[(z - \boldsymbol{u})/\hat{o}]d\boldsymbol{u}$ is an edge correction equivalent to the volume under the scaled kernel centred on $\boldsymbol{z}$**,** which lies inside of A (Diggle 1985). The disk radius $\boldsymbol{\tau}$ is the most important parameter to consider when generating kernel density surfaces as it controls the amount of data smoothing. For this research, $\boldsymbol{\tau}$ was set equal to 2 km, optimizing improvements to data visualization while retaining detail. Also this value is sufficiently large to be relatively robust with respect to any errors in the locations of the points (approximately 25 m maximum). Further, given the size of the kernel relative to the study area, the impact of edge effects was considered negligible and no edge correction was applied.

In brief, the method for incorporating uncertainty in kernel-estimated density surfaces is as follows. Possible realizations of point locations and attribute values are generated by randomly drawing values from a gamma distribution, whose parameters were estimated by fitting a distribution to the field data using a maximum likelihood estimator. Spatial uncertainty is incorporated by randomly drawing values for both the x and y coordinates from a normal distribution with a mean of 0 and standard deviation of 1. These values are scaled to ±25 m, which is the spatial uncertainty estimated by field crews. One hundred point realizations are generated and a kernel density surface is produced for each realization. The 100 kernel density surfaces are summed and averaged to generate a final kernel density surface incorporating uncertainty. Most often, aerial survey attributes are overestimated; therefore, when kernel density surfaces are corrected, attribute values generally decrease (Fig. 3 and Fig. 4).

Figure 3. Kernel density surfaces estimated from aerial points and attributes.



A) Kernel density surface without consideration of data uncertainty.
B) Kernel density surface including data uncertainty. Darker tones are higher values.

Exploratory Spatial and Spatial-Temporal Analysis

Kernel-estimated density surfaces are useful for investigating spatial patterns in a single time period and may be used to relate landscape characteristics to variations in infestation magnitude. Using the corrected kernel-estimated density surfaces, infestations were categorized as intense or non-intense, where intense infestations are defined as values in the 90th percentile of the kernel density surface frequency distribution (Fig. 5). The 90% threshold identifies areas with landscape characteristics that were distinctive relative to less infested and non-infested areas. The spatial distributions of intense and non-intense infestations were compared with landscape characteristics such as pine age, percent of pine in a stand, elevation, aspect, and slope in the northern, central and southern portions of the study area. The relationship between infestation intensity and forest age is demonstrated in Figure 6. Forest age classes were determined using the forest inventory data representative of forest characteristics in 1999. Forest age classes were as follows: 1 (1-20 years); 2 (21-40 years); 3 (41-60 years); 4 (61-80 years); 5 (81-100 years); 6 (101-120 years); 7 (121-140 years); 8 (141-250 years); and 9 (> 250 years).

In the northern sub-area, the pine age classes underlying both intense and non-intense infestations approximately follow the distribution of age classes in the area. While age class 8 (141-250 years) is most heavily infested, it is not attacked more often than anticipated if the mountain pine beetle randomly selected host trees. This is likely related to the infestation history. The mountain pine beetle infestations in the north were intense in 1996 and 1997. By 2001 there was little mature pine remaining as most has been infested or harvested. However, the forest age data is based on conditions in 1999; thus, there appears to be more mature pine than would actually be available in 2001 and 2002.

In the central sub-area, mountain pine beetle preferred age class 7 (121-140 years) when the infestation was intense and age class 8 when the infestation was non-intense. In this area, stands of age class 7 have a higher percentage of pine (mode = 70% pine) than stands with age class 8 (mode = 30% pine). As a result, most age class 8 stands have relatively few trees available for infestation, so the most intense infestations are found elsewhere.

