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Spatial and spatial-temporal analysis of mountain pine beetle infestations at a landscape scale

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SPATIAL AND SPATIAL-TEMPORAL ANALYSIS OF MOUNTAIN PINE BEETLE INFESTATIONS AT A LANDSCAPE SCALE

by

Trisalyn Anna-Lisa Nelson
(Geography M.Sc., University of Victoria, 2001)

THESIS
Submitted to the Department of Geography
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ABSTRACT

The impact of the current mountain pine beetle (*Dendroctonus ponderosae* Hopkins) epidemic in British Columbia underscores the need for scientifically informed management practices. During an epidemic it is necessary to manage large areas and an understanding of landscape scale spatial and spatial-temporal processes is required. With the recent availability of large area, multi-temporal data sets there are new opportunities for landscape scale studies of the mountain pine beetle over space and through time.

In this thesis large area spatial and spatial-temporal patterns of lodgepole pine (*Pinus contorta* var. *Latifolia*) mortality are explored using point data collected through helicopter surveys. As with all large area data sets, mountain pine beetle data are prone to uncertainty. Using field measurements collected to supplement the helicopter data set, we explore the nature and amount of error in point data. Based on error estimates, a method is presented for incorporating uncertainty when visualizing data via kernel density estimation.

Locations that are hot spots, or have the most intense infestations, are identified and used to explore dispersal behaviour. Comparing hot spots to various landscape characteristics allows investigation into how mountain pine beetle utilize the forest in space and through time. Locations of change are also identified and explored in terms of spatial-temporal patterns and associated landscape characteristics. The relatedness of hot spot and change locations is investigated.

A randomization approach is also used to supply the spatial pattern of large area infestations by evaluating observed data relative to a null expectation conditioned on a model of forests at risk to beetle attack. Investigating the landscape characteristics associated with unexpected locations enabled exploration into the cause of differences between empirical and modelled patterns.

ACKNOWLEDGEMENTS

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DEDICATION

To my mom.

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1 INTRODUCTION

1.1 CONTEXT

The mountain pine beetle (*Dendroctonus ponderosae* Hopkins) is endemic in pine (*Pinus*) stands throughout Western North America (Safranyik *et al.,* 1974). At endemic levels, the impact of the mountain pine beetle on forests is relatively minor. However, periodic epidemics, or outbreaks, result in large areas of lodgepole pine (*Pinus contorta* var. *Latifolia*) mortality. Currently, British Columbia is experiencing the largest infestation on record, with more than seven million hectares of lodgepole pine affected by the mountain pine beetle(Westfall, 2004). Particularly in the interior of British Columbia, where communities are built on forest-based employment, the economic impacts of the mountain pine beetle outbreak will be severe. With no foreseeable end to the current epidemic, there is a reinforced need for scientifically informed management practices.

As with many natural phenomena, spatial and spatial-temporal interactions are an essential aspect of mountain pine beetle behaviour (Turchin, 1989; Logan *et al.*, 1998; Liebhold and Gurevitch, 2002). Examples of spatial behaviour include: the aggregation of individual mountain pine beetles in response to chemical signals (Geiszler *et al.*, 1980), the effect of the spatial distribution of individual trees on the spatial pattern of attack (Mitchell and Preisler, 1991), and differences in the spatial pattern of infestations resulting from endemic and epidemic populations (Logan *et al.*, 1998). Although there is much evidence that spatial components of mountain pine beetle behaviour are important, spatially explicit research is limited.

The development of spatial mountain pine beetle research parallels, generally, the process by which spatially explicit studies became mainstream in ecology. For ecologists, spatial structure was initially considered a nuisance, invalidating assumptions of homogeneity (McIntosh, 1985). However, in the 1980's perspectives on spatial structure changed (Liebhold and Gurevitch, 2002). Spatial structure began to be viewed as a source of information, and it was recognized that spatial knowledge was necessary for understanding the physical environment and our interactions with it (Legendre and Fortin, 1989; Kareiva, 1994; Perry *et al.*, 2002). By the mid 1990s, the utility of considering space was widely recognized, yet direct spatial studies of ecological phenomena were few and explicit exploration of space was still seen by some as the final frontier for ecologists (Kareiva, 1994).

Discipline-wide recognition of the importance of space was only the first step to acquiring spatial knowledge. Integrating space with ecology required techniques that allowed for spatial heterogeneity, the availability of spatial data sets, and ecologists with spatial expertise. Much of the groundwork for current spatial research in ecology was carried out in the 1980s and early 1990s as scale, spatial heterogeneity, and spatial pattern were explored (Legendre and Fortin, 1989; Wiens, 1989; McIntosh, 1991; Levin, 1992). Owing to this earlier work, significant efforts have now been undertaken in the exploration of spatial processes and spatially explicit studies are frequently found in a wide range of ecology-focused journals (*e.g.*, Liebhold and Gurevitch, 2002; Matthiopoulos, 2003; Wu, 2004).

In spatial mountain pine beetle research, a similar series of developments are ongoing. While the importance of considering space has been acknowledged for some time (Bentz *et al.*, 1993; Logan *et al.*, 1998), an understanding of mountain pine beetle spatial behaviour is still in its infancy (Hughes, 2002). Spatial studies, carried out by a handful of researchers, have undoubtedly improved our understanding of spatial mountain pine beetle behaviour (*e.g.*, Mitchell and Priesler, 1993; Powell *et al.*, 1996; Powell *et al.*, 2000). Although the number of spatial studies is increasing, spatial research on the mountain pine beetle, and more generally in entomology, is not yet mainstream.

The current understanding of large area mountain pine beetle spatial and spatial-temporal behaviour is cursory. Most spatial and spatial-temporal studies of mountain pine beetle have been undertaken at forest stand or finer spatial scales. While knowledge of fine scale mountain pine beetle spatial processes is necessary, it should not be assumed that the same processes operate at a landscape level. Given the size of the current infestation in British Columbia, there is a particular need to understand mountain pine beetle spatial behaviour at a landscape scale, as outbreaks impact large areas.

There are several practical reasons for the lack of landscape scale spatial studies of the mountain pine beetle. First, mountain pine beetle behaviour is complex and when spatial parameters are considered, the additional dimensions result in computationally expensive analysis (Powell *et al.*, 1996). While increases in analytical complexity are often manageable for small area studies, over larger areas, computational requirements may become prohibitive. A second difficulty inherent to landscape scale spatial research is the limited availability of large area data sets. Until quite recently, large area data on mountain pine beetle infestations have been difficult to obtain and multi-temporal data sets unavailable. Changes in technology, such as faster computers and increased storage capabilities, and improved data availability, due to increased funding for mountain pine beetle monitoring and better access to remotely sensed imagery, mean that large area analysis of mountain pine beetle spatial behaviour is now possible.

The spatial-temporal behaviour of the mountain pine beetle, which is also understudied, is fundamental for improving mountain pine beetle prediction and modelling. Spatial-temporal analysis has additional limitations over pure spatial analysis owing to the existence of relatively few methods for analyzing both space and time, or changes in space through time (Anselin, 2000; Box, 2000; Jacquez, 2000). The lack of spatial-temporal methods poses difficulties for spatial analysis in general, while fundamental concerns regarding data representation in space and time have yet to be resolved (Heuvelink, 1996; Peuquet, 1999). Aside from technical limitations, spatial-temporal analysis of the mountain pine beetle is further complicated by a lack of theoretical information on space-time processes. Many basic spatial-temporal questions regarding mountain pine beetle dynamics, such as the definition of meaningful change in infestation magnitude, have not been addressed. These fundamental gaps in knowledge suggest that space is not the final frontier for ecologists. Rather, led by the increasing temporal resolution of data sets, and concern with issues such as climate change, there is a pressing need to consider spatial-temporal patterns and processes. Only by exploring both space and time is it possible to make meaningful environmental predictions and informed decisions.

Another factor, impacting both spatial and spatial-temporal studies, applies broadly to the transfer of spatial analysis to many disciplines. Proper use of spatial analysis methods requires consideration of several issues; therefore, a certain amount of expertise in spatial theory and spatial analysis software is required to ensure the integrity of analysis. For instance, consideration must be given to data representation (Miller, 2000), analysis resolution and extent (Wiens, 1989), neighbourhood definition (Davis *et al.*, 2000), and the selection of appropriate null models (Fortin and Jacquez, 2000). Often individuals with knowledge of specific applications do not have expertise in spatial analysis, and vice versa. This may explain why the majority of spatial research in entomology is carried out by a small group of researchers (*e.g.*, Liebhold *et al.*, 1994; Powell *et al.*, 2000).

As will be discussed in Chapter 2, most spatial studies of mountain pine beetle observe or model spatial processes, rather than consider spatial pattern. A spatial pattern is the expression of one or more spatial processes (Getis and Boots, 1978; Haining, 1990), and a process is considered spatial when changes in state are due to the spatial properties of the attribute (Haining, 1990). Observations of mountain pine beetle spatial processes are made locally via mark recapture studies. Alternatively, mathematical models may be used to mimic spatial processes. While modelling has an important role in furthering our understanding of mountain pine beetle spatial behaviour, efforts would benefit from a better understanding of spatial processes (Hughes, 2002).

A limitation of the spatial process approach is that, as with many environmental phenomena, direct data on spatial processes of the mountain pine beetle, particularly over large areas, is difficult if not impossible to obtain. In such cases, spatial pattern may be used as a surrogate for studying spatial processes. By characterizing spatial patterns we make inferences regarding processes (Getis and Boots, 1978; Sokal *et al.*, 1998; Jacquez, 2000). Unfortunately, the relationship between pattern and process is complex (Fortin *et al.*, 2003). Most often a spatial pattern will result from several processes, and it may be difficult to identify all contributing processes or to know the impact of each process on the pattern (Jacquez, 2000). For example, the spatial pattern of trees infested by mountain pine beetles is affected by factors such as forest age (Safranyik *et al.*, 1974), climate (Logan and Bentz, 1999), and the spatial pattern of trees previously infested (Mitchell and Preisler, 1991). To further complicate matters, there is often positive feedback between pattern and process. For instance, it is understood that the process of mountain pine beetle infestation impacts the spatial pattern of individual tree mortality during a mountain pine beetle epidemic; yet, it appears that the pattern of individual trees may impact the process of infestation (Preisler and Mitchell, 1993). While spatial patterns often provide the best available information on spatial processes, it is difficult to isolate which process(es) are responsible for a pattern. This combined complexity (*i.e.,* multiple processes give rise to a single pattern) and necessity (*i.e.,* spatial pattern is often the only available spatial information), may be one reason that pattern-process interactions have been highlighted as a major research priority in landscape ecology (Wu and Hobbs, 2002).

1.2 GOALS AND OBJECTIVES

Our research goal is to explore landscape scale spatial and spatial-temporal patterns of lodgepole pine mortality caused by epidemic mountain pine beetle populations. Understanding the spatial structure of infestations will allow us to characterize the spatial behaviour of the mountain pine beetle over the landscape, and will generate new information for modellers and decision makers working towards improved knowledge and better management practices. The goal of this research will be met using the objectives listed below.

1. To investigate the information content of point-based, aerial surveys of mountain pine beetle infestations, and to demonstrate appropriate techniques for visualizing spatial patterns in infestations while considering data uncertainty (Chapter 4).

2. To explore spatial and spatial-temporal variation in mountain pine beetle infestation intensity by locating attack hot spots, characterizing the persistence of hot spots through time, investigating spatial-temporal relationships between hot spot patches, and relating the presence and persistence of hot spots to landscape characteristics (Chapter 5).

3. To identify locations of spatial-temporal change in mountain pine beetle infestations, investigate spatial relationships in change through time, and relate change to landscape characteristics (Chapter 6).

4. To study the spatial correspondence between hot spots and change (Chapter 7).

5. To investigate landscape level application of a stand scale forest risk model, by identifying locations where infestation intensity is unexpected relative to a random expectation conditioned on forest risk, to represent unexpected areas through time, and to investigate the landscape properties underlying unexpected locations (Chapter 8).

First however, we provide background information on the biology and spatial studies of the mountain pine beetle (Chapter 2), and describe the study area and the data sets used throughout this thesis (Chapter 3).

2 MOUNTAIN PINE BEETLE BACKGROUND

2.1 MOUNTAIN PINE BEETLE AND PINE BIOLOGY

As the mountain pine beetle is a native species in Western North America, they are an important component of forest disturbance, development, and health. By infesting and killing lodgepole pine, western white pine (*Pinus monticola*), and ponderosa pine (*Pinus ponderosa*), the mountain pine beetle naturally disturbs the forest and aids forest succession (Safranyik *et al.*, 1974; Parminter, 1998). In this chapter we provide background information necessary for justifying the goals and interpreting the results of this thesis. We begin with a discussion of mountain pine beetle and forest biology, and then review spatial research on the mountain pine beetle.

Although the mountain pine beetle mechanism for host selection is debateable, it has been well documented that mature pines are preferred (Safranyik *et al.*, 1974; Geiszler *et al.*, 1980; Preisler and Mitchell, 1993). Large trees provide the mountain pine beetle with optimal food resources (thicker phloem), protection from cold and predators (thicker bark), and are less able than younger trees to resist beetle attacks (Safranyik *et al.*, 1974; Larsson *et al.*, 1983). However, in trees older than 150 years, phloem may become too thin to support mountain pine beetle broods (Shrimpton and Thomson, 1985). Stand age impacts the duration and intensity of an infestation and older stands will typically have longer and more intense infestations (Safranyik *et al.*, 1999). Even though within a stand larger trees are attacked first, once the infestation has established, younger trees will also be infested (Safranyik *et al.*, 1974; Mitchell and Preisler, 1993). A key reason for the current epidemic in British Columbia is the abundance of mature lodgepole pine.

Mountain pine beetle attacks on pine are initiated by female, pioneer beetles (Safranyik *et al.*, 1999) and involve a complex series of interactions between beetles and the tree (Geiszler *et al.*, 1980). Through a reaction with a pine chemical compound (myrcene), the mountain pine beetle produces an aggregation pheromone (brevicomin) initially attracting males (when concentrations are high) and eventually both sexes (as concentrations decrease) (Powell and Rose, 1997; Barclay *et al.,* 1998). To ensure that limited resources are not over-exploited, male beetles produce an anti-aggregation pheromone (verbenone) (Amman, 1994; Powell and Rose, 1997; Barclay *et al.,* 1998). As the host reaches carrying capacity the anti-aggregation pheromone becomes stronger than the aggregation pheromone, and pioneer mountain pine beetles move to another host.

Mountain pine beetles attack *en masse* to overwhelm the defence system of the pine tree (Geiszler *et al.*, 1980). After boring through a tree's bark, the beetle carries blue stain fungus to the phloem and xylem (Figure 2.1 - A). The fungus disturbs water flow, which the pine tree requires to generate a resinous pitch used to saturate the phloem and sapwood around the borehole (Safranyik *et al.*, 1974; Raffa and Berryman, 1982; Unger 1993). This process is called "pitching-out" and is a key defence against attacking mountain pine beetles. Mature and unhealthy trees have lower pitch production than young vigourous trees. Therefore, as age and stress increase, there is a decrease in the tree's resistance to infestation (Raffa and Berryman, 1982; Larsson *et al.*, 1983; Mitchell *et al.*, 1983; Berryman, 1982). It has been suggested that the pine's ability to respond to blue stain fungal invasion is the main characteristic that determines the tree's ability to resist mountain pine beetle attack (Raffa and Berryman, 1982).

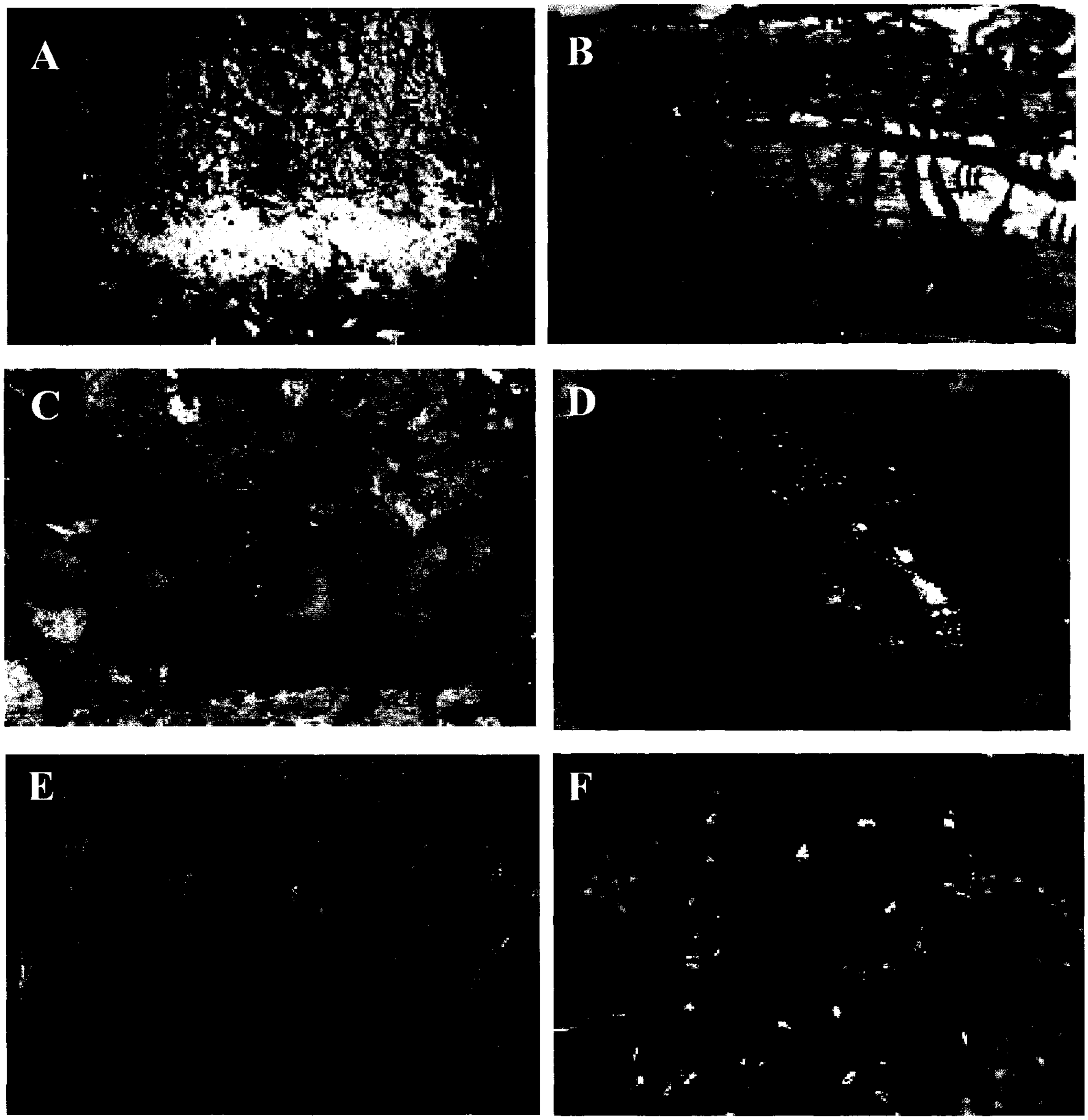


Figure 2.1. The biology of the mountain pine beetle and pine. A) Boring dust. B) Egg galleries. C) Oval chambers used for the transformation into pupae. D) The adult mountain pine beetle. E) Phases of tree mortality. F) Pitch tubes or resin created by the pine to plug boreholes. (Photos from http://www.for.gov.bc.ca/hfp/mountain_ pine_beetle/bbphotos.htm. Last accessed April 17, 2005.)

Pine mortality tends to be greatest when stand densities are intermediate (Amman *et al.*, 1988). As a result, stand thinning is one approach that has been investigated to improve tree vigour (*e.g.*, Larsson *et al.*, 1983; Preisler and Mitchell, 1993; Whitehead *et al.*, 2001). Under certain conditions, silvicultural treatments such as thinning, may minimize stand loss and susceptibility (Mitchell *et al.,* 1983; Anhold and Jenkins, 1987; Whitehead *et al.*, 2001). Stand thinning increases canopy openness, causing changes to the microclimate and tree vigour, and may result in a short-term reduction in tree susceptibility (Powell *et al.*, 2000; Whitehead *et al.*, 2001). Although thinning may be beneficial in some scenarios, under epidemic conditions mature trees are susceptible regardless of stand management (Preisler and Mitchell, 1993).

If the mountain pine beetle successfully overcomes the tree's defence mechanisms, egg galleries 30 to 90 centimetres long will be constructed below the bark (Figure 2.1 - B) (Safranyik *et al.,* 1999). Eggs are laid 0.5 centimetres apart and are tightly packed with frass or boring dust, hatching in 10 to 14 days. Larvae feed on phloem over the winter and mature in the early summer when they excavate an oval chamber to use during transformation into pupae (Figure 2.1 - C). After a short period as pupae they become adults (Figure 2.1 - D) and emerge by boring back through the bark.

Mountain pine beetle emergence has a significant influence on the success and size of populations. Mass, simultaneous emergence is required for the mountain pine beetle to have a large impact on the forest, as many individuals are required to successfully attack even a single host. The timing of emergence is influenced by seasonal and daily temperatures (Safranyik *et al.,* 1989), whereas the number of emerging beetles is related to the size of attacked trees. The larger the tree, the more beetles will emerge (Safranyik *et al.,* 1974); and if trees are small, fewer beetles will emerge from the tree than were required to kill it. In that way, small trees act as beetle sinks. Although emergence usually occurs once a year, if summers are unusually warm, parent adults may re-emerge and establish a second brood (Reid, 1962; Safranyik *et al.,* 1999).

Development of an infestation on the landscape is based on the spatial arrangement and age distribution of trees, the size and timing of the emergent beetle population, and beetle dispersal (Safranyik *et al.*, 1989). Although poorly understood, dispersal is one of the most important factors of mountain pine beetle biology (Powell and Rose, 1997; Safranyik *et al.*, 1989). Mountain pine beetle dispersal may occur below or above the canopy and is influenced by temperature, light, wind direction, and chemical signals. Within a stand, mountain pine beetles tend to fly downwind when temperatures are between 19 and 41 degrees Celsius, and newly emergent beetles seem to prefer direct sunlight (Shepherd, 1966; Safranyik *et al.,* 1996). Preference for sunlight may explain the beetle's tendency to infest southern and western slopes during outbreak development (Safranyik *et al.,* 1974). During dispersal, aggregative odours may override other factors, as mountain pine beetles have been observed to fly directly towards attractants regardless of other influences (Safranyik *et al.*, 1989). While direction of dispersal can be associated with wind direction, mark recapture studies show that trapping declines sharply with distance (Safranyik *et al.,* 1999). When chemical traps are used, beetle capture decays with distance from the dispersal site and the majority of beetles are captured in traps within three kilometres of where they emerge (Safranyik *et al.*, 1992).