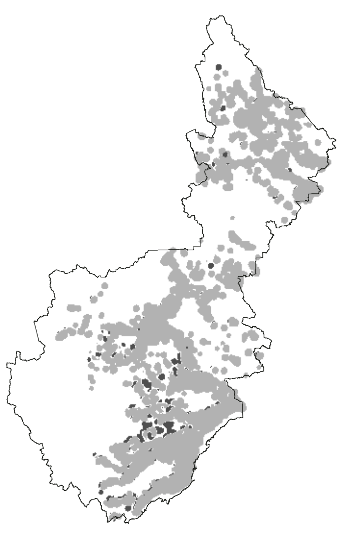


Figure 4. Difference in kernel densities calculated with and without corrections. Gray represents areas where the correction resulted in a decrease in infestation values and black represents locations where the correction generated an increase.

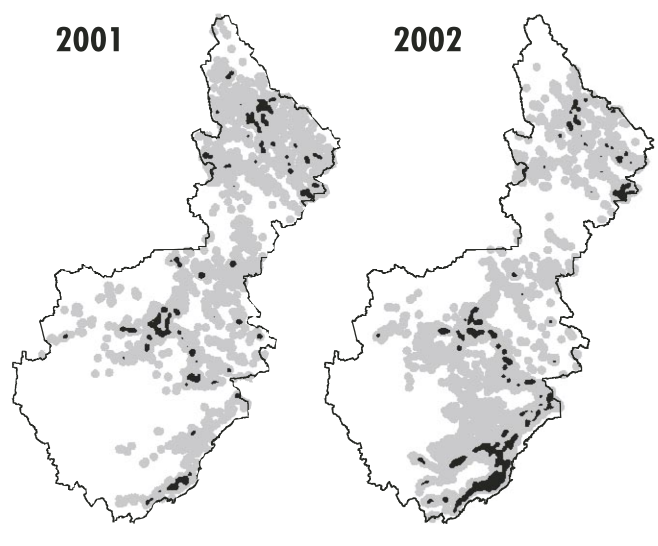


Figure 5. Variation in infestation intensity in 2001 and 2002. Black represents intense infestations, grey represents non-intense infestations, and white represents no infestation.

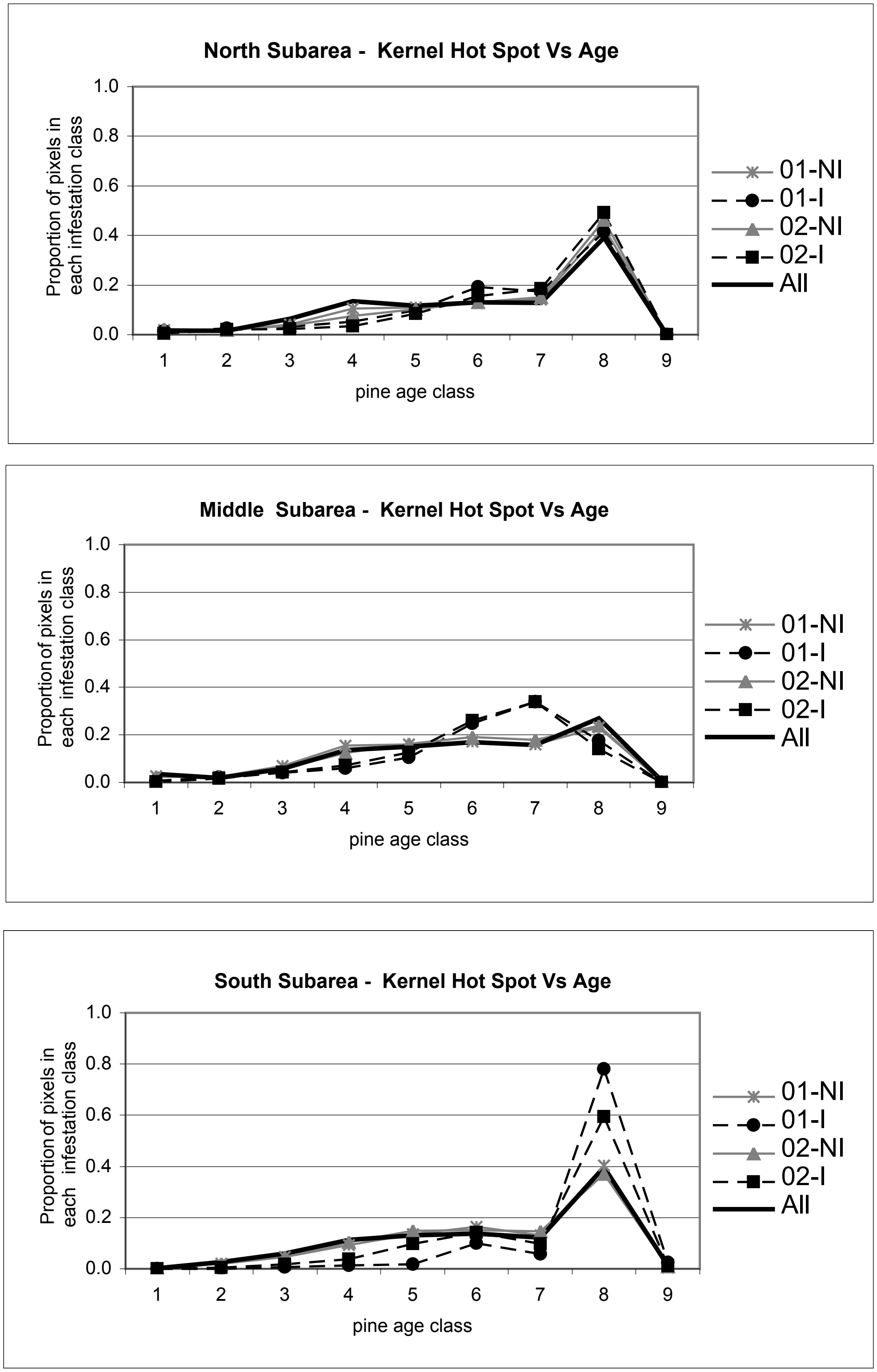


Figure 6. Comparison of pine age classes underlying intense and non-intense infestations in 2001 (01) and 2002 (02). I = intense infestations, NI = Non-intense infestations, and All = the distribution of all pine locations within the study area.

In the southern sub-area, age classes associated with non-intense infestations have a similar distribution to the overall distribution of forest age. However, the intense infestations rarely occur when trees are young and are most frequently associated with age class 8. Clearly, host age selection is not random. In 2001, almost all intense infestations occurred in age class 8. In 2002, most intense infestations were associated with age class 8 forests, although intense infestations were increasingly found in younger forest age classes. In the south, mountain pine beetles first appeared in large quantities in 2000. Therefore, in 2001 many age class 8 trees, which are the hosts preferred by mountain pine beetle, were available. By 2002, fewer age class 8 trees were available, so the mountain pine beetle began infesting younger age classes.

Kernel-estimated density surfaces can also be used to explore spatial-temporal patterns in mountain pine beetle infestations. By differencing surfaces, we can represent temporal change in the spatial pattern of mountain pine beetle infestations and investigate methods of defining meaningful change. Here we define meaningful change in mountain pine beetle infestations using the 5% tails of the distribution of a surface of change (e.g., surface 2002 – surface 2001). An example is shown in Figure 7 where change is represented between 2001 and 2002. While this definition allows the threshold for significant or meaningful change to vary depending on mountain pine beetle activity in the whole area, 10% of the infested area is always considered to have changed meaningfully. From the perspective of forest monitoring, this method is useful as it is flexible enough to identify areas of change relative to resources available for mitigation. For instance, if resources are available to treat 25% of the affected Forest District, the thresholds can be changed to identify the most impacted 25%. To better understand why change varies over space, change will be compared with landscape characteristics and methods of treating mountain pine beetle infestations.

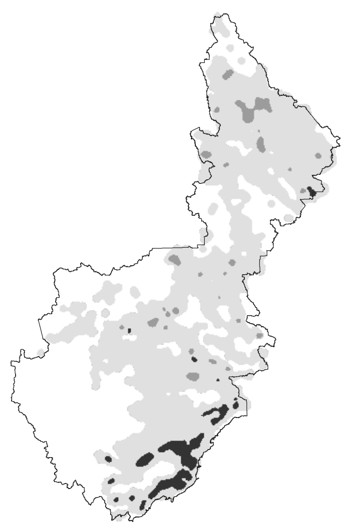


Figure 7. Change between 2001 and 2002. Significant change is defined as values in the 5% tails of the distribution of a surface of change. Black areas represent locations where mountain pine beetle activity has increased significantly, dark gray areas represent a significant decrease, and light gray areas represent locations of change that are not significant.