During outbreak conditions, infestations are observed to spread progressively from infestation centers (Safranyik *et al.*, 1974), but new attacks are also found to occur well beyond the vicinity of the outbreak (Borden, 1993). While progressive spread suggests short-range dispersal, the occurrence of infestations at distant locations may indicate that long-range dispersal is also taking place (Borden, 1993). As mountain pine beetles are not strong flyers, long-range dispersal is likely facilitated by wind (Safranyik *et al.*, 1989). Upward convection on fair days will carry the mountain pine beetle above the canopy where strong winds transport beetles long distances (Furniss and Furniss, 1972). Some researchers suggest that mountain pine beetles may have a metabolic necessity to engage in dispersal flight (Borden, 1993), perhaps explaining why beetles will disperse past suitable trees during host selection (Safranyik *et al.*, 1989). Long-range beetle dispersal may also be a mechanism to minimize the overexploitation of resources in an area (Mitchell and Preisler, 1991). The maximum distance of mountain pine beetle dispersal is unknown, although they have been shown to disperse as far as one kilometre (Turchin and Thoeny, 1993), entomologists suggest that long-range dispersion may occur over much farther distances (*i.e.* 10 – 100 kilometres) (Carroll, pers com).

The availability of an adequate number of mature pine and climate conditions are the main factors that enable an endemic mountain pine beetle population to become epidemic (Cole, 1981). Although outbreaks typically last eight to nine years the extent, duration, intensity, and repeat occurrence of infestations are governed by climatic factors (Safranyik *et al.*, 1974). Warm dry conditions, and mild winters are favourable for mountain pine beetles. Under such conditions, mountain pine beetle will have a large impact in a short time period, as populations quickly peak and collapse (Safranyik *et al.*, 1999). Cold temperatures are linked to high levels of mountain pine beetle mortality. Yet, mountain pine beetle cold hardiness changes throughout the year (Safranyik *et al.*, 1974; Bentz and Mullins, 1999). If temperature declines gradually mountain pine beetle will produce "antifreeze" (an accumulation of glycerol) allowing survival even when the temperature is cold (Safranyik and Linton, 1998). A sustained cold spell, as low as -40 degrees Celsius, or a sudden cold snap at an unseasonable time of year is required for significant mountain pine beetle mortality (Safranyik and Linton, 1998). British Columbia has experienced many warm winters since the mid 1990s, which in part has resulted in the current epidemic. Due to climate change, more warm winters are expected and may further exacerbate the mountain pine beetle situation (British Columbia Ministry of Forests, 2003).

Linked to climate is the impact of elevation on mountain pine beetles. Mountain pine beetles range from Northwest British Columbia to Northern Mexico. Maximum elevations are 750 metres in the north and 3650 metres in the south (Safranyik *et al.*, 1999). Cooler temperatures found at higher elevations tend to increase mortality and delay development, in some cases, requiring greater than one year to produce a single generation of beetles (Amman, 1973). Elevation impacts mountain pine beetle populations, as poor synchrony of the life cycle with local weather conditions causes increased mortality (Amman, 1973).

When a pine tree is attacked by mountain pine beetles, usually in late July or August, crown foliage changes successively from green to yellow, to brown, to red, and eventually needles drop off the tree leaving the grey stem and branches (Safranyik *et al.*, 1974) (Figure 2.1 - E). While the first visually detectable change to foliage colour typically occurs in the spring following attack, hot and/or dry summer conditions may cause foliage to begin changing in the fall (Safranyik *et al.*, 1974). One year after attack crown foliage is yellow green or yellow brown. By two years after the attack, the foliage is usually red and needles fall off in the third year. The rate of foliage change varies substantially (Wulder *et al.,* 2004). For instance, crown foliage may become red in a single year and trees may retain red and brown needles for as long as three years. Areas with active infestations older than two years commonly have trees with a combination of grey, red, and fading foliage. Most often, by the time foliage has turned red and attacks are clearly visible, mountain pine beetles have emerged and moved to a new host (Safranyik *et al.*, 1974). The sequence of change in pine trees attacked by mountain pine beetle is the same as change in pine killed by other means. Verification that pine mortality is the result of mountain pine beetle activity requires the tree stem be investigated for frass or boring dust, pitch tubes (Figure 2.1 - F), and galleries below the bark (Figure 2.1 - B) (Safranyik *et al.*, 1974).

2.2 SPATIAL STUDIES OF THE MOUNTAIN PINE BEETLE

The spatial behaviour of the mountain pine beetle, particularly at a landscape scale, is not well understood. However, in the last decade research has indicated that spatial dynamics play an important role in mountain pine beetle behaviour (Bentz *et al.*, 1993; Powell and Rose, 1997; Logan *et al.*, 1998; Powell *et al.*, 2000). In this section we focus specifically on spatial studies of the mountain pine beetle, which may be categorized as process- or pattern-based. Pattern-based studies typically use pine mortality to explore the nature of mountain pine beetle spatial behaviour, whereas process studies focus on direct observation or modelling of mountain pine beetle emergence, dispersal, and host selection.

2.2.1 Pattern Studies

Emergence, dispersal, and host selection are difficult to observe; therefore, spatial patterns are sometimes used as a surrogate for studying these processes. Spatial pattern investigations allow inference to be made regarding processes in disciplines such as biology (Sokal *et al.,* 1998), ecology (Levin, 1992), and epidemiology (Jacquez, 2000). Other spatial pattern studies in entomology are important to note. For instance, Liebhold and Elkinton (1989) use global join counts to characterize the spatial and spatial-temporal patterns of gypsy moth defoliation; Powers *et al.* (1999) uses the *k*-function to assess the spatial pattern of points representing patches of Douglas-fir beetle attacks; Cooke and Roland (2000) used Global Moran's I to assess the spatial autocorrelation of tent caterpillar outbreaks.

In mountain pine beetle research, Priesler and Mitchell published a pair of papers on the spatial pattern of individual trees attacked by the mountain pine beetle (Mitchell and Preisler, 1991; Preisler and Mitchell, 1993). The goal of the first study (Mitchell and Preisler, 1991) was to investigate the theory that mountain pine beetles initially attack large trees, and when a host is at carrying capacity will attack the next largest target (Geiszler *et al.*, 1980). The locations of individual trees were mapped for 0.5 hectare areas and characteristics such as diameter at breast height (dbh) and the presence of mountain pine beetle recorded. Diameter at breast height is a measure of trunk diameter taken at 1.3 metres above the ground. Infestation activity was surveyed over five years, and logistic regression used to investigate how individual tree characteristics correlate to mountain pine beetle attacks. As well, the spatial-temporal relationships of attack were visualized using a series of plots showing tree location, size, and the presence of mountain pine beetle populations. This analysis demonstrated that the likelihood of attack increases with nearness to an infested tree and is higher for trees with large diameters. It was also demonstrated that mountain pine beetles do not move to the next largest target, but fly short distances to pioneer new locations.

In the second study, Preisler and Mitchell (1993) utilized similar methods to investigate the spatial pattern of infested trees in thinned stands. This study found that while thinned stands are initially less attractive to the mountain pine beetle, once attacked the spatial pattern of infestation is similar to that of unthinned stands. Although the questions in these papers are spatial in their nature, spatial patterns were not quantified and the authors suggest that investigation of spatial interactions would benefit from more quantitative investigations (Mitchell and Preisler, 1991).

Peltonen *et al.* (1998) investigated the impact of the spatial scale of observation on bark beetle studies. Occurrences of bark beetles were collected for several plots of various size (10, 20, 40, 80, 160 metres squared). For each plot environmental variables were also recorded. Logistic regression was used to relate environmental variables (tree species, soil type, forest site type, stand characteristics, and forest management history) to beetle presence and absence. Coarse scale data were more related to environmental indicators than fine scale data. However, poor correlations between environmental variables and the six most common species may suggest that factors regulating bark beetle distributions operate at scales coarser than 160 metres (Peltonen *et al.*, 1998). The trends in this study may also reflect a general quality of environmental data, whereby spatially coarse data usually have less variance and more predictability than finer data (Wiens, 1989; Costanza and Maxwell, 1994).

2.2.2 Process Studies

The majority of mountain pine beetle spatial studies deal directly with emergence, dispersal, or host selection through mark recapture studies or modelling. In some cases the results of these models are compared with theoretical or observed spatial patterns of mountain pine beetle infestations. As a point of interest, the majority of spatial entomological studies have been carried out by a single group of researchers, who use continuous data and geostatistics to study and predict gypsy moth behaviour (*e.g.*, Liebhold *et al.*, 1994; Sharov *et al.*, 1996).

Direct observations of mountain pine beetle dispersal and host selection have only occurred at local scales via mark-recapture studies (Safranyik *et al.*, 1989; Safranyik *et al.*, 1992; Turchin and Thoeny, 1993; Barclay *et al.*, 1998; Safranyik *et al.*, 2000). Mark-recapture is a technique whereby mountain pine beetles are marked with a florescent pigment and traps are used to recapture the insects (Safranyik *et al.*, 1989). Traps may be baited with pheromones to simulate the occurrence of pioneer beetles and the presence of attractive odours (Barclay *et al.*, 1998; Safranyik *et al.*, 2000). These studies are particularly useful in understanding reactions of mountain pine beetle to stimuli such as light and temperature, for providing data on flight paths and movement (Turchin and Thoeny, 1993; Safranyik *et al.*, 2000), and for generating quantitative data on the distance and direction of mountain pine beetle movement (*e.g.*, Safranyik *et al.,* 1992). Mark-recapture techniques are limited to use with tree or stand level studies.

Most modelling studies of mountain pine beetle processes may be categorized into two groups. The first, use diffusion to model mountain pine beetle movement; the second, model the local interactions of chemical signals, and responses between the beetle and the trees. It should be mentioned that while several of these studies consider spatial pattern in some way they are included in this section as they focus on a process approach to understanding the spatial behaviour of the mountain pine beetle.

Turchin and Thoeny (1993) used both mark recapture data and diffusion modelling to investigate spatial patterns. Mark-recapture data were used to develop recapture-distance curves of southern pine beetles (*Dendroctonus frontalis* Zimm). Results from a simple diffusion model were compared to the recapture-distance curves to determine if the distance of beetle travel could be modelled. The diffusion model was found to generate results that reflect the recapture-distance curves.

Another example of mountain pine beetle modelling that emphasizes diffusion is Polymenopoulos and Long (1990). They combine a mountain pine beetle density model with a diffusion model of movement, to predict mountain pine beetle mortality in a stand. The model was developed based on three years of data, collected for a one hectare area, on the location and magnitude of mountain pine beetle attacks.

Understanding the importance of incorporating space into ecological models in general, and mountain pine beetle models specifically, a group of researchers developed a spatial model of mountain pine beetle pheromone ecology and single tree processes (Powell *et al.*, 1996; Powell and Rose, 1997; Logan *et al.*, 1998; Powell *et al.*, 2000). This model uses chemically-based aggregation and dispersal patterns around a single tree, to predict individual tree mortality. The variables included are summarized in Table 2.1 and are dependent on spatial locations and time (Powell *et al.*, 1996; Powell and Rose, 1997).

Table 2.1. Variables in a local model on mountain pine beetle chemical interactions.

Variables
Population of flying mountain pine beetles
Population of nesting/eating mountain pine beetles
Concentration of pheromones
Concentration of volatiles released by attacked trees
Resin outflow
Resin capacity
Number of entrance holes bored

Using this model Logan *et al.* (1998) simulated localized mountain pine beetle spatial processes and generated an expected spatial pattern of pine mortality. By varying input parameters, endemic and epidemic scenarios were simulated. Researchers found that under endemic conditions the spatial pattern of an attack correlated strongly with the pattern of weak trees, whereas epidemic mountain pine beetle populations lead to a more clustered pattern of attack. Differences in attack patterns indicate that information about spatial autocorrelation may be useful for differentiating between endemic and epidemic levels of mountain pine beetle (Logan *et al.*, 1998). Also this investigation found that the spatial pattern of currently attacked trees impacts which trees are infested in the future, and that the larger the distance between weak trees the lower the likelihood of an epidemic.

This model of mountain pine beetle chemical ecology was combined with a model of stand demographics, based on forest age and available water (Roberts *et al.*, 1993), to generate a stand-based, spatial risk model (Powell *et al.*, 2000). Forest risk is typically a description of the likelihood of a mountain pine beetle outbreak, tree mortality, or stand loss during a specific time period (Bentz *et al.*, 1993; Shore *et al.*, 2000). Incorporating space is important when identifying locations at risk, as the transition between endemic and epidemic populations includes many factors, but appears spatially mediated (Powell *et al.*, 2000). The authors argued that by considering both chemical ecology and the spatial arrangement of trees, their risk model has improved handling of spatial processes.

In a subsequent study, the tree-based chemical ecology model was used to simulate the effect of landscape pattern on the mountain pine beetle (Hughes, 2002). The landscape extent was five square kilometres. Hughes' study highlights both the benefits and limitations of studying mountain pine beetle using processes. By studying spatial processes, Hughes (2002) was able to tentatively conclude that forest fragmentation has only minor impacts on mountain pine beetle behaviour, due to the overriding influence of long-range above canopy dispersal. The caveats that made the conclusion tentative were difficulties with model parameterization and the sensitivity of the model to small changes in processes. Hughes demonstrated that, even at local scales, there are many unknowns related to mountain pine beetle processes.

It is important to point out the use of time in spatial studies of the mountain pine beetle. With the exception of mark-recapture research and the study of spatial scale by Peltonen *et al.* (1998), spatial studies of the mountain pine beetle are multi-temporal. Spatial processes and patterns are either modelled or observed over time. Although knowledge of spatial behaviour of mountain pine beetles is important, it is an understanding of spatial behaviour over time that is necessary for improved prediction and management.

3 STUDY AREA AND DATA

3.1 MORICE TIMBER SUPPLY AREA

One area impacted by the current infestation in British Columbia is the Morice Timber Supply Area, which for simplicity will be referred to as Morice (Figure 3.1). Morice is part of the British Columbia Ministry of Forests'Nadina Forest District and is centred on the small town of Houston. Bordered to the west by the Coast Mountains and to the south by Tweedsmuir Park, the topography is gentle to the north and east, becoming more mountainous in the southwest. There are three major rivers in the area (the Bulkley, the Morice, and the Nadina). There are also two large lakes; Babine Lake to the north is the largest fresh water lake in British Columbia, and Ootsa Lake is in the south. Morice includes five biogeoclimatic zones: Sub-Boreal Spruce (59 percent), Engelman Spruce-Subalpine Fir (26 percent), Alpine Tundra (11 percent), Coastal Western Hemlock (three percent), and Mountain Hemlock (one percent). Covering an area of approximately 1.5 million hectares, this area is dominated by lodgepole pine and spruce (*Picea*). Fifty-four percent of the timber harvest land base is lodgepople pine. The proportion of pine is less in Morice than in many other districts in the interior of British Columbia, some of which have upwards of 70 percent pine.

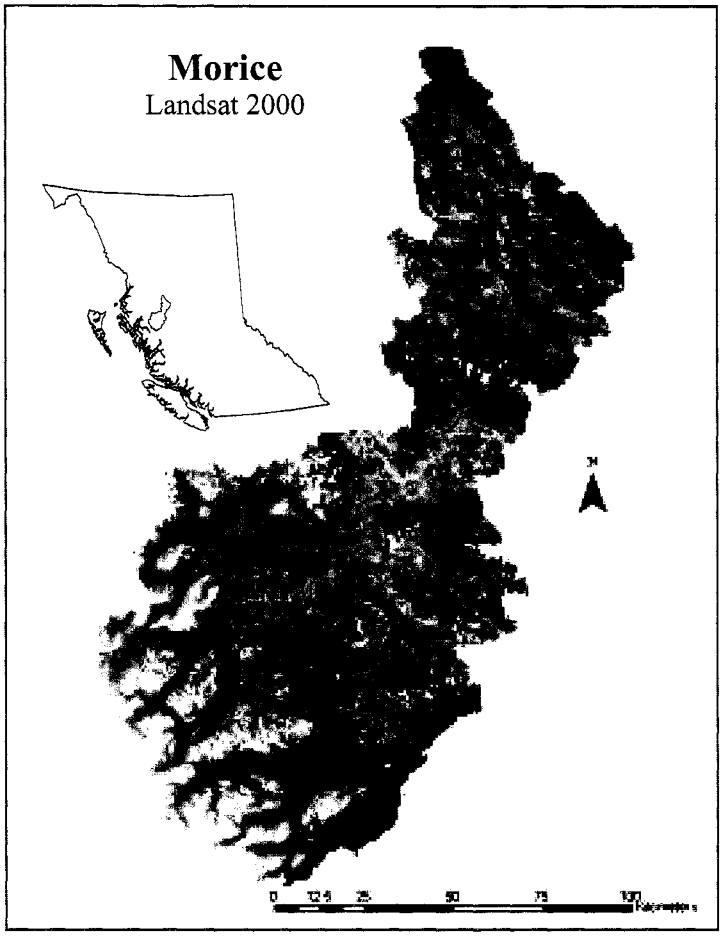


Figure 3.1. Location of the Morice Timber Supply Area.

3.2 DATA

3.2.1 Mountain Pine Beetle Data

In Morice, mountain pine beetle infestations have been monitored since 1995 using point-based, global positioning system (GPS) aerial surveys. Aerial surveys of mountain pine beetle infestations use indicators of pine mortality, mainly changes in crown foliage colour, to monitor mountain pine beetle activity. The response of pine foliage to a successful mountain pine beetle attack is discussed in Chapter 2. During aerial surveys, clusters of visually infested trees, typically those with yellow and red crowns, are identified and a GPS is used to map cluster centres with a point. For each cluster, the number of infested trees is estimated and the infesting insect species recorded. The maximum area represented by a point is 0.031 kilometers squared, equivalent to a circle with a radius of 100 metres. Although many points represent smaller areas, variations in circle radii are not recorded. From 1995 to 2002 a total of 43,751 points were identified during aerial surveys, of which field data were collected for 6,151 points (Table 3.1).

Table 3.1. The annual number of mountain pine beetle aerial and field survey sites collected in the Morice TSA from 1995 to 2002.

Survey Sites	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**Total**
Aerial	2,181	6,076	8,461	2,418	4,669	5,333	5,836	8,777	43,751
Field	0	0	0	0	223	104	3004	2820	6151

During field data collection, ground crews locate infestation clusters recorded via aerial surveys and determine the cause of lodgepole pine mortality. If the mountain pine beetle is the cause of tree mortality, crews record the number of green trees currently under attack (Green Attack), the number of trees attacked the previous year (Y1), the number of trees attacked two years previous (Y2), and the number of trees attacked and now grey (Greys) (Nelson *et al.*, 2004). Green Attack trees have no visible foliage discolouration. Crews also note the presence of any non-mountain pine beetle insect infestations. From the cluster centroid, ground crews walk a 100 metre radius looking for further evidence of mountain pine beetle activity. If infested trees are found, an additional 100 metre sweep is conducted. This is continued until no infested trees are located during a 100 metre sweep. Like all observed data, the mountain pine beetle data are prone to uncertainty. Details of measurement error, as well as methods for addressing uncertainty, are provided in Chapter 4.

3.2.2 Supplementary Data

British Columbia Ministry of Forests' inventory data were used in this study. Forest inventory data are primarily generated via aerial photo (1:15,000) interpretation and were last updated in the mid 1990s. The key forest inventory attributes used were: age, dbh, and species percent (Figure 3.2). Stand age is the age, in years, of the forest stand on the date of polygon classification, and is based on ring counts from a bored core or is estimated from aerial photographs. Diameter at breast height is the quadratic mean stand dbh and is calculated based on forest age and site index. The quadratic mean is the square root of the arithmetic mean of squared values and gives greater weight to large trees. Typically, the quadratic mean is used for calculating stand dbh as it relates to other forest characteristic more meaningfully than does the arithmetic mean (Curtis and Marshall, 2000). Tree species and percentages are given for the six most dominant forest species. The dominant tree species, (noted as species_one in the database), occupies the largest percentage of the stand. Both the commercial species or brush, and the percentage of the stand composed of this species are recorded. The same attributes are listed for the next most common species, species_two, and so on to species_six. The inventory data were provided in irregular polygon format, but were converted to 200 metre grid cells for comparison with the kernel density estimated surfaces described in Chapter 4.

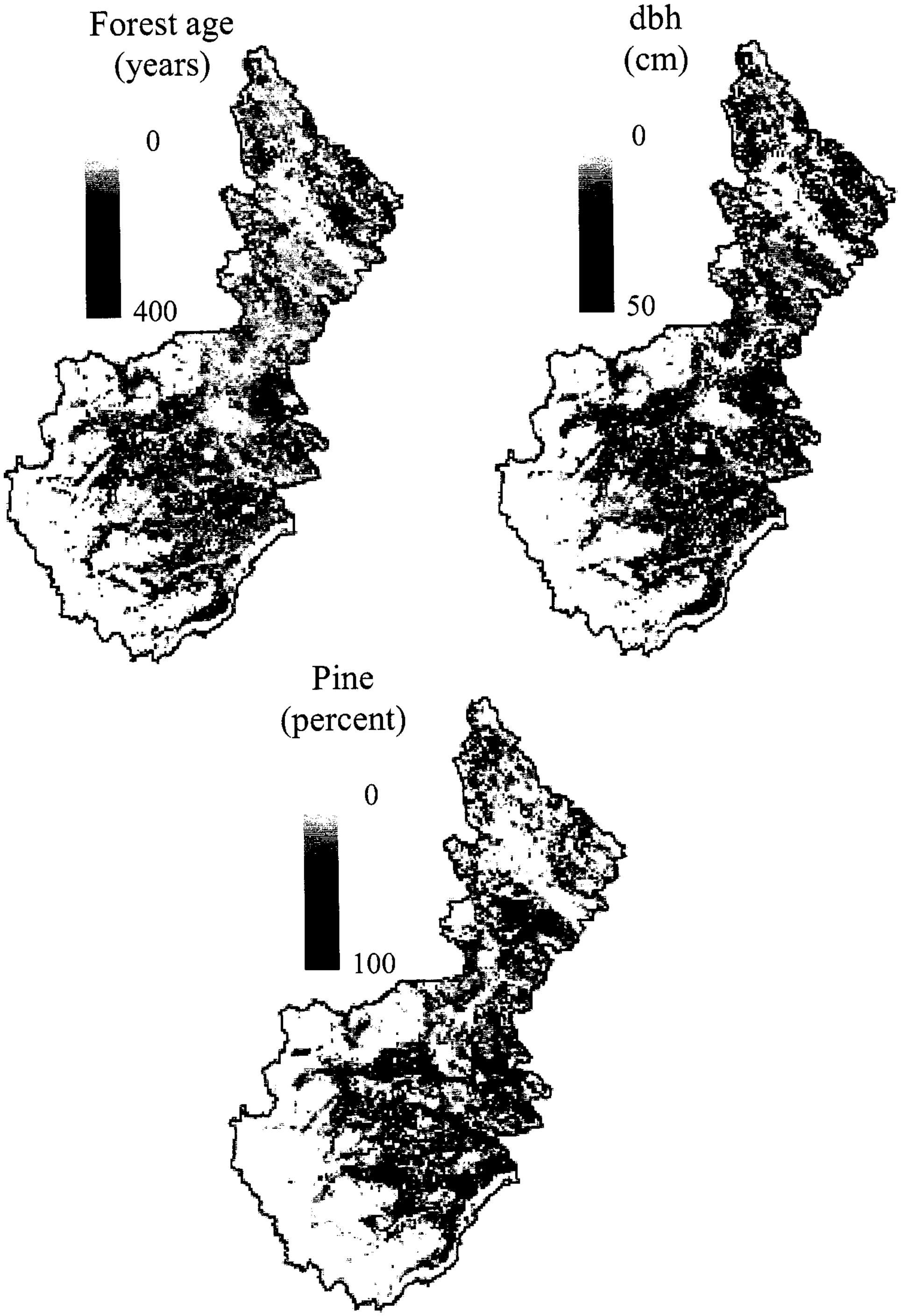


Figure 3.2. Morice TSA forest inventory polygon attributes used in this analysis.

Other supplementary data included elevation and aspect. Aspect was generated from a digital elevation model (DEM) provided by Morice (Figure 3.3). The original elevation model was created from 1:20,000 Terrain Resource Information Management data (Province of British Columbia, 1996), and grid cell size was 25 square metres. The data were interpolated using a linear process and the DEM is accurate within 10 metres. When used in this study, the DEM cell size was aggregated to 200 square metres, allowing for comparisons with the kernel density estimated surfaces described in Chapter 4. Aspect data were derived from the DEM. Aspect is calculated as the down-slope direction of the maximum rate of change in elevation value from each cell to its neighbours.

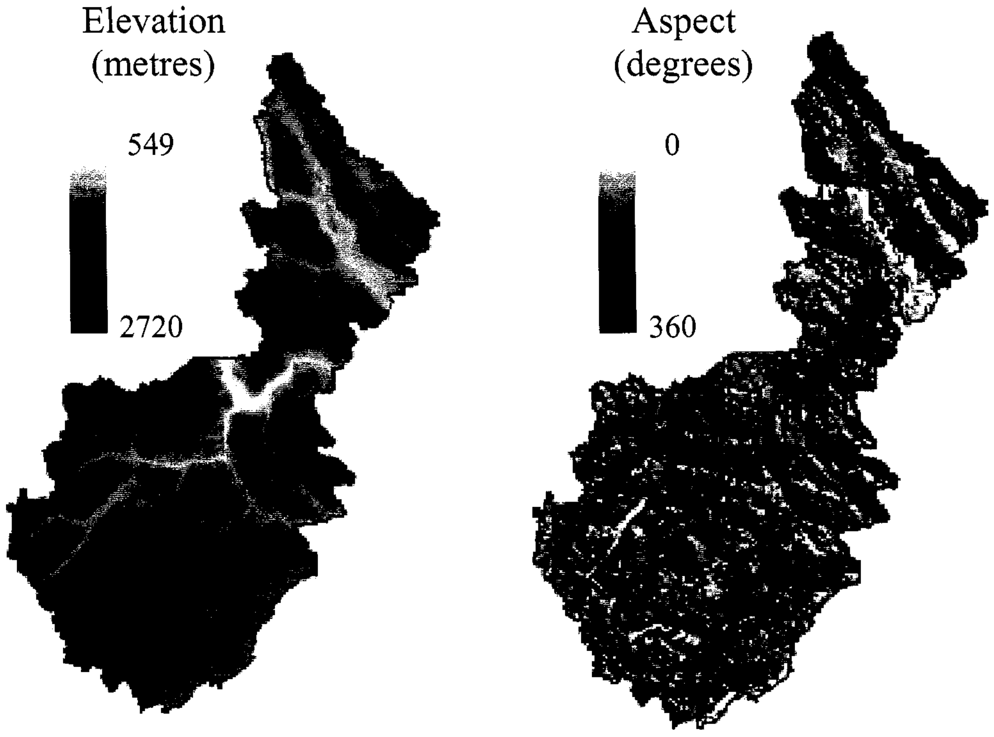


Figure 3.3. For the Morice TSA, the Province of British Columbia generated elevation and aspect data. Grid cell size equals 25 square metres.

3.3 DELINEATION AND DESCRIPTION OF SUBAREAS

Mountain pine beetle populations in the north, middle, and south of Morice tend to have different behaviour. While cursory investigations show that partitioning Morice based on the year of initial infestation allowed for more meaningful analysis, the exact boundaries for partitioning were unclear (Figure 3.4). We conducted boundary sensitivity analysis by digitizing several possible boundaries and comparing the distribution of point attributes in all years. Two boundaries were drawn in the south and three in north (Figure 3.5). This resulted in six different realizations of the Middle subarea. Kolmogorov-Smirnov tests were conducted to compare the distribution of attribute values for different realizations of all subareas. In each comparison, the null hypothesis that distributions were similar could not be rejected. Therefore, the analysis is unlikely to be sensitive to the minor variations in boundary placement. For the remaining analysis, North1, Middle1, and South1 subareas were used. Initial analyses were always conducted on subareas. However, in certain cases results were consistent between subareas, or trends more easily interpreted when all results were considered together (*e.g.*, individual subareas may result in few observations). In such instances, results are reported for the entire study area.

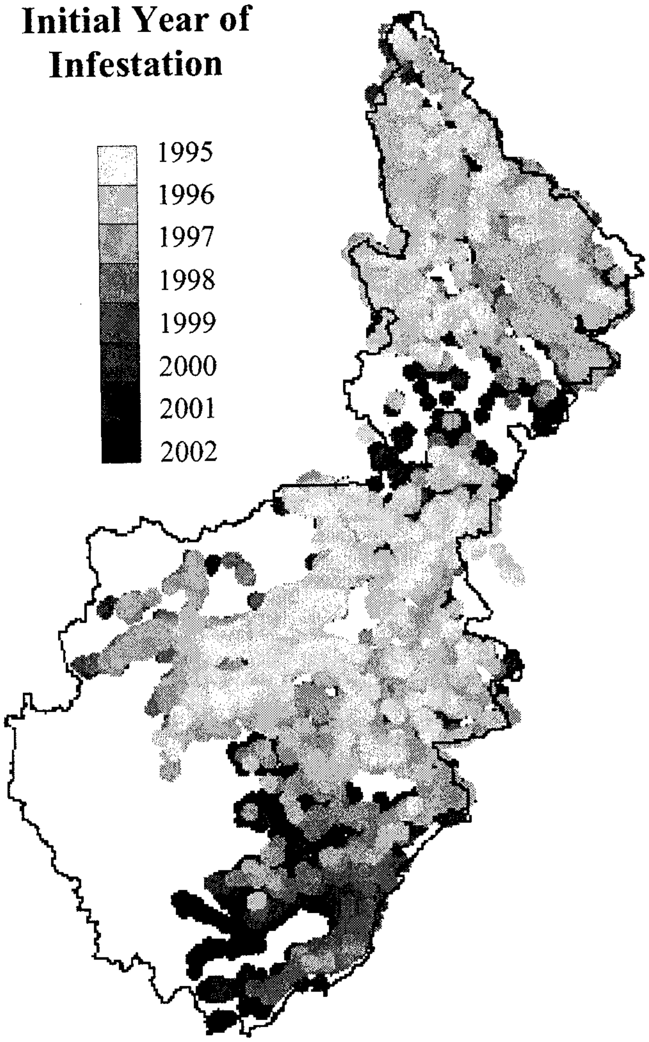


Figure 3.4. Initial year of mountain pine beetle infestation in the Morice TSA.

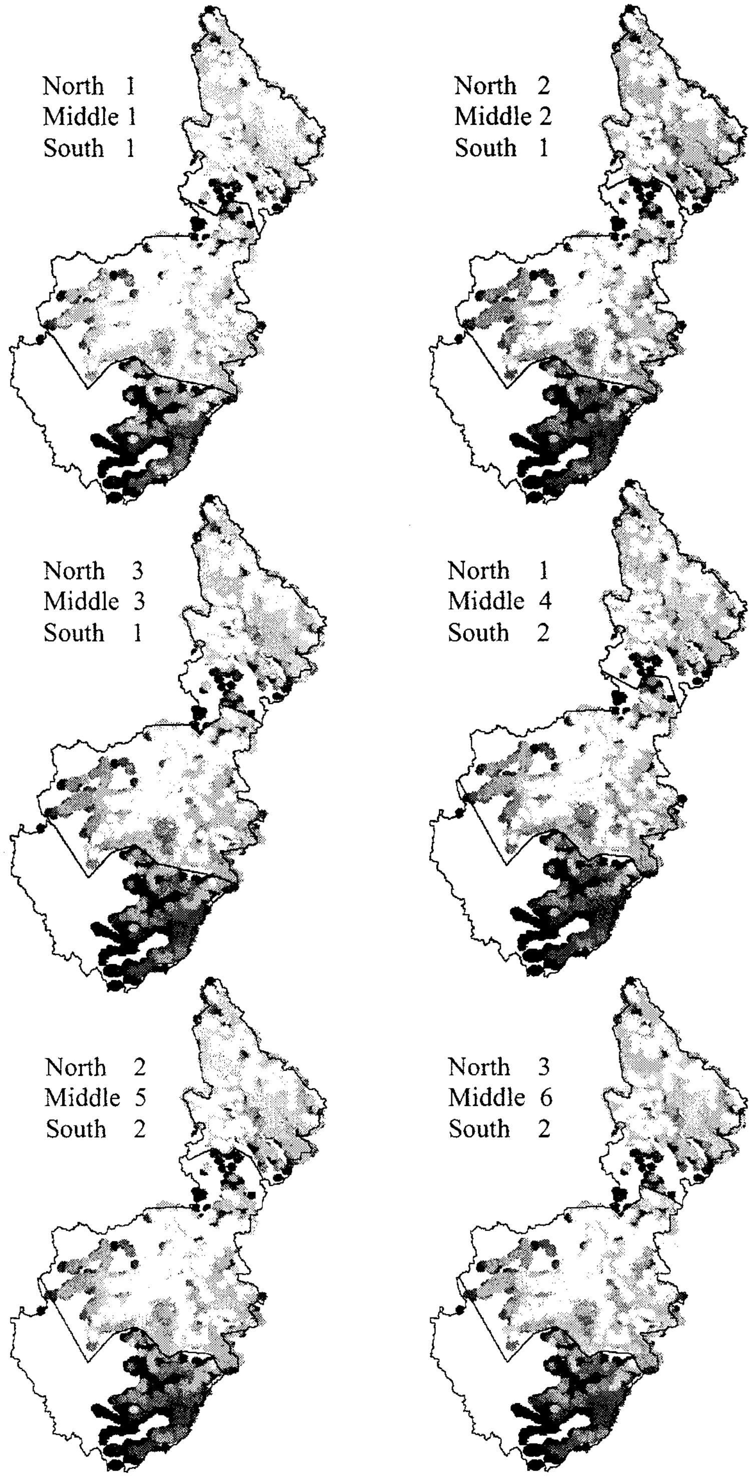


Figure 3.5. Possible partitions of the Morice TSA based on the initial year of infestation. Colours represent the initial year of infestation as shown in Figure 3.4.

Mountain pine beetle behaviour in each of the subareas is likely a response to different management strategies, variability in the magnitude of mountain pine beetle populations, and differences in the characteristics of the underlying landscape. In the North subarea, most of the mountain pine beetle activity occurred in the mid to late 1990s and infestations tend to be localized and intensively managed via harvesting. By 2002, management and mountain pine beetle activity had removed most of the mature pine in the North subarea. When data collection began in 1995, the Middle subarea was the most heavily infested. Infestations in this region also tend to be localized and less rigorously managed. In the South subarea, the nature of the infestation is quite different. This area was not heavily infested until 1999. Rather than localized infestations, the attack in the South appeared continuous with large areas being infested rapidly. Due to the magnitude of the infestation, mountain pine beetle management has had limited impact in this region. The South subarea is unique, as monitoring of this area began prior to the infestation. Usually insect infestation data are not collected until after an outbreak occurs (Logan *et al.*, 1998). Data captured in the early stages of infestation in the South subarea, provide a unique opportunity to investigate the characteristics of infestation establishment.

4 AERIAL SURVEYS: EXPLORING ACCURACY AND DATA REPRESENTATION

4.1 INTRODUCTION

Mountain pine beetle monitoring is necessary to assist decision making at several management levels; therefore, mapping occurs at various spatial scales. For provincial use, mapping of mountain pine beetle infestations is generally undertaken via sketch mapping from a fixed-wing aircraft at a scale of 1:100,000. Sketch mapping is relatively inexpensive and is an efficient method for monitoring infestations over large areas. During sketch mapping, surveyors delineate areas of insect infestations and categorize the estimated percentage of attack. By providing general information, sketch mapping assists strategic planning and management activities such as provincial forest health reporting and the setting of annual allowable cuts (Wulder *et al.*, 2004).

Forest districts have a mandate to manage local regions and require data at a fine spatial scale. This is often acquired by helicopter surveys that use GPS to mark centroids of individual infestation clusters as points. In some districts, additional field data are also collected. These point surveys provide spatial detail necessary for tactical planning at a local level. For instance, point data are used to guide mountain pine beetle mitigation and harvesting.

Remotely sensed imagery may also be used for mapping mountain pine beetle infestations at a variety of spatial scales. While the utility of mapping mountain pine beetle infestations with remotely sensed imagery has been demonstrated (Franklin *et al.*, 2003; Skakun *et al.*, 2003), remotely sensed imagery is not yet used operationally. Over time, as methods improve and cost declines, remotely sensed imagery may be better able to meet operational demands. Already high spatial resolution imagery, such as IKONOS panchromatic imagery with a spatial resolution of a metre squared, has been shown to support tactical planning with detailed information analogous to aerial photography (White *et al.*, 2004)

Mountain pine beetle monitoring programs generate valuable data sets necessary for management. However, as with any large area data set, these surveys are prone to uncertainty. For example, misidentification of the cause of tree mortality may impact both the accuracy and information content of aerial surveys. As well, information available from aerial surveys is often difficult to visualize. Large extents, sizeable data sets, and uncertainty complicate data visualization and representation. A flexible mechanism for considering uncertainty when visualizing and exploring data would facilitate effective use of information for decision making and scientific inquiry.

In this chapter we focus on point-based aerial surveys. While such surveys are produced for management purposes, they also provide spatial detail suitable for landscape level spatial pattern analysis aimed at better understanding mountain pine beetle behaviour over large areas. Our goal is to explore the information content of point-based, aerial surveys of mountain pine beetle infestations and to demonstrate an appropriate technique for visualizing infestation data while considering data uncertainty. To reach this goal, three objectives are considered. First, we explore the nature of error and uncertainty in aerial survey data. Second, we demonstrate an effective technique for visualizing variations in infestation magnitude over large areas. Third, we extend the visualization method to incorporate data uncertainty.

4.2 BACKGROUND ON AERIAL SURVEY DATA

To provide a context for the discussion of uncertainty in the mountain pine beetle data (data are described in section 3.2.1), we present an overview of the limitations of point aerial surveys as well as potential sources of attribute error. Attribute uncertainty is defined both in terms of error in point values and the presence of points. Points located where infestations do not exist, or having overestimated attribute values, represent commission errors (false positives), whereas infestations that are not located or points with underestimated attribute values represent omission errors (false negatives).

Using lodgepole pine mortality as a surrogate for mountain pine beetle populations limits the stage of infestation that can be detected. Pre-visual infestations, or green attack, cannot typically be detected by aerial surveys (Wulder *et al.*, 2004). Aerial surveys most often capture trees with red foliage that represent the location of mountain pine beetle in the previous year. Trying to relate mountain pine beetle infestation data to a single time frame is difficult due to the nature of change in pine foliage, and is further limited by the time taken to complete aerial surveys for large areas. Over the duration of a survey, which is often several months, foliage continues to change. If areas flown at the beginning of the aerial survey were to be inventoried at the time of survey completion, different trees would likely display visible evidence of attack.

Another source of uncertainty in aerial surveys is the required assumption that all lodgepole pine mortality is caused by mountain pine beetles. Aside from mountain pine beetle activity, lodgepole pine mortality may be caused by root rot, blow down, animal activity (*e.g.*, porcupine and beavers), and water or nutrient stress. Since the sequence of foliage colour change is the same regardless of the cause of tree mortality, fieldwork is necessary to determine conclusively the presence of the mountain pine beetle.

Misidentification of the tree species under attack may also lead to incorrect attributes. In areas with mixed forests, multiple infestations may occur simultaneously. For example, in Morice there are both pine and spruce infestations. While the species of live tree crowns are relatively easy to identify, the species of stressed or dieing trees can be more difficult to determine.

Operational considerations will also impact aerial surveys. Infestation magnitude can be difficult to estimate aerially. Aircraft speed, movement, view angle, and flying height will impact survey quality. As well, shadow, weather conditions, and surveyor experience may result in over and/or underestimates of infestation magnitude.

Issues that are specific to error in point-based aerial surveys include the sampling design and point characteristics. The sampling design of point-based aerial surveys is frequently irregular and may impact the completeness of the survey. Infestation clusters are represented by a single point and variations in the area, shape, and compactness of clusters are not recorded. Also, typically, no information is provided on healthy trees.

4.3 QUANTITATIVE ASSESSMENT OF AERIAL SURVEY UNCERTAINTY

The above description of aerial survey uncertainty is not meant to be overly critical. Aerial surveys are an efficient means of collecting infestation data over large areas and provide meaningful information to managers. In order to capitalize on available information, users need to be cognisant of the sources of error and uncertainty in aerial data. With that in mind, we use a combination of aerial and field data to assess both the information content and uncertainty of aerial data. Although field data were not collected for accuracy assessments, they provide some capability for investigating error. While field data does not include information on the spatial error of points, Morice data collectors and users have suggested that the spatial error of cluster centroids is approximately ±25 metres (Nelson *et al.*, 2004).

Aerial survey estimates of infestation size were compared to the following field attributes: Green Attack, Y1, Y1+Y2, and All. All is the sum of Green Attack, Y1, Y2, and Greys (for definitions of attributes see the section 3.2.1). This comparison allowed quantification of accuracy and errors of omission and commission. We conceptualize accuracy and error in two ways. The first is based on field survey points, whereby the percentage of points having the correct number of infested trees, omission error, or commission error can be determined. The second approach, based on the trees, provides additional insights on the amount of error that occurs when aerial attributes are incorrectly estimated. While commission errors can be characterized using both approaches, there are limitations to quantifying omission error in terms of missed survey points. It is not possible to characterize the impact of infested regions that are missed entirely during aerial surveying.

In Table 4.1 we present the number of field points with attributes that are accurate, have omission error, or have commission error. When compared with Green Attack, less than six percent of point attributes are correctly estimated during aerial surveys. This is not surprising as most Green Attack trees have no visible foliage discolouration and cannot be detected during aerial surveys. The number of points with attributes correctly estimated increases to 28.3 percent when compared to Y1+Y2 field values. Both Y1 and Y2 field data represent trees with visually detectable foliage change. Omission error, or missed trees, is highest when compared with All infested trees and lowest when compared only with Y1 trees. Commission error is lowest when compared with All infested trees and highest when compared with Y1 trees. Overall Y1 and Y1+Y2 field attributes are more related to aerial point attribute values than are Green Attack and All attributes.

Table 4.1. The accuracy of aerial helicopter surveys in Morice reported using a point-based approach to accuracy assessment, and categorized by the phase of attack identified during field monitoring.

Field	**Correct**		**Omission**		**Commission**	
Green Attack	362	5.9%	2569	41.8%	3220	52.4%
Y1	1399	22.7%	1198	19.5%	3554	57.8%
Y1 + Y2	1738	28.3%	2111	34.3%	2302	37.4%
All	685	11.1%	4326	70.3%	1140	18.5%

Continuing our assessment of aerial survey attribute accuracy, we investigate how attribute accuracy varies with infestation cluster size (Figure 4.1 A-C). Only results of comparisons with Y1 and Y1+Y2 data are provided, as the aerial data best represent these attributes. Generally, the percentage of points with correct attribute values decreases as aerial attribute values increase (Figure 4.1 - A). This is encouraging as the majority of aerial survey attribute values are small (Figure 4.2). While it is recognized that there are omission errors that are not detected during field surveys, based on available data omission errors are highest when aerial attribute values are between eight and 20 (Figure 4.1 - B). Attribute values of nine, which are uncommon, are the exception to this trend. Clusters of nine trees are likely an anomaly as attributes represent estimates and surveyors are prone to record 10 infested trees rather than nine, as 10 is a natural break. While omission error is lowest when attribute values are large, this is offset by sizeable commission error (Figure 4.1 - C). These results suggest that when an infestation cluster is large, surveyors are more likely to overestimate the number of attacked trees than when clusters are small. Commission error is relatively low when the attribute value is less than three, is considerable but steady for attribute values between three and 20, and increases when attribute values are greater than 20.

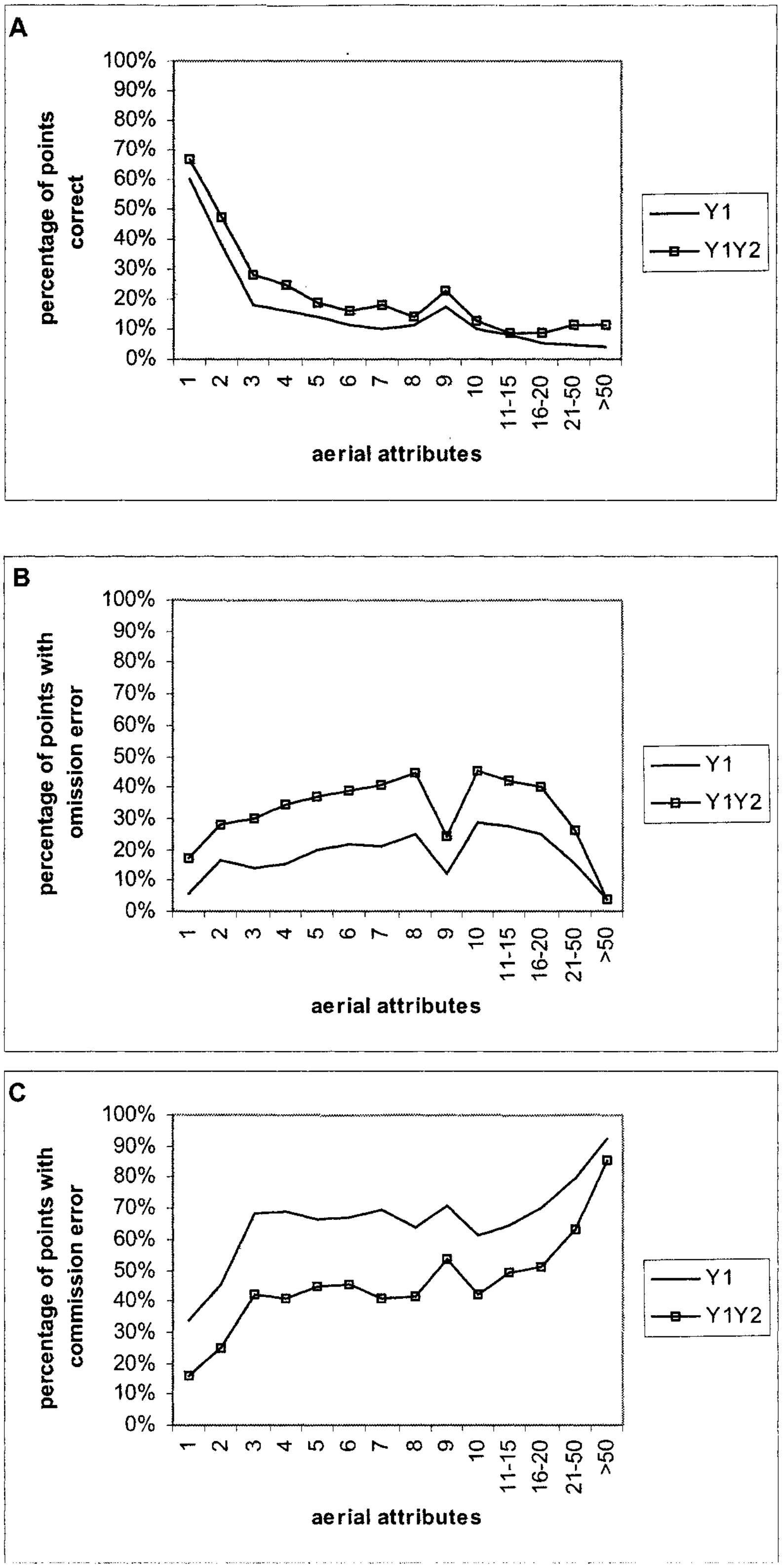


Figure 4.1. The percentages of aerial survey points with attributes that are correct, have omission errors, or have commission errors. Aerial attributes are equal to the number of trees.