Comparing Observed Data with Mountain Pine Beetle Model Expectations

Quantitative analysis of spatial patterns generally involves the comparison of an observed spatial pattern to some expected pattern. Most often, the expected pattern is generated assuming a process of complete spatial randomness (Upton and Fingleton 1985). However, due to aggregative behaviour and mountain pine beetles' need of lodgepole pine, it is unlikely that the spatial pattern of infested trees is random. Thus, comparing observed patterns in infestation data to a random expectation seems inappropriate.

A more suitable expectation of spatial pattern may be generated based on the present understanding of mountain pine beetle behaviour. For example, we know that the location of trees infested by mountain pine beetles in the current year is not random, but rather related to the site of infested trees in the previous year. An expectation that incorporates knowledge of mountain pine beetle behaviour will allow statistical significance to be used to identify hot spots or locations where the pattern is unexpected based on the current understanding.

The Shore and Safranyik forest risk model (Shore and Safranyik 1992; Shore et al. 2000) calculates the probability that forests will be infested based on forest characteristics, beetle location, and population size. The probability of risk derived from this model may be used to condition the randomization of attributes within a specific time period, thereby allocating more infestations to locations with a higher likelihood of risk. Based on this model, we can identify hot spots, or locations where the spatial pattern of mountain pine beetle infestations is unexpected.

As hot spots will be detected using randomizations conditioned on the forest risk model, the value of our quantitative analysis is directly related to the quality of the forest risk model, which, in turn, is impacted by the quality of the input data. Inputs to the forest risk model include forest inventory data and mountain pine beetle aerial survey data, both of which are prone to error. Consequently, it will be useful to investigate methods to incorporate data uncertainty when modelling forest risk.

There are two sources of uncertainty that are of concern when working with forest inventory data. First, the attribute values attached to different forest characteristics tend to be uncertain. Secondly, in some instances, the input parameters required for modelling forest risk are not provided in the forest inventory data. As no other data source exists, surrogate input parameters available from the forest inventory data must be used and the impact of this should be investigated. There are also two important considerations regarding error in the mountain pine beetle data. The first is the spatial and attribute error discussed above. The second issue is that some areas are treated to mitigate mountain pine beetle populations, while others are not. Two mountain pine beetle populations of similar size, one treated and the other not, will likely have different impacts on forest risk. How to deal with these sources of uncertainty when modelling forest risk will be considered.

Investigating Hot Spots

Hot spots represent areas that are poorly predicted, based on our present understanding of mountain pine beetles. Therefore, investigations into the characteristics underlying hot spots may provide new insights as to why mountain pine beetle activity in some areas is poorly predicted. Landscape characteristics of particular interest include elevation, aspect, slope, forest age, and stand species compositions.

Conclusion

Understanding landscape-scale spatial and spatial-temporal processes of mountain pine beetle infestations is important when modelling and predicting mountain pine beetle behaviour. New, large area data sets provide a vehicle for understanding spatial processes through the exploration of observed spatial patterns. Knowledge of the error and information content of aerial survey data is essential when using such data for spatial pattern analysis. Improved visualization, which includes the incorporation of data uncertainty, allows examination of spatial and spatial-temporal patterns. Quantitative analysis undertaken by comparing observed spatial patterns to those expected, based on our current understanding of mountain pine beetle behaviour, allow hot spots, or areas where the spatial pattern does not meet our expectation, to be identified. By investigating the landscape characteristics underlying hot spots we hope to generate new insights that can be meaningfully combined with ongoing mountain pine beetle modelling.

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Trisalyn Nelson is a Ph.D. candidate at Wilfrid Laurier University.

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