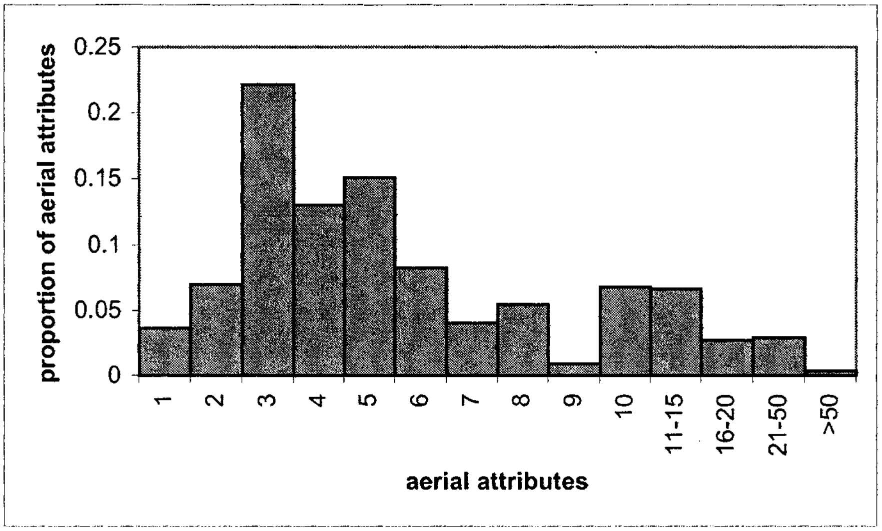


Figure 4.2. For all years, the proportion of aerial survey attributes. Aerial attributes equal the estimated number of infested trees.

To better understand the impact of error, we partitioned the points based on whether aerial attribute values were correct, had omission error, or had commission error. We then shifted our analysis to tree-based comparisons to determine the number of trees correctly estimated, underestimated, and overestimated (Table 4.2). As anticipated, tree-based comparisons of aerial attributes and Green Attack values result in relativity few trees (1,729) being correctly identified. When aerial data are compared to Y1+Y2 attributes, the number of correctly identified trees is highest (6,105). The percentage of omission error is lowest when data are compared to the Y1 attributes (48.6 percent) and highest when compared with Green Attack attributes (75.0 percent). The percentage of commission error is lowest when comparisons are made using All attributes (59.5 percent) and highest when Y1 or Y1+Y2 field attributes are used for comparison (71.2 percent). Overall, the aerial data best relates to Y1 or Y1+Y2 field attributes. While Y1+Y2 comparisons have a higher proportion of correctly estimated point attributes and lower commission error, Y1 comparisons have reduced omission error.

Table 4.2. The accuracy of aerial helicopter surveys in Morice reported using the tree-based approach to accuracy assessment, and categorized by phase of attack identified during field monitoring.

Aerial Vs Field	**Correct**	**Omission**			**Commission**		
	Trees	Aerial Trees	Field Trees	% Missed Trees	Aerial Trees	Field Trees	% False Trees
Green Attack	1729	14792	59112	75.0%	21879	6490	70.3%
Y1	4179	7518	14625	48.6%	26703	7684	71.2%
Y1 + Y2	6105	13042	27620	52.8%	19253	5540	71.2%
All	3701	26115	101334	74.2%	9210	3726	59.5%

One difficulty with tree-based accuracy assessment is that the total number of trees identified during aerial surveys stays constant, while the number of trees in each field attribute class varies (Table 4.3) (*i.e.,* the sum of Green Attack attributes is 67,331, whereas the sum of Y1 attributes is 26,488). It is helpful to convert tree-based accuracy values to the weighted proportion of field data accounted for by aerial data. Using the values in Table 4.2, we calculated a weighted proportion of field data accounted for by aerial data using the following equation:

$$\left(\frac{\text{sum of correct aerial attributes}}{\text{sum of all aerial attributes}}\right)+\left(\frac{\text{sum of omission aerial attributes}}{\text{sum of all aerial attributes}}*(1-\text{missed\%})\right) \quad 4.1$$
$$+\left(\frac{\text{sum of commission aerial attributes}}{\text{sum of all aerial attributes}}*(1-\text{false\%})\right)$$

Using equation 4.1, the percentage of trees accounted for is 31 percent when aerial survey point attributes are compared to Green Attack attributes, 41 percent when Y1 attributes are used for comparison, 46 percent when Y1+Y2 attributes are used for comparison, and 54 percent when All attributes are considered. This suggests that Y1+Y2 attributes have the strongest association with the aerial survey estimates, although Y1 attributes are similarly associated. As above, we were interested in variations between accuracy and aerial survey attribute size (Figure 4.3). Overall, as aerial attribute values increase, accuracy decreases regardless of whether Y1 or Y1+Y2 attributes are used for comparison. Notable thresholds in this trend are three and 20. When attribute values are less than three or greater than 20, accuracy declines substantially; between three and 20, error is more stable.

Table 4.3. The total number of trees in Morice associated with field attributes categorized by the timing of mountain pine beetle attacks.

Field Attribute	Total Number of Trees
Green Attack	67331
Y1	26488
Y1 + Y2	39265
All	107296

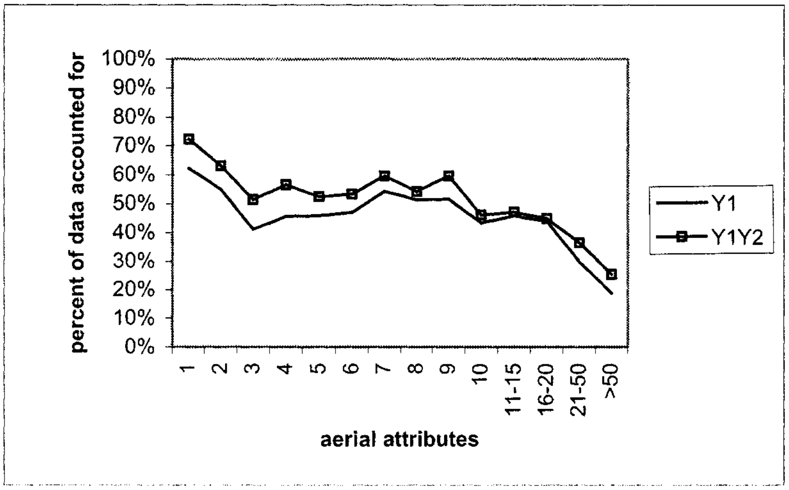


Figure 4.3. Percentage of field data accounted for by the number of trees for estimated for each aerial survey point in Morice. Aerial attributes equal the number of trees.

Using a combination of point attribute values and field crew comments, we investigated the cause of aerial survey attribute error. Based on this analysis it appears that the most common cause of both commission and omission error is the misidentification of attack phase. As previously noted, the process of lodgepole pine mortality is continuous and the rate of crown foliage discolouration depends on factors such as tree health prior to attack. Consequently, it is unlikely that all trees with similar foliage discolouration were attacked at the same time. As a result, it appears there may be a tendency for trees surveyed in one year to be resurveyed the following year. Other less common sources of error include misidentification of tree species, and tree mortality caused by factors other than mountain pine beetle, such as porcupines, root rot, and blow down.

4.4 VISUALIZING AND PRE-PROCESSING OF DATA

Point-based, aerial surveys generally produce large data sets, which can be difficult to visualize, particularly when points have associated attributes. Although simple cartographic methods, such as proportional symbols or colours, can be used to indicate attribute values, they may be insufficient to allow for meaningful interpretation of data. For example, it can be difficult to avoid symbol overlap that leads to some data becoming obscured.

Kernel density estimators are a powerful and flexible method for visualizing point data (Silverman, 1986; Gatrell, 1994; Bailey and Gatrell, 1995) that have advantages over traditional cartographic tools (Figure 4.4). Instead of representing clusters of infested trees as discrete events (points), kernel density estimators can be used to create a continuous surface that displays the intensity of infested trees over the study area.

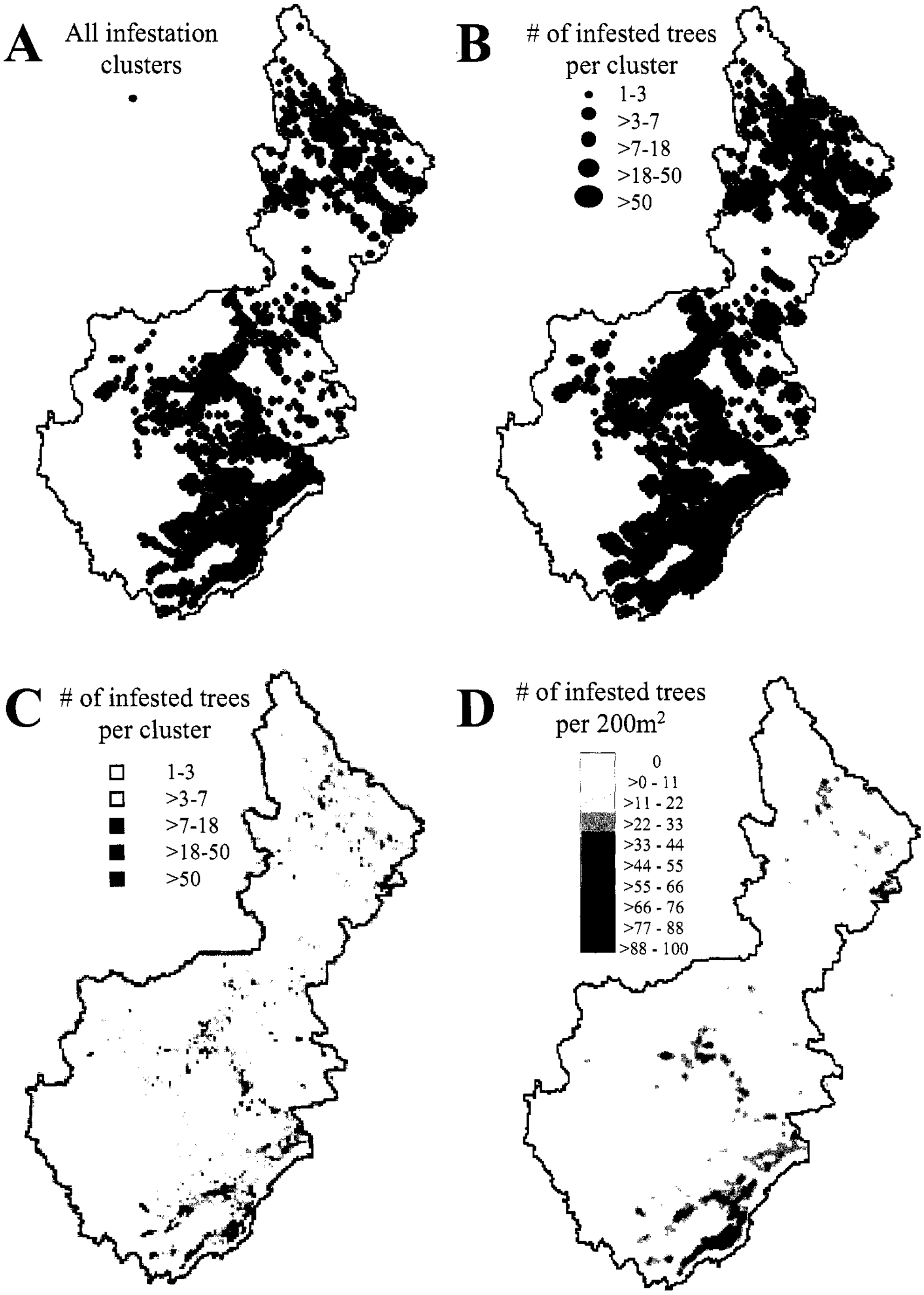


Figure 4.4. Comparison of techniques for visualizing large point data sets. A) Aerial survey points with no enhancements. B) Aerial survey point attributes represented as proportional symbols. C) Aerial survey point attributes represented as proportional colours. D) Aerial survey point attributes represented using a kernel density estimator with a two kilometre search radius, quartic kernel shape, and 200 metre cell size.

Kernel density estimators have benefits beyond improved visualization. An important conceptual benefit is that kernel density estimators enable a continuous representation of the data. When mountain pine beetle populations are at endemic levels beetles are found throughout pine forests. At epidemic levels the spatially continuous nature of mountain pine beetle populations is even more apparent, and infested trees seem to result from spatially continuous, rather than discrete or isolated, processes. A second benefit to kernel density estimators, which will be demonstrated in this chapter, is that it is possible to incorporate spatial and attribute uncertainty when visualizing point patterns with kernel density estimators. We are unaware of approaches for incorporating data uncertainty into methods that use proportional symbol or colour mapping. Additional technical benefits and issues associated with the use of kernel density estimators are described below.

Conceptually, the intensity $\lambda(z)$ at a particular location 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, $\hat{\lambda}_\tau(z)$ is defined by

$$\hat{\lambda}_\tau(z) = \frac{1}{p_\tau(z)}\left\{\sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{(z-z_i)}{\tau}\right) y_i\right\} \quad z \in A \qquad 4.2$$

where z and A are defined as above, τ is the search radius of a disk centred on z, $k(\,)$ is the kernel or a probability density function that is symmetric around about the origin, z_i ($i = 1, \ldots, n$), are locations of n observed events, and y_i is the attribute value at z_i. The term $p_\tau(z) = \int_A k[(z-\boldsymbol{u})/\tau]d\boldsymbol{u}$ is an edge correction equivalent to the volume under the scaled kernel centred on z which lies inside of A (Diggle, 1985).

There are three issues that are commonly considered when working with kernel density estimators: the type of kernel $k(\,)$, the size of the search radius τ, and edge effects. The kernel determines how events within the search radius will be weighted. For example, in this case we use a kernel with a quartic distribution function, which weights events in terms of their distance from z. The quartic kernel, is more peaked, but has a similar shape to the normal kernel, and approximates normal when $\tau / 2$ (Silverman, 1986). Although the kernel definition may be theoretically important, it does not have a large impact on kernel output.

Kernel density estimators are much more sensitive to τ, which controls data smoothing. A function of kernel density estimation is that data are smoothed. Such pre-processing can be particularly beneficial when working with large data sets, which are typically uncertain. Smoothing is a beneficial when data are uncertain, as high values are suppressed and low values are enhanced, and in addition the impact of spatial errors are reduced (Silverman, 1986). For kernel density estimated surfaces, as τ increases, so does the amount of data smoothing (Kelsall and Diggle, 1995); if τ is too large, data variability will be lost, while if too small, data trends will not be visible. If the study area is a unit square, a good starting point for determining an appropriate value for τ is $0.7n^{-0.2}$, where n is the observed number of events in the study area (Bailey and Gatrell, 1995). However, often kernels need to be calculated for several values of τ and kernel outputs compared. We compared several kernel sizes and chose a two kilometre search radius, optimizing tradeoffs between detail and the representation of infestation trends. The two kilometre search radius is also large enough to be relatively robust with respect to errors in point locations.

Kernel density estimators may also be impacted by edge effects. In this study, edge effects do not have a significant impact, as the area we are studying is large relative to τ, so the edge correction term in equation 4.2 was not implemented. An additional issue, which arises in software used to implement kernel density estimators, is the definition of surface cell size. Here we use a 200 metre grid cell, which is approximately equal to the maximum area represented by an aerial survey point. In future chapters, kernel density estimated surfaces become the basis for spatial pattern analysis. As with any surface-based analysis the cell size, or resolution, will impact analysis results (Atkinson and Curran, 1997). In future research, it may be beneficial to explore the impact of kernel density estimated surface cell size and spatial pattern analysis. While the subjectivity involved in choosing an appropriate cell size may be problematic, using raster representations for space-time analysis has the benefit of producing consistently indexed spatial units that may be tracked through time.

4.5 CORRECTING FOR UNCERTAINY WHEN VISUALIZING DATA

We have explored mountain pine beetle aerial survey data by investigating the information content of data and presenting a technique to improve data visualization. Recognizing the importance of these two issues, we expand the kernel density estimator approach to incorporate data uncertainty. Since kernel density surfaces will be used to explore annual spatial patterns of mountain pine beetle infestations, we addressed uncertainty relative to Y1 attribute values, as these are most representative of mountain pine beetle populations within one year. Our general approach to incorporating uncertainty in kernel surfaces is to generate a number of possible representations of the point data by drawing values from distributions that model spatial uncertainty and Y1 attribute values. For each representation, a kernel density surface is created and all kernel density surfaces are averaged to produce a surface incorporating uncertainty (Figure 4.5).

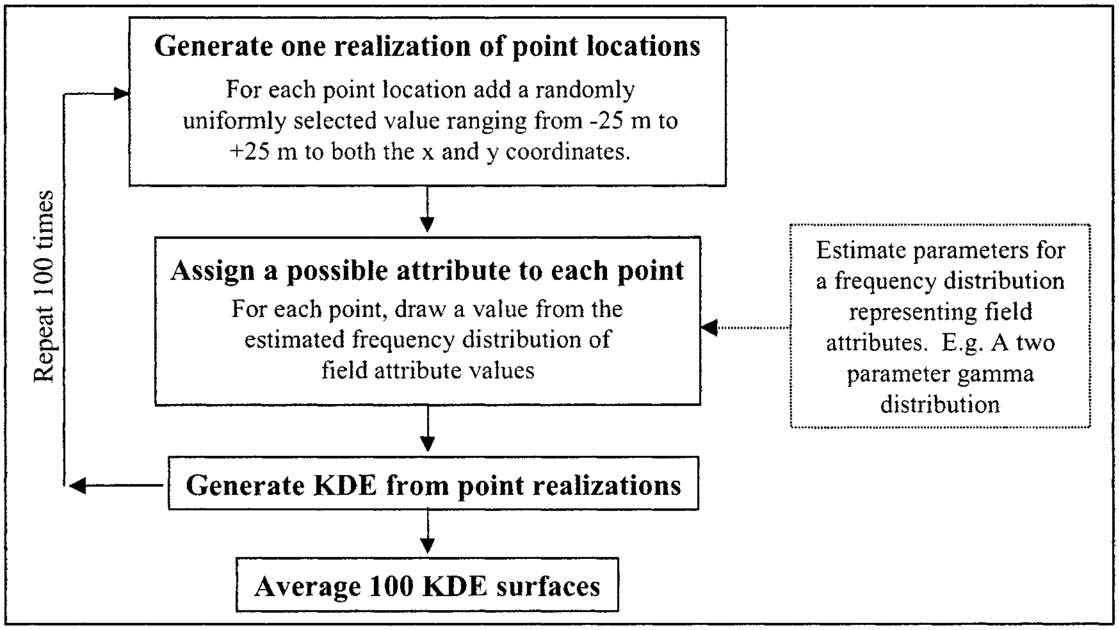


Figure 4.5. Summary of method for incorporating uncertainty when generating kernel density estimated surfaces.

The spatial error for each point, or cluster centroid, is estimated by field crews to be within ±25 metres. In order to simulate spatial error, values were drawn from a normal distribution with a mean of zero and standard deviation of one. These values were then scaled between ±25 and added to both the *x* and *y* locations of each point. Although the distribution of GPS error is not normally distributed, the distribution of error in either the *x*- or *y*-axis is near normal (Leva *et al.*, 1996 pg. 279). Spatial uncertainty was simulated 100 times to generate 100 different spatial representations of the point data.

Aerial survey attribute error was also simulated by drawing values from a distribution. To determine an appropriate distribution for attribute simulation, point data having both aerial and Y1 field attributes (6,135 points) were randomly partitioned so that half could be used for method development and the other half for method testing. It should be noted that 16 points with aerial or attribute values greater than 100 were considered outliers and removed from the analysis. In order to consider uncertainty in the next phase of analysis, the goal for this stage of analysis was to identify a distribution useful for simulating Y1 values based on aerial survey attributes. Cursory exploration suggested that more than one distribution would be necessary for generating realizations of attribute. Based on natural breaks in the frequency distribution of aerial survey attribute values, aerial survey data were split into three categories with attributes equal to: one to five, six to 10, and greater than 10 (see Figure). We did not deal with aerial values equal to zero as these only occur when field data are available, and therefore do not need to be corrected.

For each category, distributions of Y1 attributes were skewed right, having many small values, and appeared to be of a gamma form (Figure 4.6). Maximum likelihood estimates (MLEs) were used to estimate parameters that best fit two-parameter gamma distributions to the frequency distribution of Y1 values in each of the three data categories. The gamma parameters were adjusted to optimize the fit between observed and estimated distributions (Table 4.4).

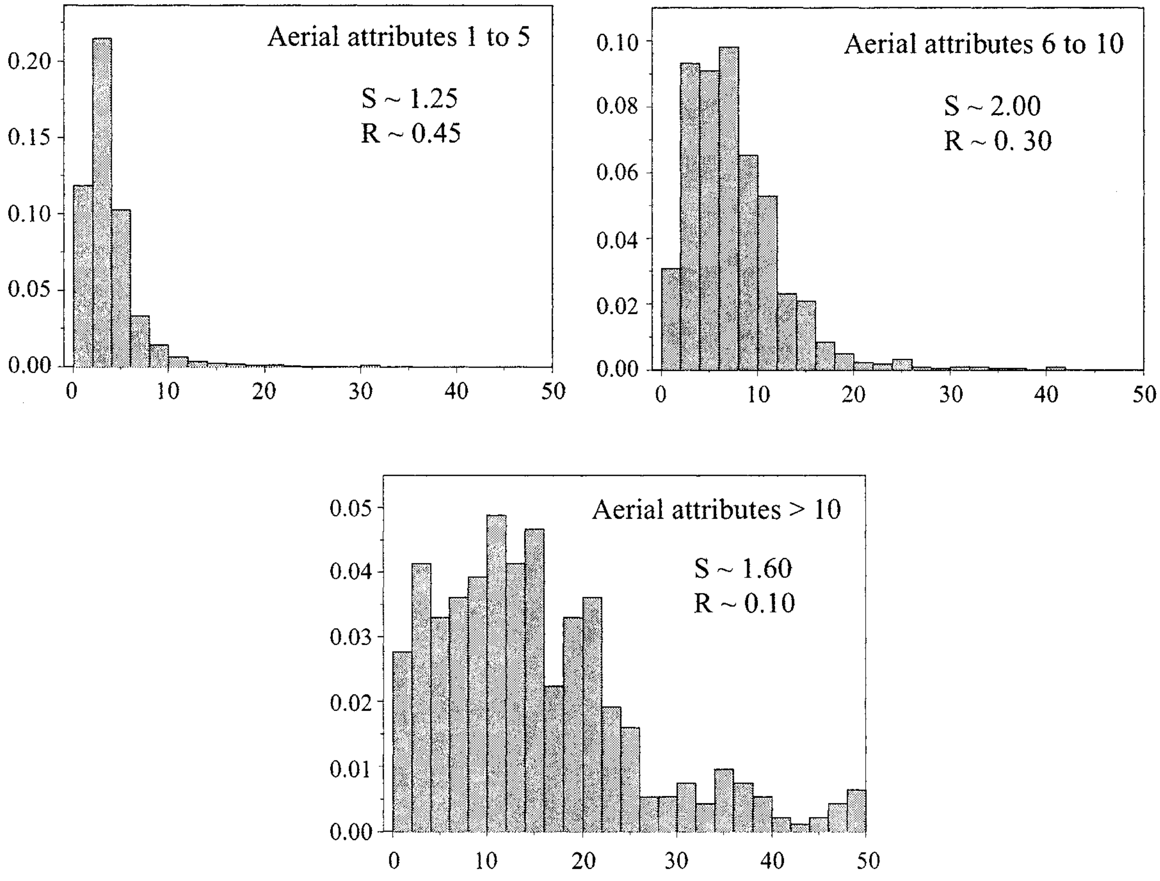


Figure 4.6. Frequency distributions of Y1 values for each of the aerial attribute categories. S (shape) and R (rate) are the parameters of the 2-parameter gamma distribution fitted to the data. The x-axis is the number of infested trees identified, for each point, during field surveys and the y-axis is the relative frequency of data.

Table 4.4. Two-parameter gamma distribution characteristics used for generating realizations of aerial survey attribute values. S (shape) and R (rate) are the parameters of the 2-parameter gamma distribution.

Aerial values	**S_MLE**	**R_MLE**	**S_Adjusted**	**R_Adjusted**
1 to 5	1.93	0.55	1.25	0.45
6 to 10	1.99	0.27	2.00	0.30
>10	1.36	0.06	1.60	0.10

Although the gamma distribution relates meaningfully to our data, there are two problems with using it to simulate the Y1 data. First, gamma distributions are continuous, whereas the number of infested trees is discrete. Since a discrete gamma distribution may be generated by binning data values (Yang, 1994), we rounded values drawn from the gamma distribution, thus producing a finely binned distribution. Secondly, gamma distributions do not include zeros, whereas the data do. To accommodate this limitation, the percentages of zeros in the Y1 data were retained in the simulations. Although these solutions may lack elegance, the alternative is to generate a distribution based on the observed data, which would be "chunky" and requires the assumption that the observed data represent the entire error population, rather than a sample of possible errors.

Once the gamma distribution parameters were estimated, drawing values from each distribution simulated point attributes. The zeros retained in each simulation were treated as additional random draws. To assess the effectiveness of this approach, attribute values from five simulations were averaged together and compared to the testing data using the Kolmogorov-Smirnov test. At the 95 percent confidence level, the fit between the simulated data set and the test data could not be rejected. Once the spatial locations and attribute values were simulated 100 times, each data realization was converted to a kernel density surface and all 100 surfaces were averaged together. In Figure 4.7 we show kernel density surfaces for 2002, the first made without correction and the second incorporating data uncertainty. Figure 4.8 is the spatial variation in differences between the uncorrected and corrected surfaces. While the corrected surface has locations with both higher and lower infestation values relative to the uncorrected surface, there is an overall reduction in values. In 2002, when data uncertainty is incorporated the maximum number of infested trees per $200m^2$ is 101; when uncertainty is not considered the maximum number of infested trees is 268 per $200m^2$. The higher values associated with the uncorrected surface are explained by the large commission error that occurs when aerial survey attributes and Y1 data are compared. Figures 4.9 shows the corrected kernel density surfaces for 1995 through 2002.

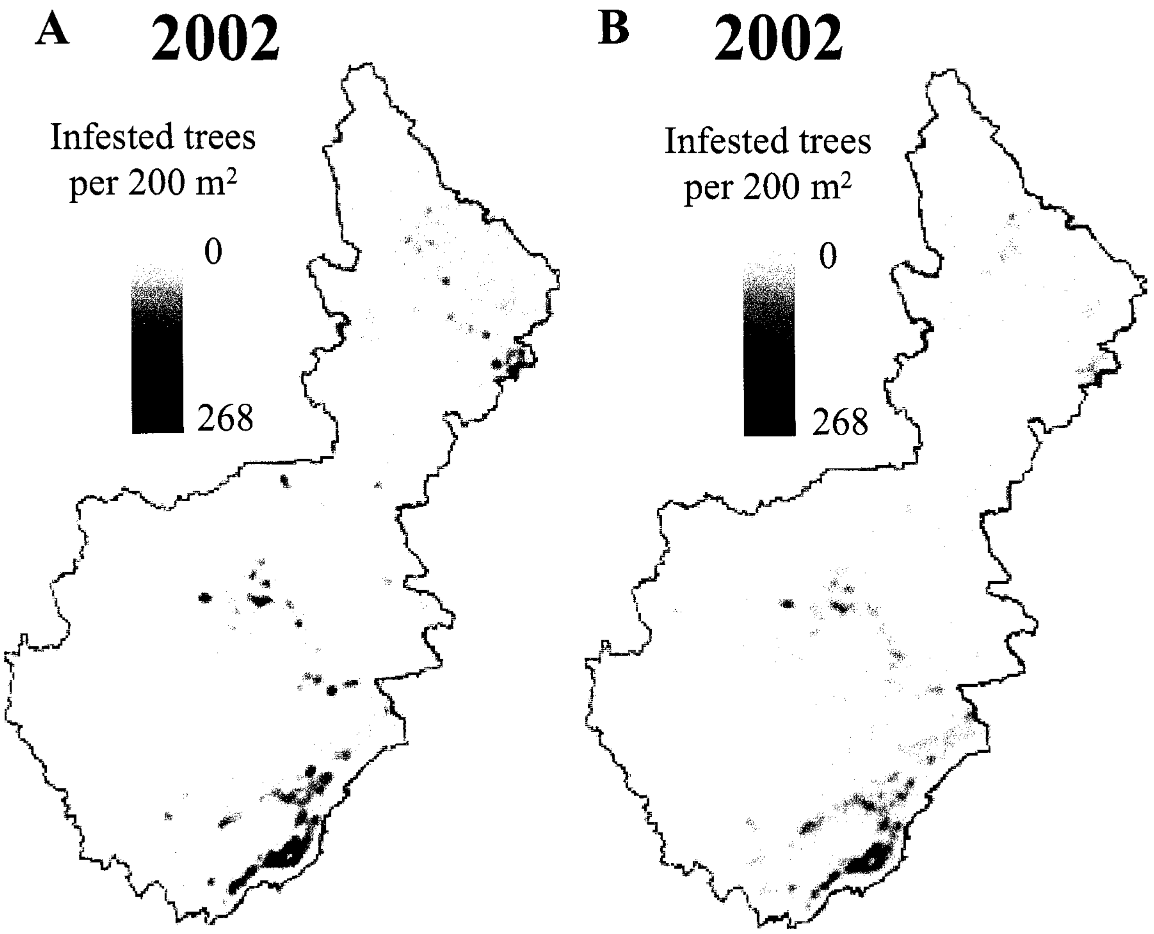


Figure 4.7. Kernel density estimated surfaces without (A) and with (B) consideration of data uncertainty in 2002 for the Morice TSA.

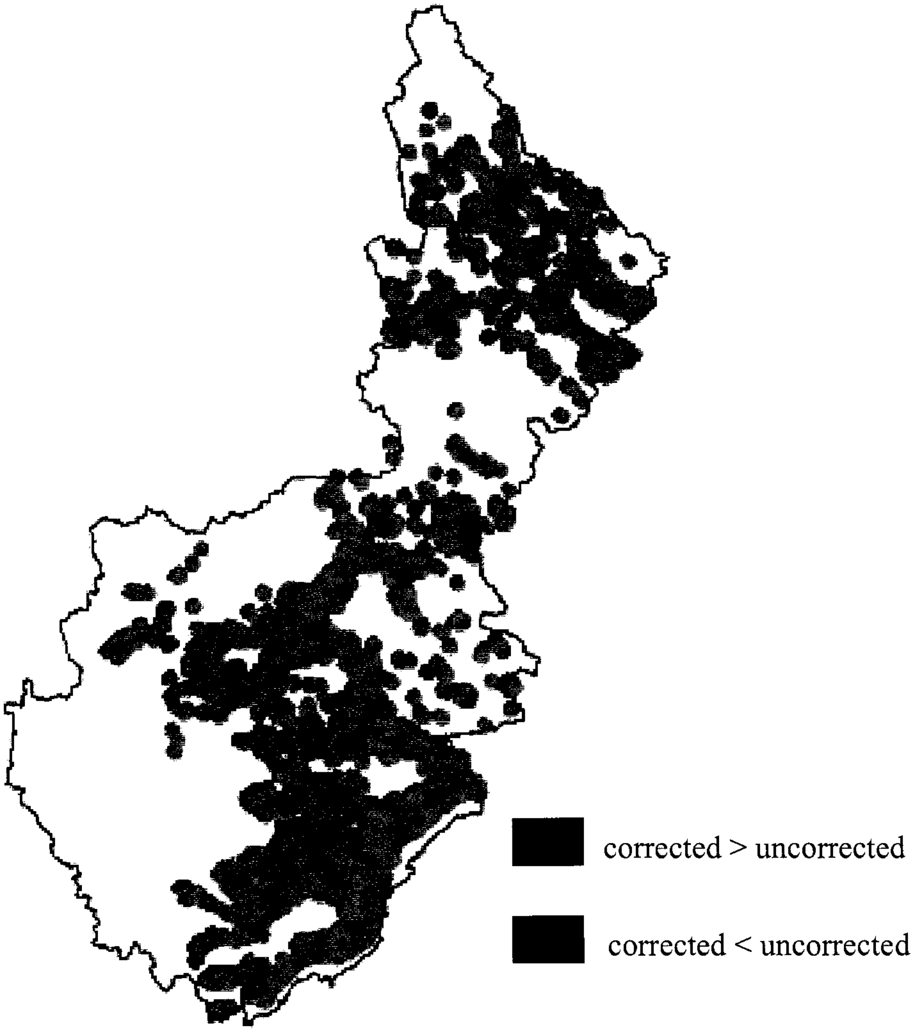


Figure 4.8. For 2002 in the Morice TSA, the difference in kernel surfaces calculated with and without corrections.

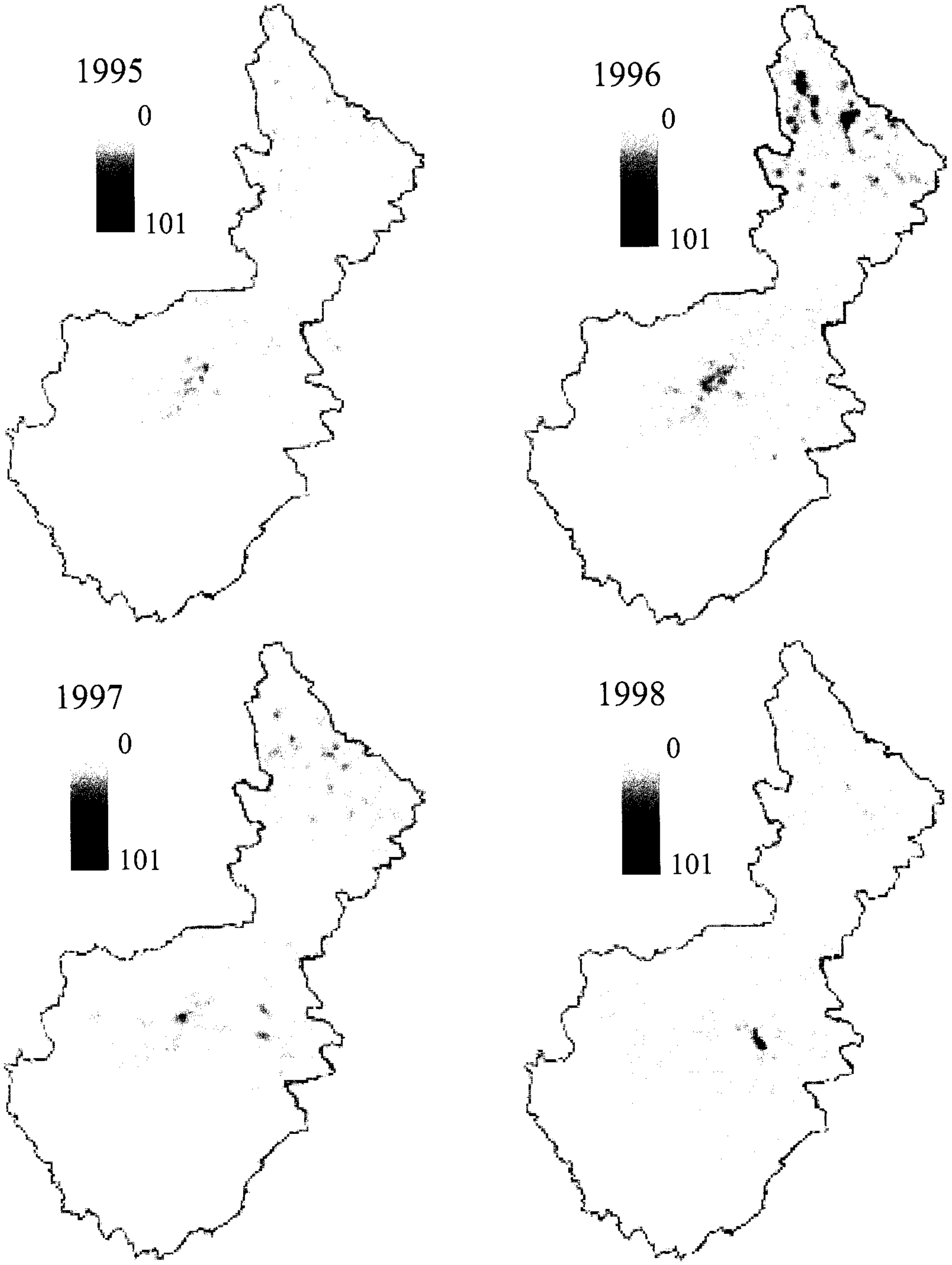


Figure 4.9. Corrected kernel density estimated surfaces from 1995 to 2002 for the Morice TSA. Legend values represent the number of infested trees per 200 m^2.

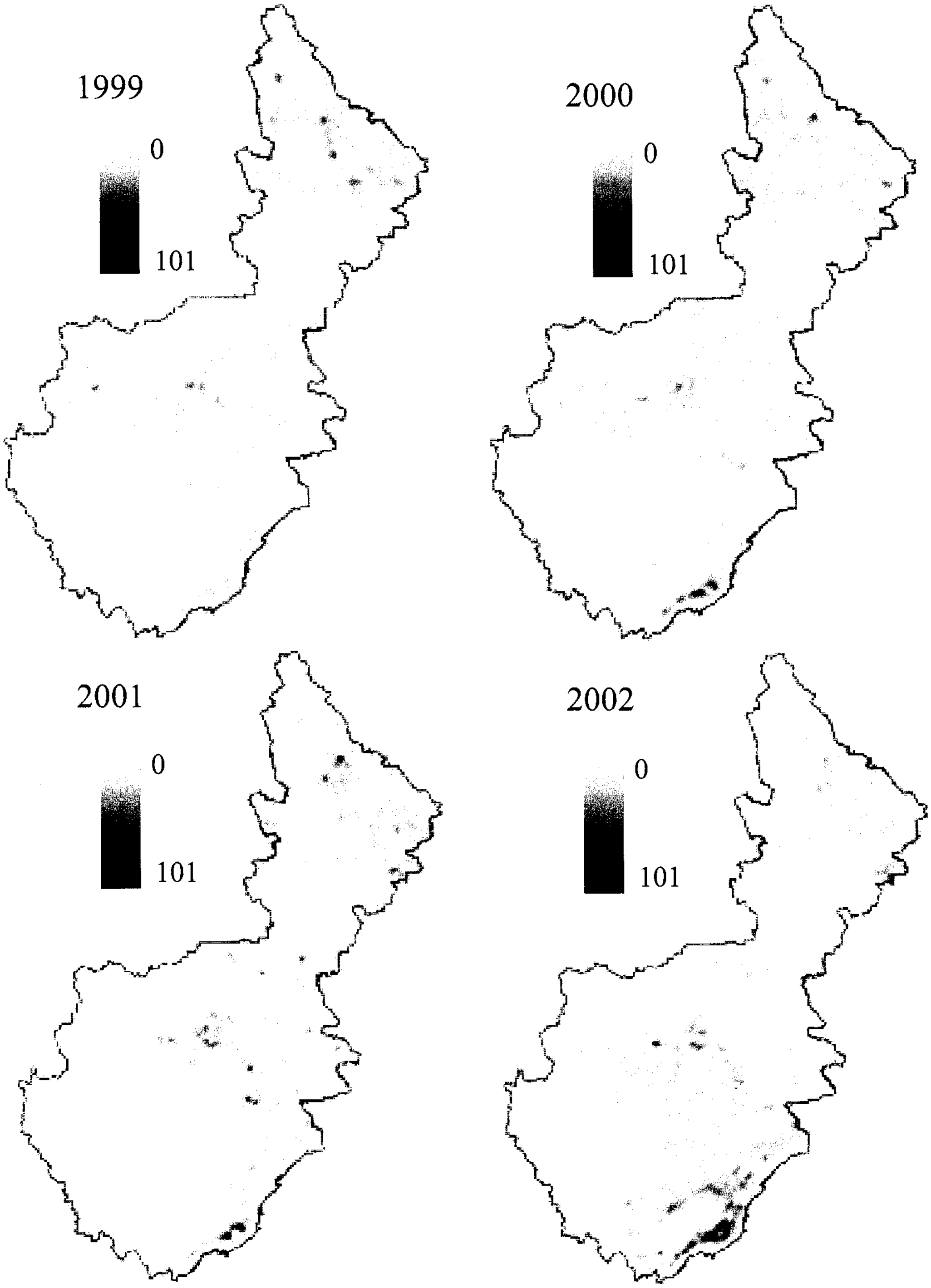


Figure 4.9 (Continued). Figure 4.9. Corrected kernel density estimated surfaces from 1995 to 2002 for the Morice TSA. Legend values represent the number of infested trees per 200 m^2.

For each pixel in a corrected kernel density estimated surface, the variance of the 100 kernel density input values, provides insight into the extent of data uncertainty at a specific location, the lower the variance, the lower the uncertainty. Variance tends to be highest where the aerial attribute values are the largest. By draping the corrected kernel density estimated surfaces over variance values, we can visualize how uncertainty changes with infestation intensity, and identify locations where confidence in data quality is high and low (Figure 4.10).

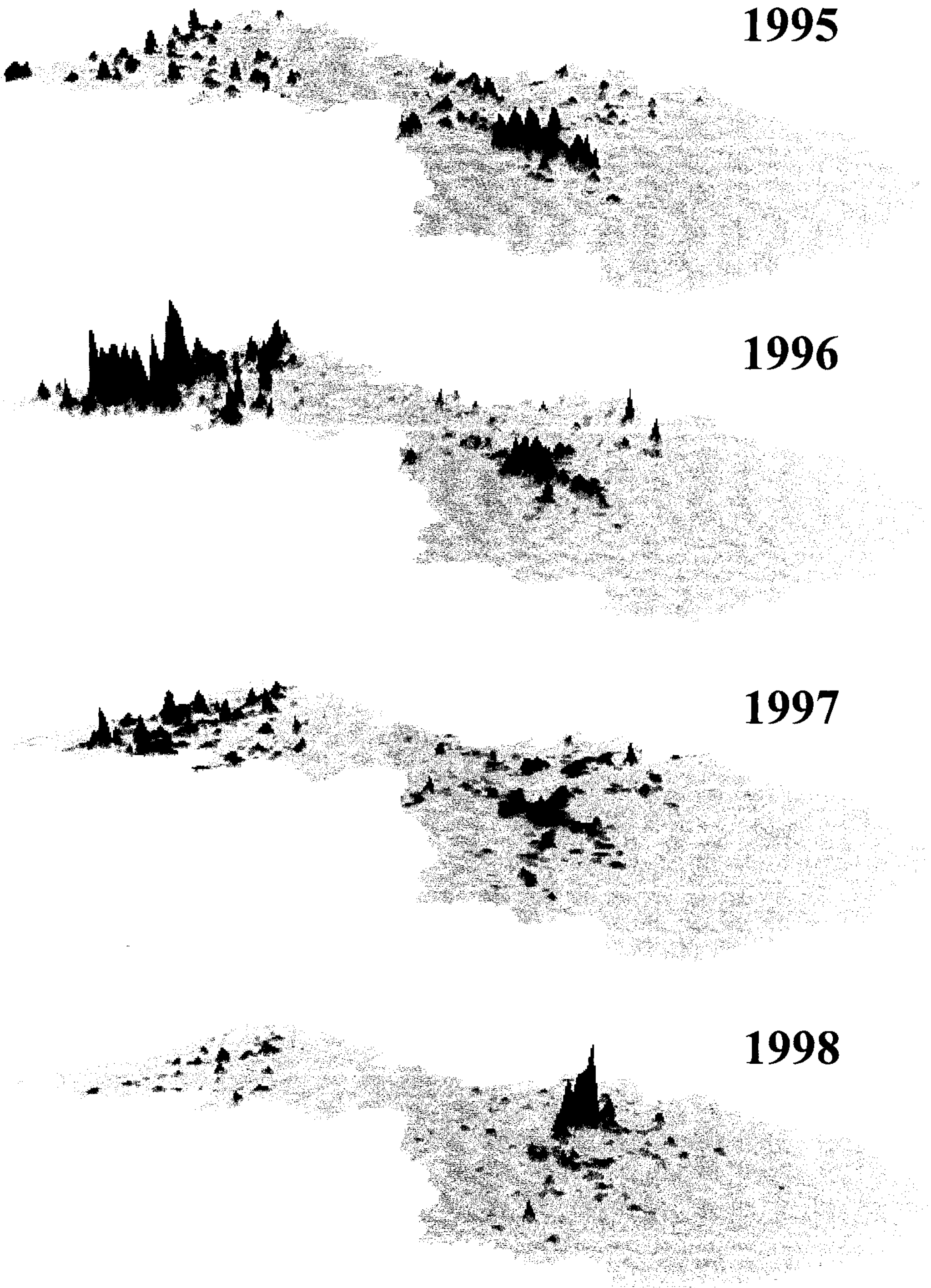


Figure 4.10. For the Morice TSA, from 1995 to 2002, infestation intensity (colour) is visualized in combination with data confidence or variability (height). Darker reds represent higher infestation values, and grey represents locations with no infestation. Higher locations have greater variance. Variance is exaggerated to aid visualization and increases with data height.

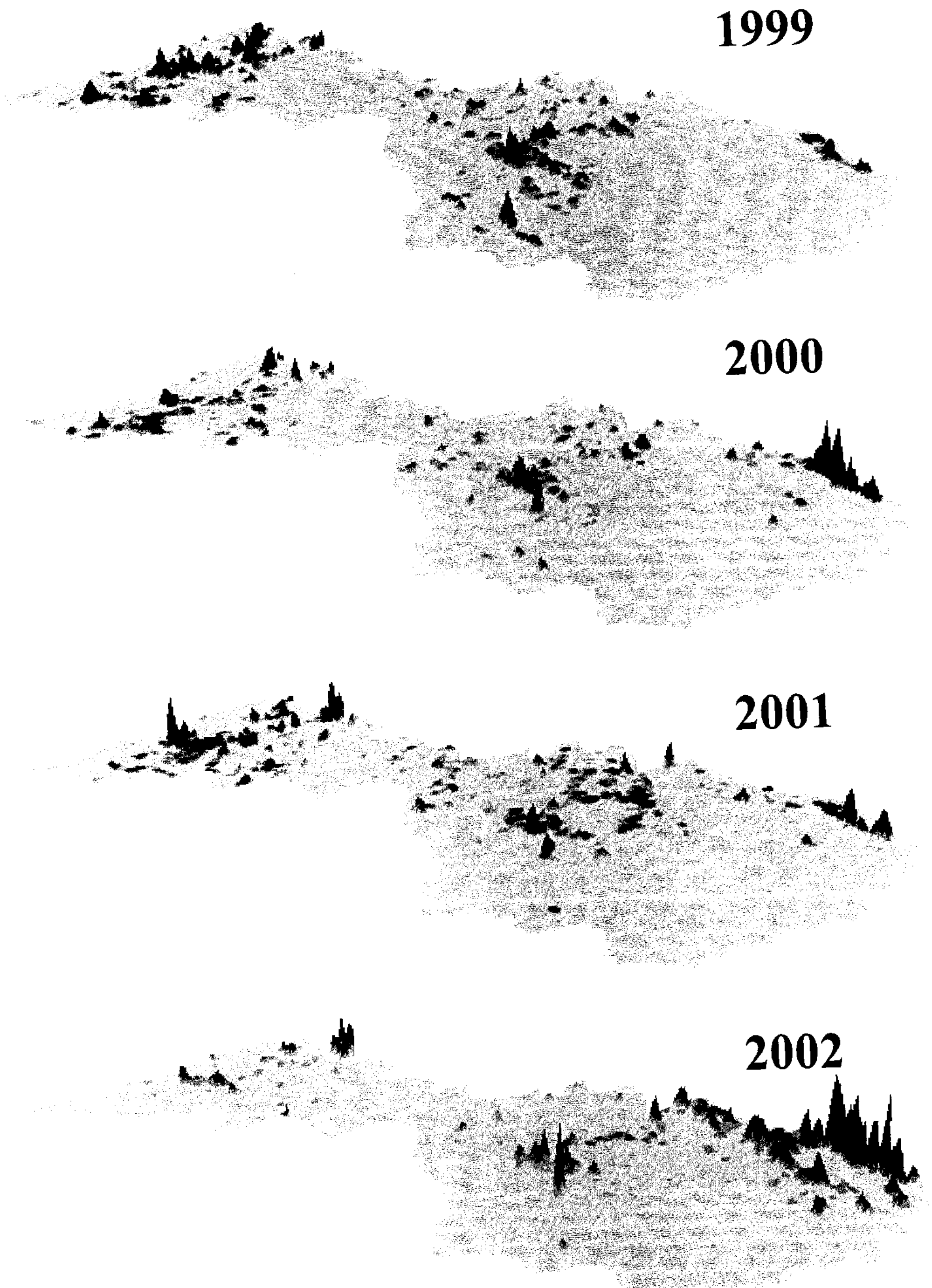


Figure 4.10 (continued). For the Morice TSA from 1995 to 2002, infestation intensity (colour) is visualized in combination with data confidence or variability (height). Darker reds represent higher infestation values, and grey represents locations with no infestation. Higher locations have greater variance. Variance is exaggerated to aid visualization and increases with data height.

4.6 SUMMARY

Monitoring efforts in the Morice TSA have generated a unique data set on mountain pine beetle infestations. By combining field surveys with spatially and temporally extensive aerial surveys, this data set provides a new opportunity for exploring the spatial patterns of infestation over landscapes and through time. Uncertainty is inherent in data sets collected over large areas or multiple time periods. As such, understanding the nature of error and the information content of data is beneficial.

Data collected by Morice of are of sufficient detail and accuracy to assist forest management, and tactical planning associated with mountain pine beetle mitigation. Attribute errors associated with aerial GPS helicopter surveys are typically small (87.2 percent of points have errors less than ±10 trees). The main factor in aerial survey accuracy is the timing of the response of crown foliage to attack by mountain pine beetles, and attributes best represent infestations that occurred one to two years previously. This research corroborates other investigations that have indicated aerial survey methods are not suitable for monitoring green attack (Wulder *et al.,* 2004).

The information content of data collected by the Morice TSA, is evidence of the benefits of continuing to monitor mountain pine beetle infestations using a combination of helicopter and field surveys. As most of the error seems to be associated with the timing of a tree's response to attack, rather than survey procedures, it is unlikely that modifications to the aerial surveying approach will lead to major improvements in the data accuracy. However, there may be benefits associated with expanding or adjusting the field program. For instance, we are unable to quantify the frequency with which infested locations are entirely missed during aerial surveying, although we anticipate such errors exist. One recommendation may be to undertake random field surveys in locations throughout the Morice TSA. This may give an indication of the likelihood of infested locations being missed during aerial surveying.

Even the most detailed and accurate data are only useful if they can be clearly communicated. Improved communication allows data to be used more effectively in decision making, facilitates information dissemination to the public, and enhances use by researchers. Kernel density estimators are a simple and effective tool for visualizing infestation data and facilitate exploration and mapping of spatial variation in infestation magnitude. Here, kernel density estimators are more effective than simple cartographic techniques, as surface generation removes point overlap, spreads attributes over areas, and allows incorporation of data uncertainty. By producing a continuous representation of the data, the kernel density estimators enable a conceptually appropriate data model and aid analysis over many time periods.

Although the uncertainty associated with most individual survey locations is minor, the cumulative impact of many small, but common, errors may have a considerable effect on spatial analysis. Adjusting kernel density estimation to incorporate uncertainty provides a new approach for dealing with uncertainty when working with large area data sets. The technique for considering uncertainty that has been outlined in this chapter may be applied to other large point data sets. Methods designed to incorporate uncertainty are essential and enable spatial investigations of a growing number of rich, but uncertain, large area and multi-temporal data sets.

5 EXPLORING SPATIAL AND SPATIAL-TEMPORAL HOT SPOTS IN MOUNTAIN PINE BEETLE INFESTATIONS

5.1 INTRODUCTION

The term "hot spot" is used by many disciplines and has several meanings. In forestry, hot spots typically refer to the presence of phenomena such as fire (Fraser *et al.*, 2000). In spatial analysis, the term hot spot may indicate the presence, abundance, or lack of phenomena (Sokal *et al.*, 1998), or an unusual spatial pattern (Ord and Getis, 2001). The hot spot definition will vary for each study; however, generally identifying hot spots or abnormalities in spatial patterns allows locations that may be interesting or atypical in terms of their spatial processes to be isolated.

Hot spots can be used to characterize and investigate spatial and spatial-temporal variation in mountain pine beetle infestations. Some reasons for spatial variation in infestation intensity are well understood. For example, the mountain pine beetle is known to prefer mature trees (Safranyik *et al.*, 1974). However, until recently, landscape level variations in mountain pine beetle infestation intensity have not been studied, as large area data sets were unavailable. There are many questions regarding mountain pine beetle behaviour over large areas that may be investigated using hot spots. Detailed definitions are provided below, however in this study hot spots are considered pixels with the most intense infestations, and hot spot patches are groups of spatially contiguous hot spot pixels.

The goals of this chapter are to identify and explore spatial and spatial-temporal patterns of hot spots and hot spot patches. To meet these goals, mountain pine beetle infestation hot spots are delineated in each year, characterized through time, and hot spot patches identified. The spatial-temporal relationships in hot spots and patches are investigated and landscape characteristics underlying both hot spots and patches are explored.

5.2 DEFINING AND IDENTIFYING HOT SPOTS AND HOT SPOT PATCHES

Hot spots are defined as individual grid cells with the most intense infestations. For each subarea, a location in the corrected kernel density estimated surface is considered "hot" if its value falls within the upper 10 percent of the frequency distribution of infestation intensities. For a description of kernel density estimated surfaces refer to Chapter 4. Kernel density estimated values represent the number of infested trees per 200 metres squared (or the number of infested trees per pixel), and were converted to integers prior to this analysis. The choice of the hot spot threshold was based on a statistical standard, the 90th percentile, and investigation of these areas demonstrated that hot spots have different underlying characteristics than all pine locations.

Identifying hot spots allows temporal variation in the spatial distribution of the most intensely infested locations to be visualized. Defining hot spots as the upper 10 percent of frequency distributions has the benefit of being sensitive to the global trends in infestation intensity. As the overall epidemic magnitude increases and decreases in response to climate and other factors, the threshold value will also become higher or lower, and 10 percent of the study area will always be identified as hot. Threshold values were generated on an annual basis for each of the subareas (Table 5.1), and were applied to the kernel density estimated surfaces to locate hot spots in each year. These values provide an indication of the general magnitude of infestation in each subarea through time.

Table 5.1. Thresholds for defining hot spots in subareas of the Morice TSA from 1995 to 2002. These values are calculated as the upper 10 percent of frequency distributions, based on kernel density cell values that estimate the number of infested trees per 200 m^2

Subarea	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
North	9.24	21.20	11.90	5.47	11.36	9.45	10.55	8.88
Middle	12.16	11.73	10.70	6.31	7.86	7.40	10.82	10.16
South	no data	2.65	2.70	3.07	9.36	22.31	17.13	14.38

Much like infestation intensity varies over space, the temporal persistence of hot spots also varies over the landscape. While portions of the landscape host hot spots for several years, other areas are only "hot" for a single year. To characterize temporal variation in hot spot persistence a vector, eight binary digits in length, was generated for each pixel (Figure 5.1). Each position in the vector represented a year and was assigned one if the location had a hot spot in that year and zero otherwise. Locations may be hot in as few as zero, or as many as eight years, and vectors may be characterized in a number of ways. In this analysis we characterize hot spot persistence over the full eight years of available data, as analysis for shorter time series (*i.e.*, two, three, and four years) revealed similar trends to single year hot spot investigations.

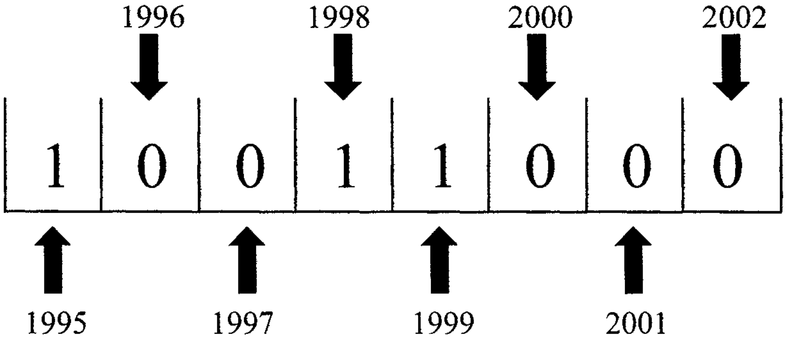


Figure 5.1. An example of a vector used to characterize spatial-temporal hot spot persistence. A value of one indicates a pixel was hot in a particular year, and a value of zero indicates the pixel was not hot.

Analyzing hot spots over eight years resulted in 190 unique persistence vectors. To reduce the number of persistence categories, vectors were classified as: 1) the number of hot spot years; 2) the maximum number of consecutive hot spot years; 3) the first hot spot year; and 4) the percentage of active years that were hot. Active years were defined as the first and last year that a cell had greater than zero infested trees; in other words, the first and last year that mountain pine beetle infestations were identified at a particular location.

The definition of a hot spot is aspatial. Yet, as will be demonstrated in the results section, hot locations cluster spatially. The spatial configuration indicates there is a spatial structure associated with locations of intense mountain pine beetle attacks. To consider the spatial characteristics of hot spots, patches are defined as groups of spatially contiguous hot spot pixels. Spatial contiguity used for delineating patches is based on the queen's definition (the eight neighbour rule). Hot spot patches include single pixel hot spots; however, of the 404 hot spot patches, 396 are composed of two or more contiguous pixels that are 200 square metres. To better understand the spatial nature of intense infestation, characteristics of hot spot patches were summarized and explored.

5.3 INVESTIGATING DISPERSAL

Dispersal is one of the most important components of mountain pine beetle behaviour. While mark recapture studies provide insight on dispersal processes over small areas (*e.g.*, Barclay *et al.*, 1998) little is understood regarding dispersal over large areas. There are three key theories on mechanisms of dispersal. The first theory suggests that during epidemics, infestations spread progressively from centres (Safranyik *et al.*, 1974). Qualitative observations of infestation patterns imply that beetles move from one susceptible host to the next, spreading short distances. A second related theory focuses on the development of large infestations. Rather than developing from a single centre, large infestations result from smaller infestations that coalesce (Borden, 1993). Several small attacks merge into a single, large infestation. A third dispersal theory is that at least a portion of the mountain pine beetle population undertakes long-range dispersal, infesting trees at some distance from the site of emergence (Furniss and Furniss, 1972; Hughes, 2002). As mountain pine beetles are weak fliers, long-range dispersal is believed to be a function of wind (Safranyik *et al.*, 1989). Long-range dispersal may explain how new infestations appear at some distance from previously observed attack locations.

To better understand dispersal mechanisms over the landscape, the spatial-temporal relationships of heavily infested locations were investigated using pixel-based analysis and an exploration of hot spot patches. Pixel-based analysis allows some spatial-temporal relationships between hot locations to be characterized, but is of limited utility as the spatial structure inherent in hot locations is ignored. Therefore, hot spot patches are also investigated to allow explicit consideration of spatial structure when investigating intensely infested locations through time.

Pixel-based investigations of the spatial-temporal relationships in hot spot locations are explored using the nearest Euclidean distance and direction between hot pixels in neighbouring time periods. Some, but not all, hot spots near the study area's boundary are impacted by edge effects. Edge effects were minimized by restricting the analysis to distances less than or equal to 10 kilometres.

The theory that infestations begin as small isolated infestations and over time coalesce into larger areas of attack, was investigated by determining the number of intersections each hot spot patch has with patches in the previous year. By correlating the size of patches to the number of intersections in the previous year, the frequency with which large hot spot patches are located where patches were previously is illustrated.

As will be shown in the results sections, only 4.5 percent of patches had more than one intersection with a patch in the previous year, therefore investigation of the spatial-temporal relationship between patches focused on scenarios with zero or one intersections. Patches with one intersection in the previous time period were split into four categories: 1) patches in t_i that completely envelop a patch in t_{i-1} (growth) (Figure

5.2a); 2) patches in t_i that are completely enveloped by a patch in t_{i-1} (shrinkage) (Figure 5.2b); 3) t_i patches that partially overlap patches in t_{i-1} and grew (Figure 5.2c); and 4) t_i patches that partially overlap patches in t_{i-1} and shrunk (Figure 5.2d). When patches completely envelop or are enveloped by other hot spot patches, growth or reduction occurs in all directions. However, the amount of change is not necessarily consistent in all directions.

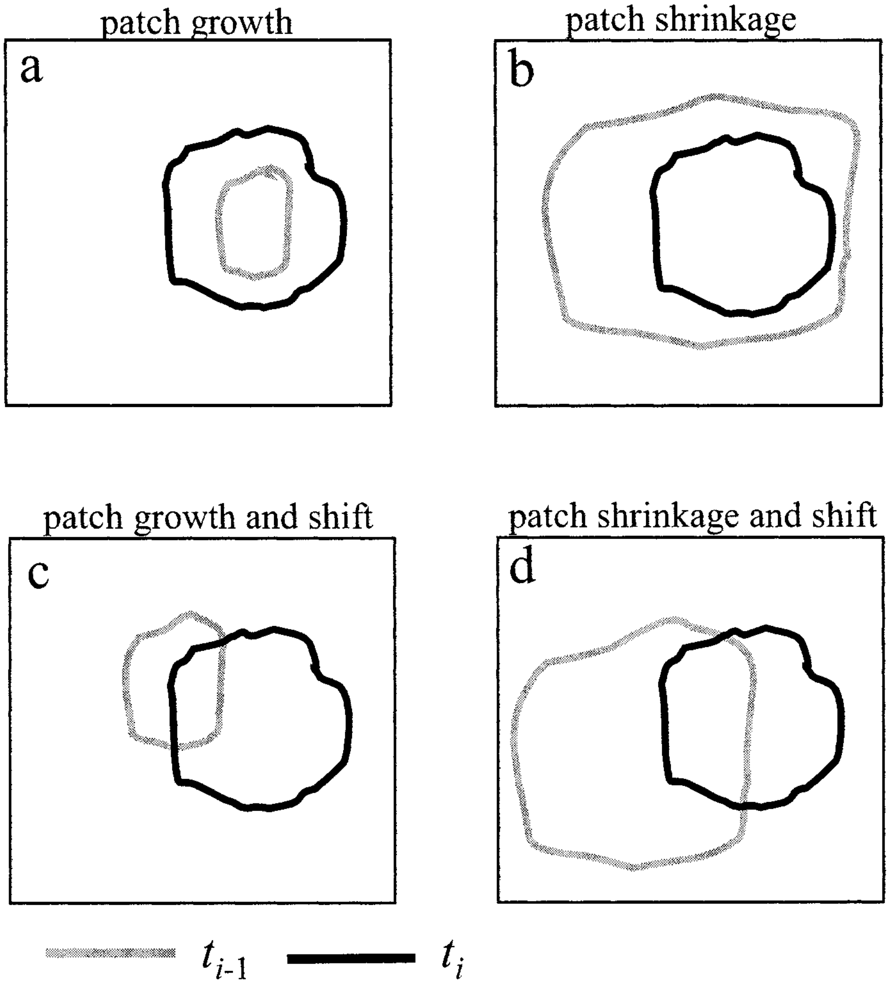


Figure 5.2. Categories used for investigating the spatial-temporal relationships of hot spot patches with one intersection.

For hot spot patches with no intersections, the minimum Euclidean distance from a patch in the previous year was determined (Figure 5.3a). The distance of infestation spread, associated with patches having one or more intersections was also investigated. In this case, the distance of spread was characterized as the maximum Euclidean distance between leading edges in t_{i-1} and t_i (Figure 5.3b). In the case where a patch shrunk and was completely enveloped by a patch in t_{i-1} there was no leading edge. For this scenario we determined the maximum distance a patch shrinks (Figure 5.3c). For patches that grew or shifted, the dominant direction of spread was also determined.

The amount of overlap between hot spot patches was also investigated. For each hot patch, the percentage of overlap with patches in the previous year (t_{i-1}) and future year (t_{i+1}) was determined. As well, the percentage of overlap with infested, but not necessarily hot, locations was characterized.

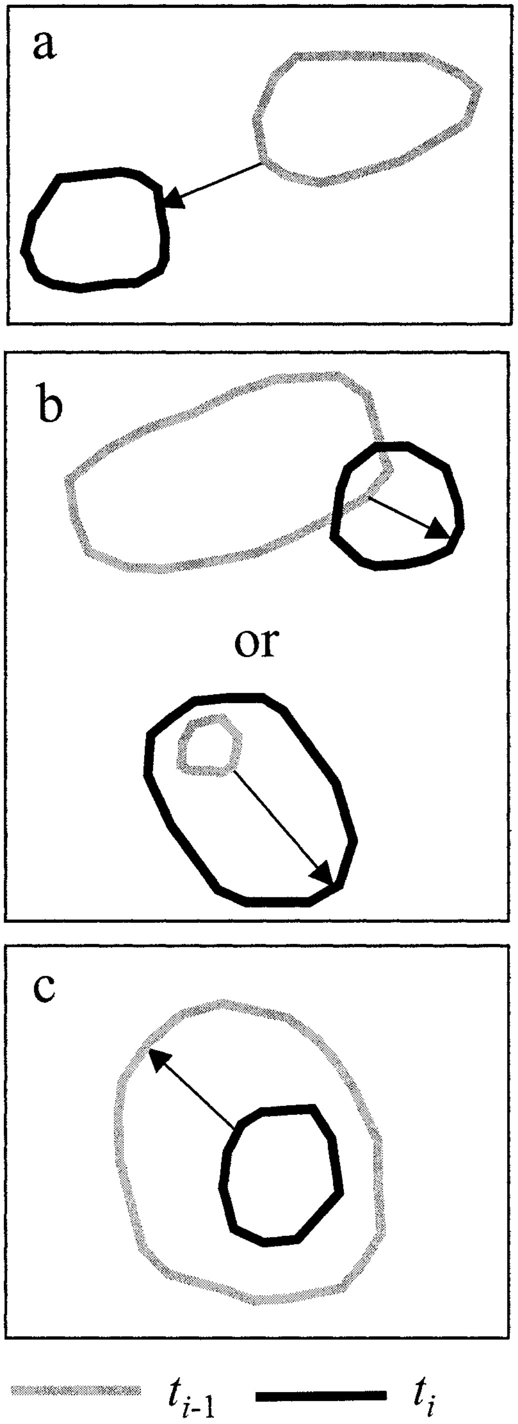


Figure 5.3. Distance relationships between multi-temporal hot spot patches. A) Minimum distance between patches that have no intersections between t_i and t_{i-1}. B) Maximum distance of leading edge spread. C) Maximum distance of leading edge shrink.

5.4 THE LANDSCAPE VERSUS HOT SPOTS AND HOT SPOT PATCHES

To better understand causes of spatial and spatial-temporal variations in infestation intensity, we explored landscape characteristics associated with hot locations. Landscape characteristics investigated include forest age, percent pine, elevation, and aspect. Such relationships may be helpful when determining the likelihood that a location will be attacked in the future, when estimating the duration of attack at a particular location, or when forecasting temporal changes in infestation magnitude.

Relationships between intensely infested locations and the landscape were investigated using two spatial units: the hot spot pixel and the hot spot patch. Using hot spot patches as the spatial unit, we investigated how the distribution of landscape characteristics change with hot spot size and time. For each hot spot patch, the distribution of a landscape characteristic is summarized using a box plot. Box plots are partitioned by subarea and year, and enable simultaneous visualization of trends in the central tendency (median), variability, and skewness.

Pixel-based analysis allowed comparison of the relative frequency distribution of landscape characteristics associated with hot and non-hot locations in single and multiple years. Pixel-based investigations are partitioned by subarea and year, and landscape characteristics of both single year hot spots and temporal categories of hot spot persistence were studied.

One difficulty with pixel-based comparisons is that even small errors, in one or both surfaces, can compound and result in inaccurate comparisons (Foody, 2002; Fuller *et al.*, 2003). For instance, a pixel-based comparison of two identical maps may show no similarities if one of the maps is offset by even a single cell (Figure 5.4). To minimize the impact of minor uncertainties on map relationships, smoothing was undertaken prior to comparison. Converting point data to surfaces via kernel density estimation, results in smoothed data; therefore, no further filtering was performed. Similarly, the original DEM was provided as 50 metre grid cells and was converted to 200 metre cells. The resampling process smoothed the grid so no additional filtering was required. Forest age class and percent pine layers were smoothed with a 5 by 5 averaging filter. A range of window sizes was tested (3 by 3 to 9 by 9). The results of each smoothing were visually compared and the 5 by 5 window was chosen as it smoothed the data, while retaining sufficient spatial detail.

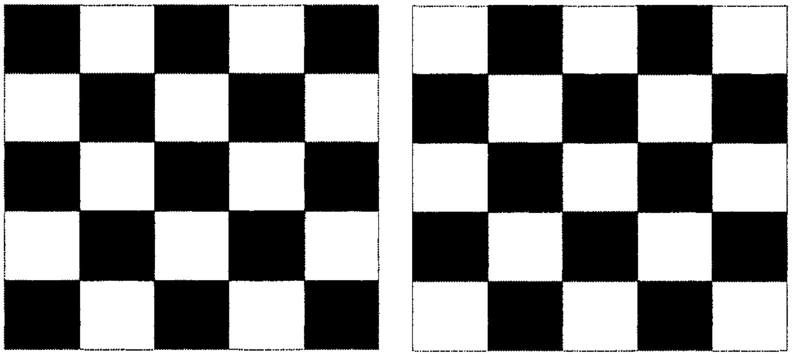


Figure 5.4. The same map offset by a single cell.

For each subarea, relative frequency distributions of landscape characteristics underlying hot spots were generated. To investigate relationships between hot spots and the physical environment, the relative frequency distributions of landscape characteristics for all pine cells were compared to the relative frequency distributions for only hot spots (in figures, relative frequency distributions for all pine cells are shown by a dotted line). If the hot spots were randomly located on the landscape, we would expect the two relative frequency distributions to have a similar form. Disparities in the shape of the relative frequency distributions were the basis for exploratory investigations into landscape properties associated with hot spots. Similar exploratory analysis was carried out for landscape characteristics underlying categories of temporal hot spot persistence. To interpret observed trends, we set the results within the context of current literature on mountain pine beetle biology, most of which is undertaken at stand, or finer, scales.

While exploratory analyses demonstrate relationships between forest conditions and hot spots, relative frequency distributions for forest age and percent pine are only representative of mid 1990 conditions, when the forest inventory was last updated. In reality however, relative frequency distributions of forest characteristics should change in response to mountain pine beetle infestations, management activities, succession, and other natural disturbances. It should also be mentioned that comparisons between hot spots and landscape characteristics resulted in a large number of plots (eight years * three subareas * five landscape characteristics * five representations of hot spots and hot spot persistence = 600); therefore, only a representative subset of comparisons is provided for visualizing trends. Figures chosen for presentation highlight the dominant trends found when all the plots were inspected. In all scenarios, the number of hot spots in eight years and the maximum number of consecutive hot spots, produced similar results; only findings of the former will be presented. The landscape characteristics of locations that were not hot were found to be consistent through time, and therefore are only presented once in the context of pixels where zero percent of years with active mountain pine beetle populations are hot. Finally, it should also be mentioned that hot spot locations were compared to slope, but trends appear random and will not be reported.

5.5 RESULTS AND DISCUSSION

5.5.1 Visualizing Single and Multiple Year Hot Spots, and Hot Spot Patches

In Figure 5.5 the spatial location of hot spots for 1995 to 2002 are shown. Due to the definition of hot spots, the number of hot cells is always proportional to the number of pixels in each subarea with some mountain pine beetle activity. Hot spots allow easy visualization of the subareas that have the most mountain pine beetle activity, and within each subarea, the locations that are most heavily infested. Initially, mountain pine beetle activity was greatest in the North and Middle subareas; however, by 2002 the South subarea had the majority of large infestations.

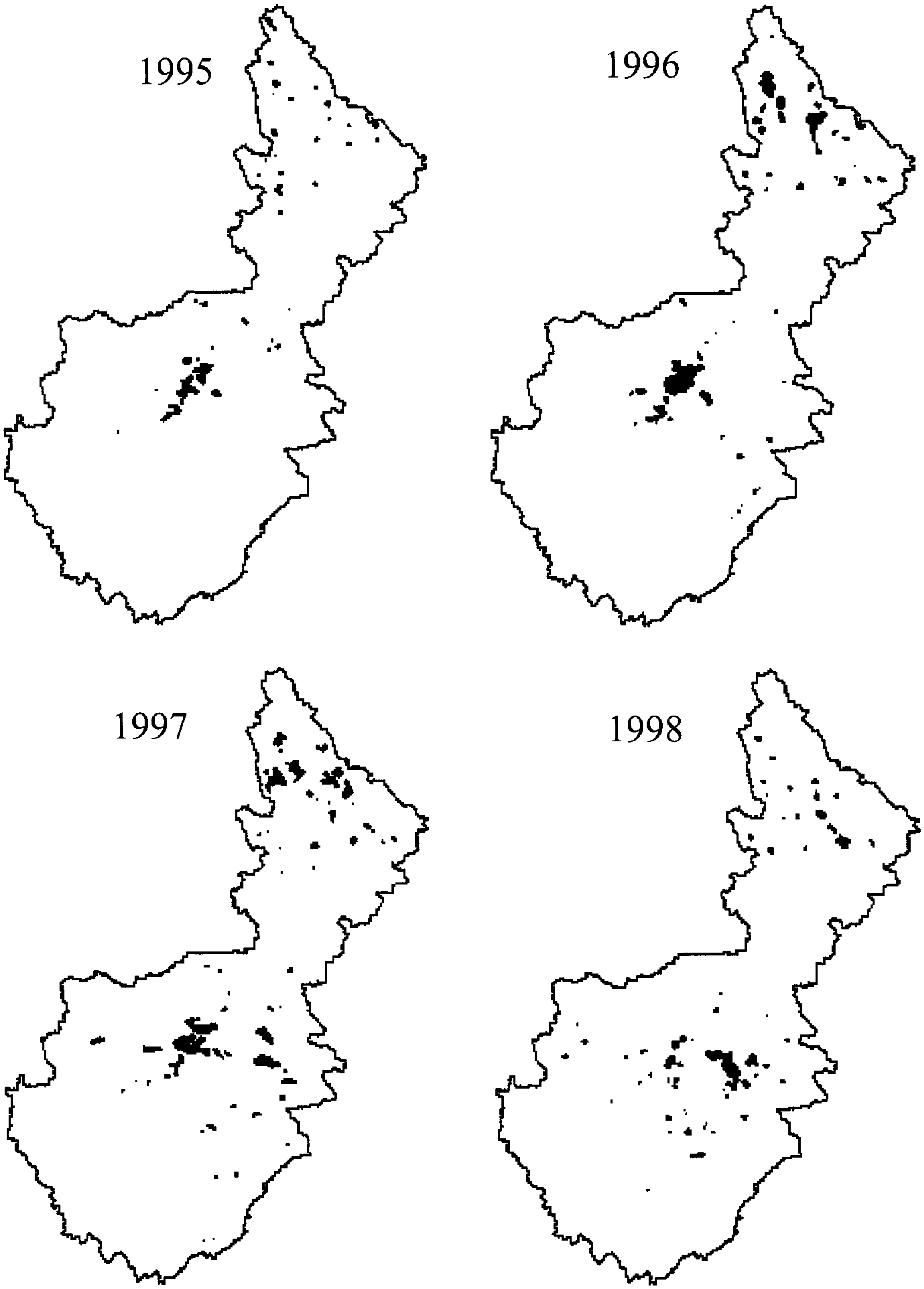


Figure 5.5. The spatial location of infestation hot spots in the Morice TSA from 1995 to 2002. Brown = hot spot, beige = infested not hot, white = not infested.

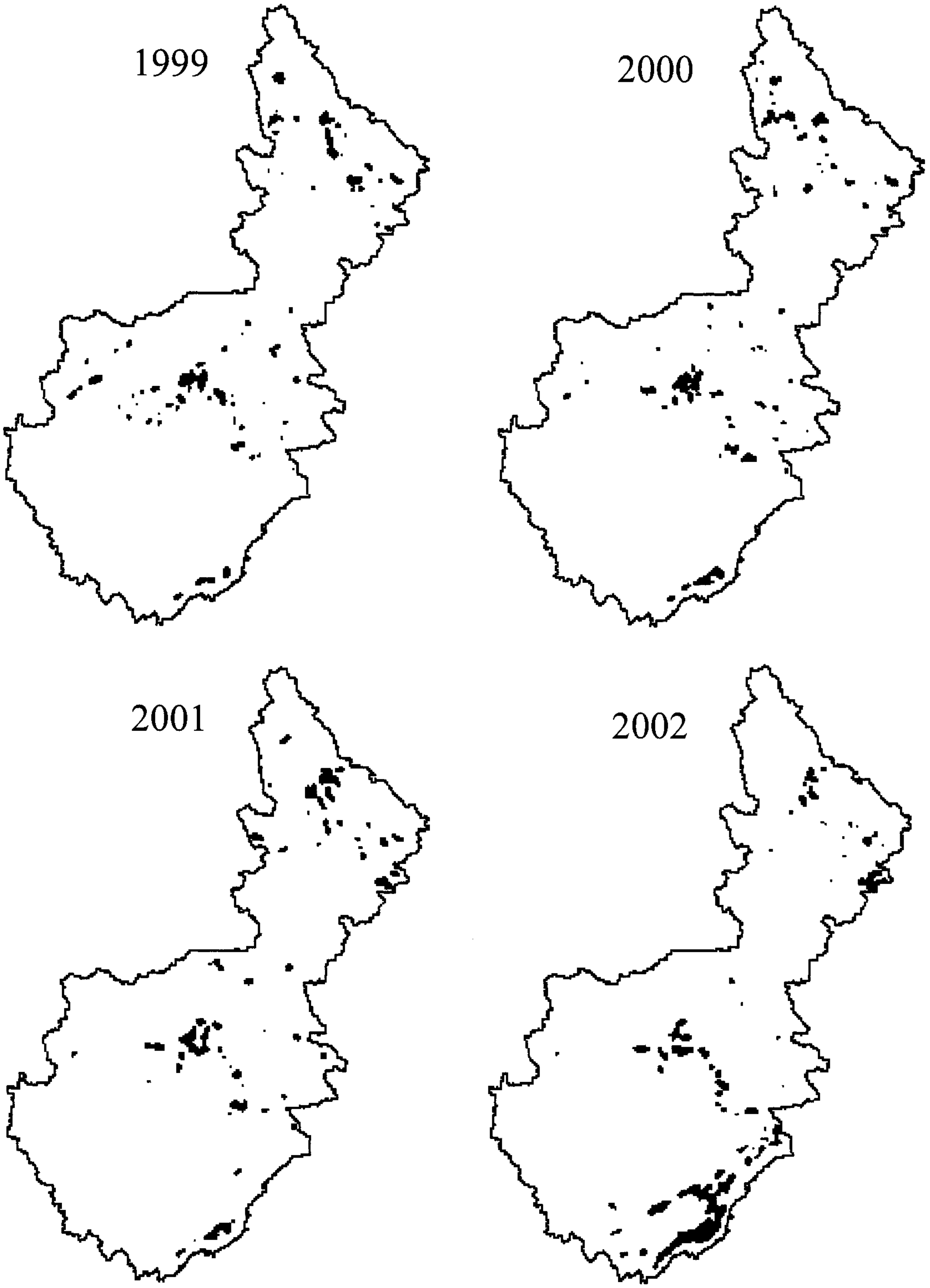


Figure 5.5 (Continued). The spatial location of infestation hot spots in the Morice TSA from 1995 to 2002. Brown = hot spot, beige = infested not hot, white = not infested.

Maps of the categorized persistence vectors are shown in Figure 5.6. The number of pixels in each category are shown in Table 5.2. Using these representations we can visualize which areas were hot for many years, when areas were initially hot, and the percentage of active years that were hot. While most of the cells with a large number of hot years occurred in the North and Middle subareas, where the duration of mountain pine beetle activity has been longest, locations in the South were hot for a large percentage of active years. Typically, both the number of hot spot years and the maximum number of consecutive hot spot years is one or two. The percentage of active years having hot spots is usually 25 percent or less. This suggests that temporally, hot spots are not very persistent. Yet, 93.6 percent of hot spot pixels occur at locations where the mountain pine beetle activity occurred in the previous year.

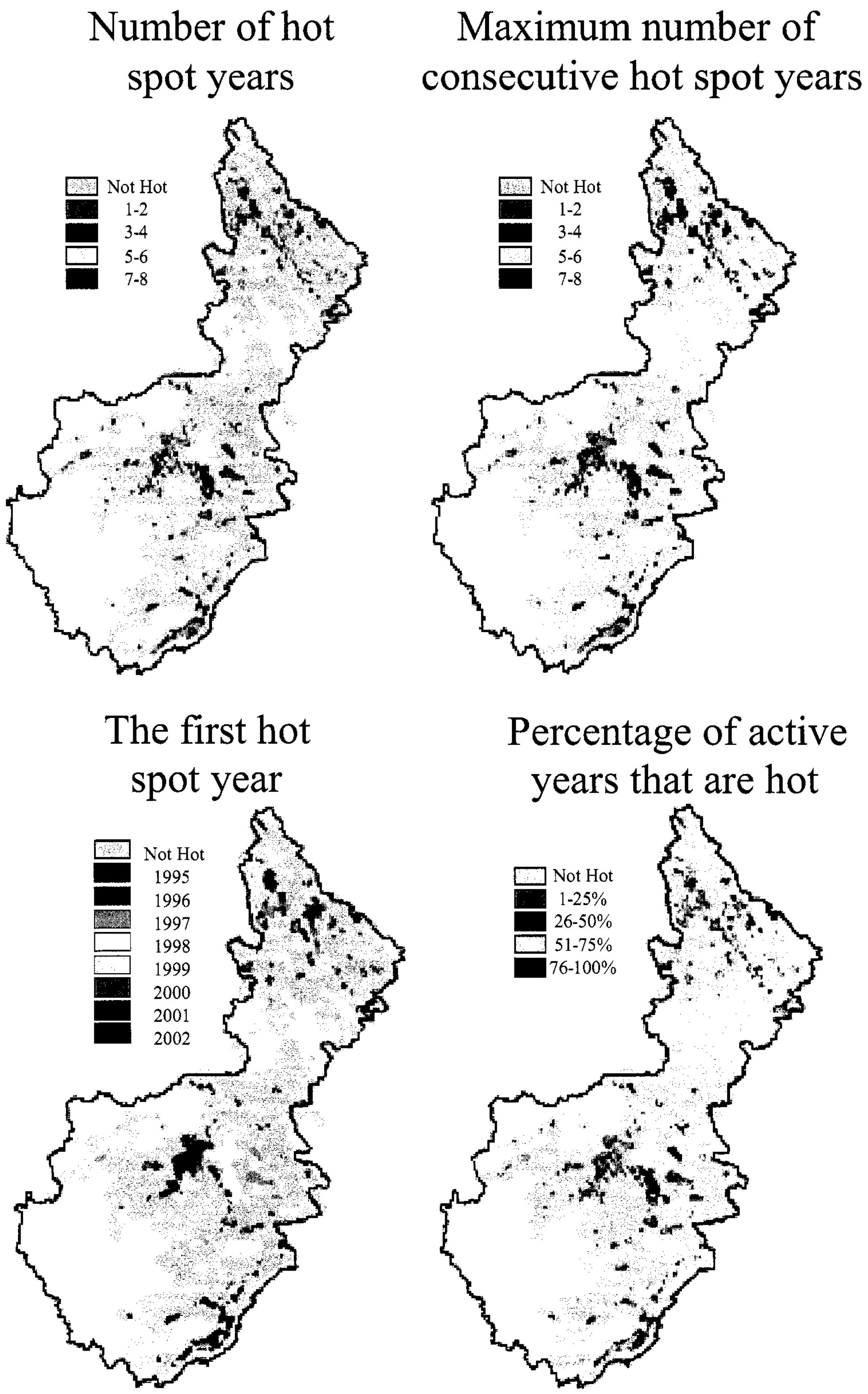


Figure 5.6. Classifications of hot spot persistence from 1995 to 2002 in the Morice TSA. Not hot areas (grey) had mountain pine beetle infestations, but were not considered hot spots in any time period. White locations were never infested.

Table 5.2. The number of pixels in each of the multi-temporal hot spot classes in Morice TSA for 1995 to 2002.

	Number of hot spot years	Max number of hot spot years	First hot year		Percentage of active years	
	n	*n*		*n*		*n*
1	17890	21392	1995	5449	1-25%	20778
2	6927	7223	1996	7027	26-50%	9771
3	4695	3841	1997	6035	51-75%	3670
4	2840	1803	1998	4359	76-100%	1184
5	1444	473	1999	3315		
6	968	241	2000	2596		
7	518	309	2001	2869		
8	121	121	2002	3753		

Analysis of hot spot patches provides additional insight into the spatial nature of intense infestations. The summary of hot spot patch characteristics is not partitioned by subarea, as trends were similar and stronger when presented over the entire region. Visualizing the relative frequency distribution of hot spot patch sizes shows that the minimum hot spot size is similar in all years, and less than 10 pixels (patches of one pixel have a size of 0.04 km^2) (Figure 5.7). In contrast, the maximum patch size varies. The largest patch sizes are in 1997 and the smallest in 1998. In 1995, 1997, 1999, 2000 and 2002 distributions are skewed towards smaller patch sizes. While some large hot spot patches exist, particularly in 1997, the majority of patches are small. In 1996 and 2001, distributions are skewed towards larger patch sizes. In 1998, when the infestation magnitudes are generally low, the distribution is not skewed and patch sizes are the least variable.

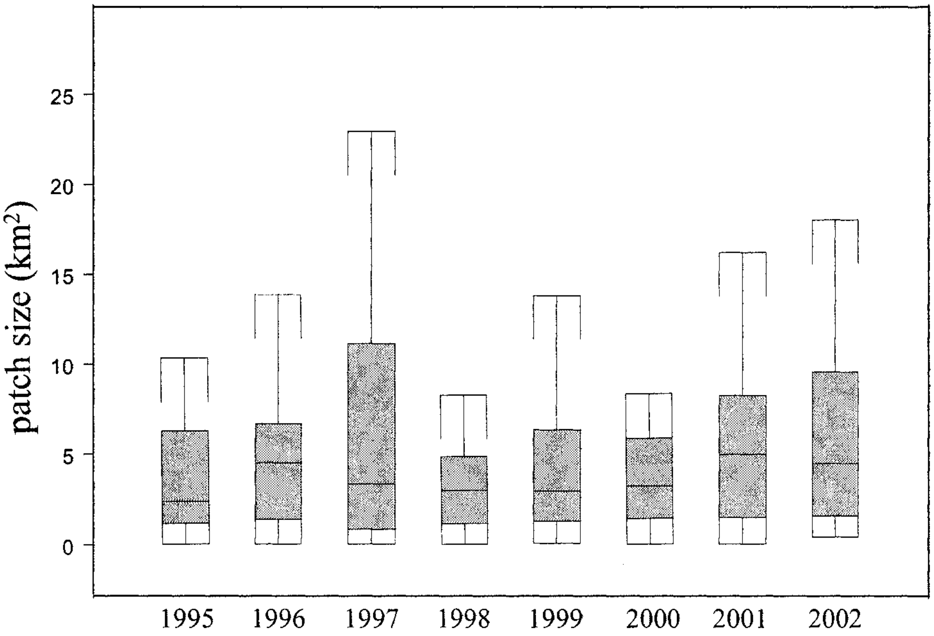


Figure 5.7. Box plots representing annual distributions of hot spot patch sizes in Morice and for 1995 to 2002. Median is used as the measure of central tendency.

By definition the number of hot spot pixels will increase with infestation intensity. While there are no constraints requiring hot spot pixels to be spatially contiguous, as the infestation intensity increases globally so does the average size of hot spot patches (Table 5.3). However, the annual number of hot spot patches is not related to general infestation intensities. From 1999 to 2002, the infestation increases globally and the mean patch size becomes larger, but the number of patches declines. This suggests that as the mountain pine beetle infestation magnitude increases, hot spot patches become larger, rather than occurring as many isolated infestation pockets.

Table 5.3. A summary of hot spot patch characteristics partitioned annually for the Morice TSA. Arrows indicate changes (increasing or decreasing) in global mountain pine beetle infestation levels between years.

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
mean size (km^2)	5.32	9.28	8.72	5.52	6.02	6.34	7.95	11.24
median size (km^2)	2.40	4.54	3.36	3.02	2.96	3.24	5.00	4.48
minimum size (km^2)	0.04	0.04	0.04	0.04	0.08	0.04	0.04	0.44
maximum size (km^2)	41.06	113.52	70.28	80.84	54.52	65.40	64.40	242.7
cv of size	1.60	2.05	1.51	2.09	1.41	1.69	1.41	2.92
number of patches	41	44	55	52	65	65	55	55
number outliers	3	4	5	6	7	7	6	4
global infestation		⬆	⬇	⬇	⬆	⬆	⬆	⬆

5.5.2 Investigating Dispersal

Spatial-temporal nearest neighbour distances between hot spot pixels are shown in Figure 5.8. As there was little variability between subareas, annual distance trends are shown for the entire study area. In all years, the modal nearest neighbour distance between hot pixels is zero kilometres. This may suggest that hot locations are typically intensely infested for more than one year. Most hot pixels occur within two kilometres, and few further than four kilometres, from hot pixels in the previous year. This distance is in line with stand scale research, which suggests that 86 to 93 percent of mountain pine beetles disperse within three kilometres of their emergence site (Safranyik *et al.,* 1992).

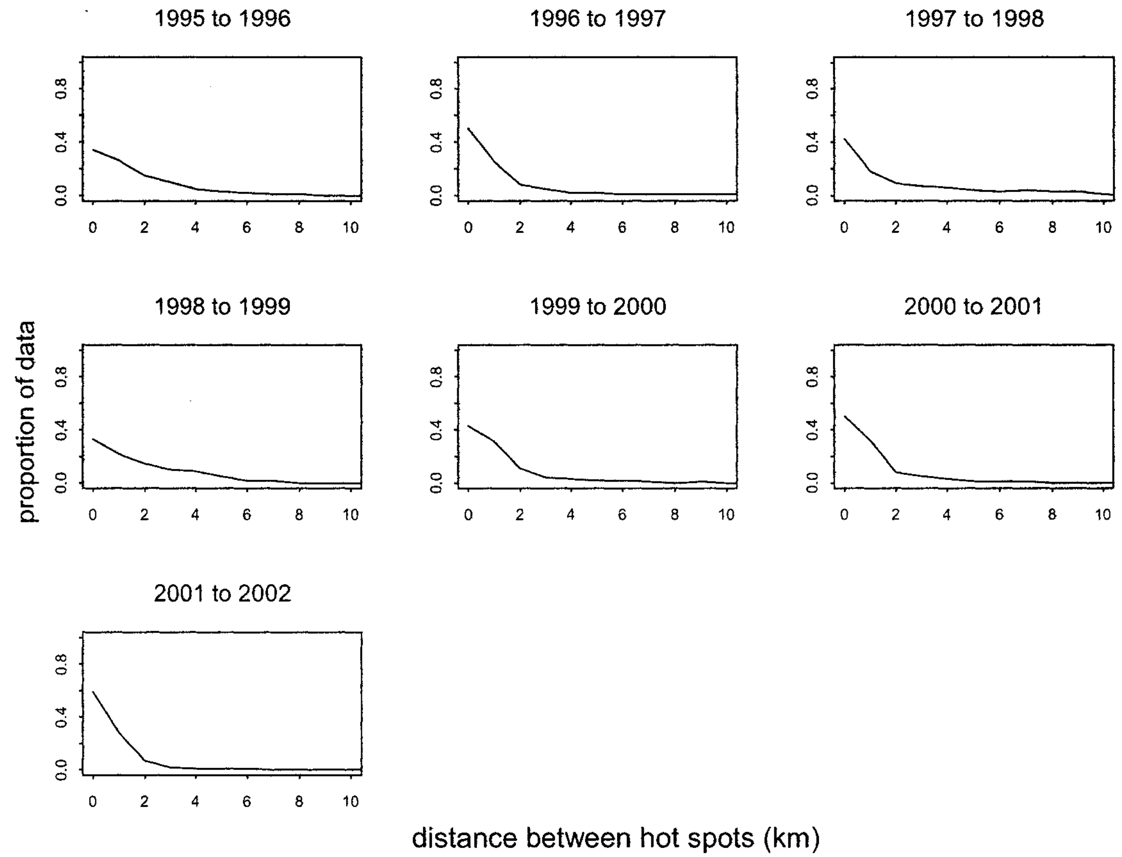


Figure 5.8. Relative frequency distributions of nearest neighbour distances between hot spot pixels in t_i and hot spot pixels in t_{i-1} in the Morice TSA.

From 1995 to 1996, and 1998 to 1999 the distance curves are flatter than in other years, with a larger proportion of hot pixels occurring at far distances. While 1998 had the lowest infestation magnitude, the other years associated with flat curves were not unusual. It is interesting that the steepest curve occurs from 2001 to 2002, which is the time period having the largest increase in infestation levels. Although further investigation is required these results may indicate that when the global infestation intensity increases, there is a decrease in the distance between hot locations in neighbouring time periods.

For all years, the relative frequency distribution of nearest neighbour distances between hot pixels in consecutive years are summarized in Figure 5.9. The relative frequency distribution of distances travelled by mountain pine beetles, post emergence, has previously been found to be approximately exponential in form, with the largest proportion of the mountain pine beetle emerging nearby (Safranyik *et al.,* 1992). An exponential curve and 95 percent confidence intervals were fitted to the observed relative frequency distribution of nearest neighbour distances. While the observed relationship is not exponential, in some situations it appears that an exponential function is an appropriate approximation.

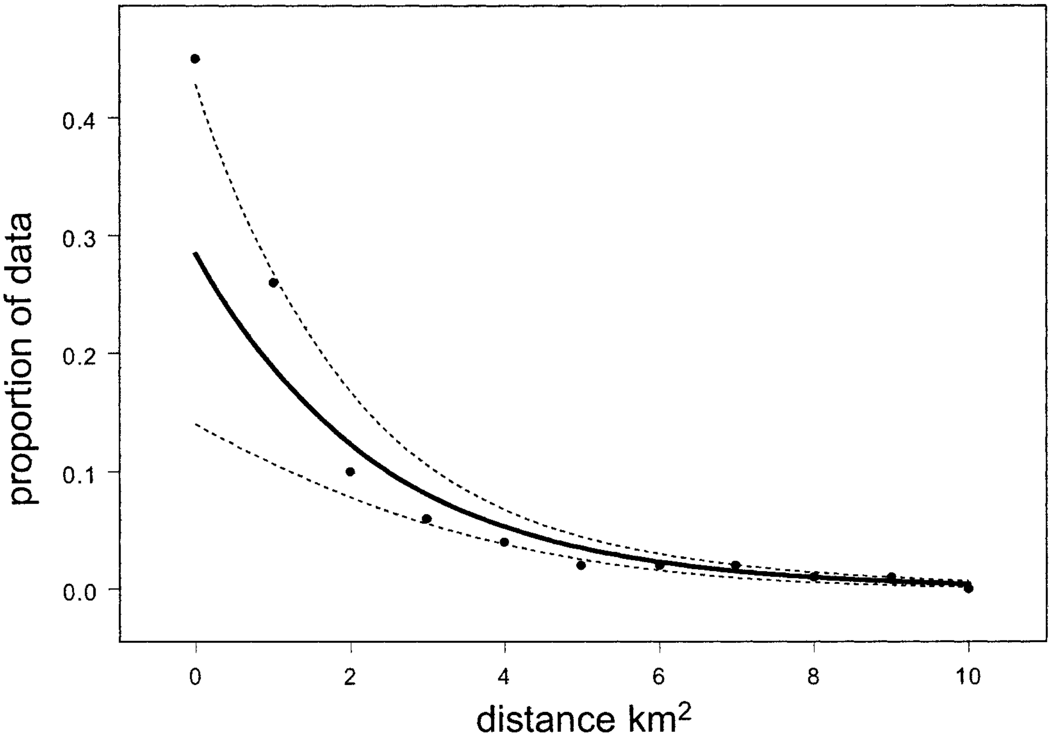


Figure 5.9. The relative frequency distribution for nearest neighbour distances between hot pixels in t_i and t_{i+1} (points) in the Morice TSA. The solid line is a fitted exponential distribution having a rate = 1/mean. Dotted lines represent 95 percent confidence intervals for the exponential distribution fitting.

Directional trends associated with nearest neighbour hot spot distances are summarized in Table 5.4. We were unable to identify trends through time and found a coarse directional breakdown the most informative. The dominant direction associated with pixel-based nearest neighbour distances between hot spots in time t_i and t_{i+1} is southwest. Global trends observed throughout the province of British Columbia have tended to be south-easterly (Carroll, pers com). In the South and Middle subareas a south-western spread may be explained by the large mountain pine beetle populations to the east of both regions. Without local meteorological data, further interpretation of directional trends is limited. Directions between nearest neighbour spatial-temporal hot spots are likely impacted by a combination of factors including wind direction, topography, and infestation magnitude in surrounding regions.

Table 5.4. Stratified by subareas in the Morice TSA, the modal directions of nearest neighbour hot spot pixels in t_i and t_{i+1} from 1995 to 2002.

	North	**Middle**	**South**	**All**
NE	14%	12%	19%	14%
SE	18%	14%	10%	15%
SW	55%	61%	50%	57%
NW	13%	13%	22%	14%

The spatial configuration of intense infestations is addressed by investigating distance and directional trends between hot spot patches. To explore the spatial-temporal relationships between patches, we determined the number of times a patch in time t_i intersected a patch in the previous year. Forty-seven percent of patches had zero intersections, 48 percent of patches had one intersection, and five percent of patches had two or more intersections (Figure 4.10). The larger percentage of patches with zero intersections shows that different trends are observed when patches, rather than pixels, are investigated. When hot spot pixels were considered, it was most common for hot locations to occur where they were previously; however, hot spot patches are frequently observed at locations free of previous infestation. Large patches have many more pixels than small patches and thereby dominate pixel-based trends. As large patches are more likely to result from coalescence, a high proportion of hot pixels occur where hot spots are previously identified, and trends associated with many small patches are masked.

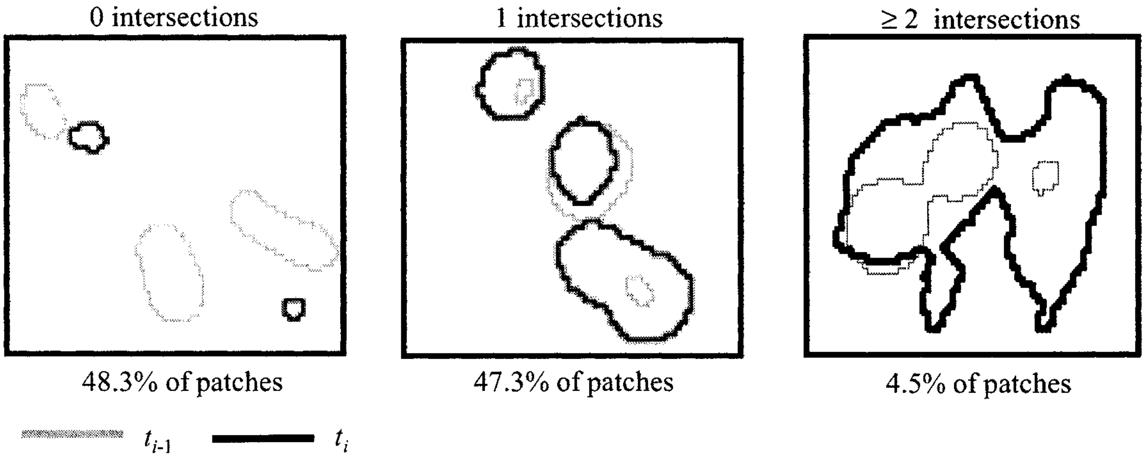


Figure 5.10. Illustration of intersection definitions used for spatial-temporal investigations of hot spot patches.

As hot spot patch size increases, so do the number of spatial intersections with hot patches in the previous year (Figure 5.11). The number of patches with zero, one, two, three, and four intersections in the previous year are 191, 195, 14, three, and one respectively. This analysis provides evidence that very large hot spot patches are generated by coalescing hot spots. Although there are only a few polygons with greater than two intersections, the behaviour of these observations is quite clear. Additional information improves our confidence in the observed trend. For instance, a visual investigation of hot spot patches through time gives the impression that hot spot patches coalesce (Figure 5.5). Other researchers have made similar observations during mountain pine beetle epidemics (Borden, 1993). While coalescence seems to be occurring, these results also indicate that this is not the dominant process, as 95.5 percent of patches have one or fewer intersections.

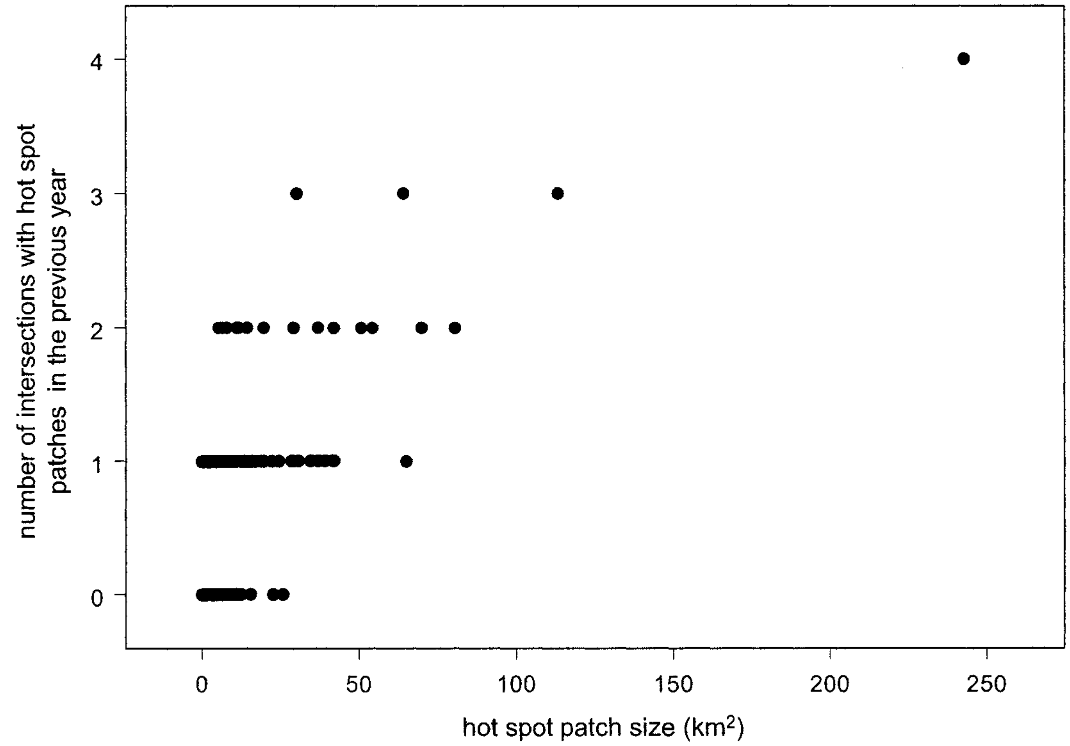


Figure 5.11. For all years and subareas in the Morice TSA, the number of intersections with hot spot patches in the previous year versus hot spot patch size.

When all years were summarized by subarea, trends in the minimum distances between hot spot patches having no intersections were consistent between the North and Middle subarea. The South subarea had so few patches that it was difficult to analyze relationships. Results are a summary for all years and subareas (Figure 5.12). The modal minimum distance between hot spot patches is 1.8 kilometres. If intense infestations were spreading from an attack location to the nearest suitable site, one would expect minimum distances between patches to be near zero. However, minimum distances near six kilometres are more common than those near zero, perhaps indicating that patches having no intersections are occurring as a result of long-range dispersal.

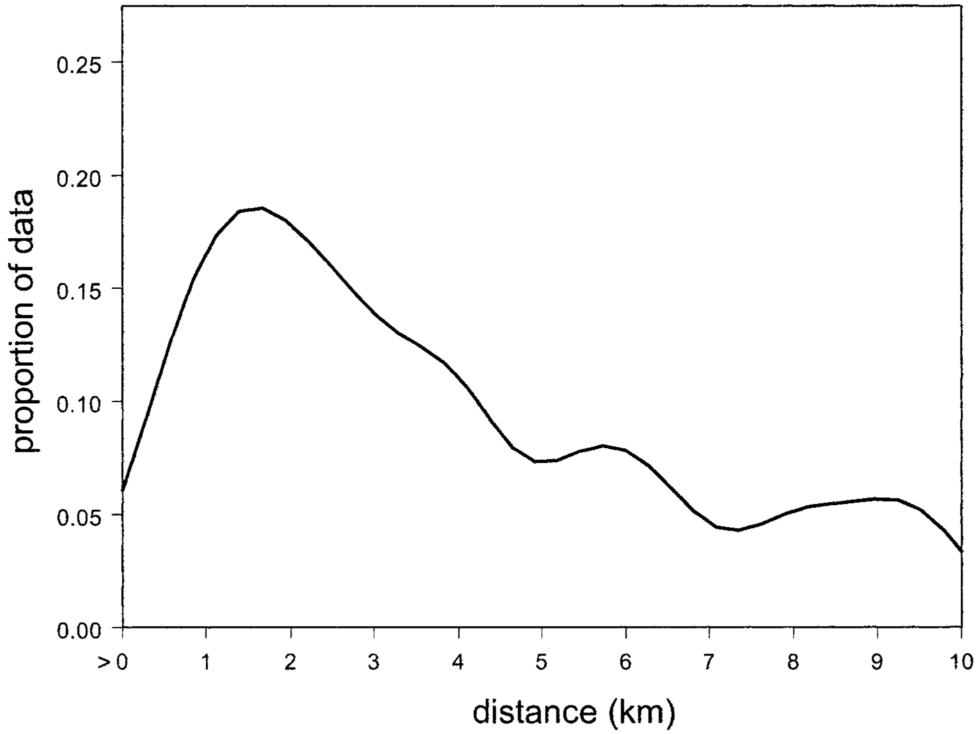


Figure 5.12. For all years and subareas in the Morice TSA, the relative frequency distribution of minimum distances between hot spot patches having no intersections between t_i and t_{i-1}.

Directional trends associated with the minimum distance between hot spot patches having zero intersections are shown in Table 5.5. In the North subarea most spread is northeast, in the Middle subarea spread is primarily southeast, and in the South subarea dominant spread directions are both northeast and southwest. Although trends are weak, directional tendencies associated with the Middle subarea reflect global trends. In the South subarea the dominance of westward movement may result from the large source of mountain pine beetle to the east of the subarea. The presence of north-easterly movement in the North and South subareas is difficult to interpret without detailed meteorological data.

Table 5.5. Stratified by subareas in the Morice TSA, the modal directions between nearest hot spot patches in t_{i-1} and t_i for hot spots with no intersections.

	North	**Middle**	**South**	**All**
NE	34%	21%	29%	25%
SE	28%	44%	21%	31%
SW	20%	28%	29%	22%
NW	18%	32%	21%	22%

The relative frequency distribution for the maximum spread distances of patches having one intersection is shown in Figure 5.13. When all patches with one intersection are considered, the maximum leading edge spread ranges from zero to six kilometres. Zero distances are associated with patches that have shrunk. Distances of zero could also indicate no change in the leading edge of a hot spot patch, however in our data this scenario never occurs. Most commonly, the maximum spread is a short distance, and the modal distance for leading edge spread is 0.3 kilometres. This may indicate that when a hot spot patch intersects with one patch in the previous year, infestations grow as the mountain pine beetle spread to nearby locations.

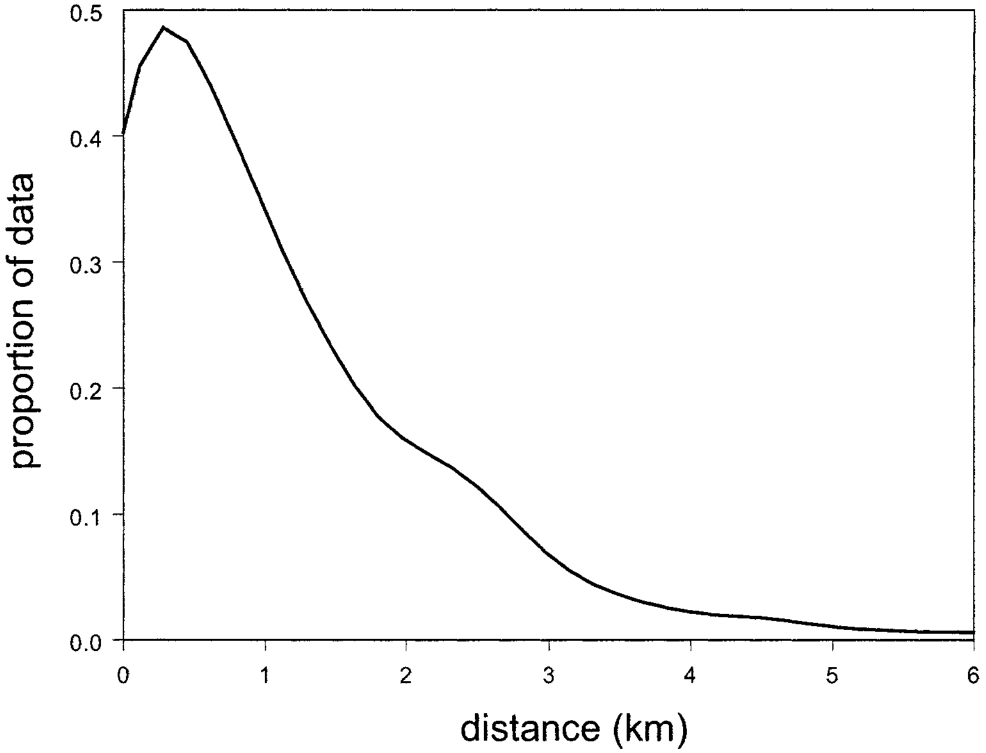


Figure 5.13. For all years and subareas in the Morice TSA, the relative frequency distribution of the maximum spread of the leading edge between two periods for hot spot patches in t_i having one intersection in t_{i-1}.

The growth and shrinkage of patches with one intersection were also investigated using four categories of spatial-temporal patch relationships (Figure 5.14). Patches in t_i having at least some growth in all directions account for 7.9 percent of the total hot spot patches. The relative frequency distribution for the distance of maximum spread is shown in Figure 5.14a. The maximum leading edge spread varies from 0.3 to 4.6 kilometres. When growth occurs in all directions, the modal leading edge spread is one kilometre. In 9.4 percent of cases hot spot patches shrink in all directions between t_i and t_{i-1} (Figure 5.14b). In these cases the maximum distance of patch shrinkage ranges from

0.4 to six kilometres, and the modal distance is one kilometre. Hot spot patches that have partial overlap and grow between t_{i-1} and t_i represent 14.4 percent of cases (Figure 5.14c). The relative frequency distribution of growth distances ranges from 0.2 to six kilometers and is of similar form to that of distances associated with hot spot patches that shrink in all directions, having a modal distance equal to one kilometer. Hot spot patches with partial overlap that shrink between t_{i-1} and t_i are the most common, occurring in 16.6 percent of cases (Figure 5.14d). In this scenario the distance of maximum spread ranges from 0.2 kilometers to nearly four kilometres, with 0.3 kilometres being the most common distance.

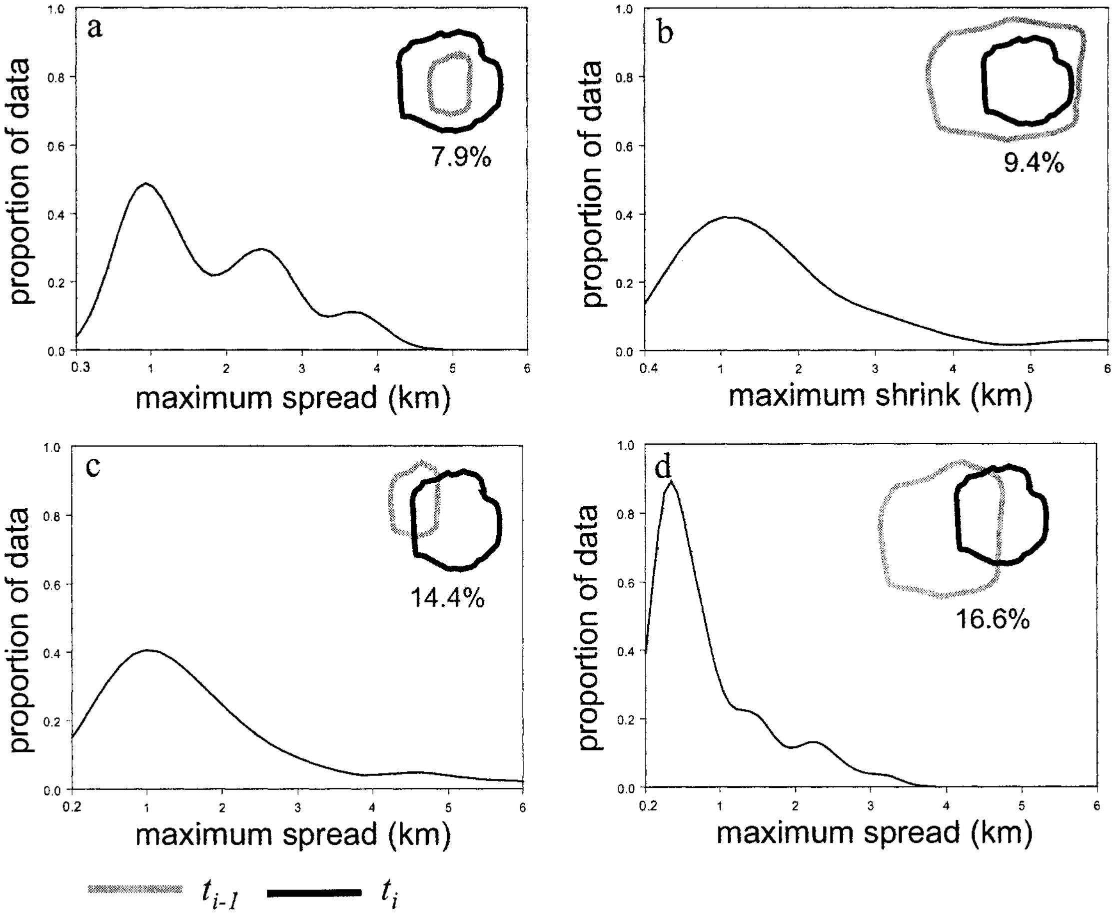


Figure 5.14. Relative frequency distributions of spread and shrinkage for hot spot patches in time t_i having one intersection in time t_{i-1} in the Morice TSA from 1995 to 2002. A) Patches grow in all directions. B) Patches shrink in all directions. C) Patches grow, but not in all directions. C) Patches shrink, but not in all directions.

Hot spot patches intersecting patches in the previous time period are more likely to shrink than to grow. Spatially, most hot spot patches grow no more than three kilometres from hot spots in the previous year. Longer distances of spread are more commonly observed when growth occurs in all directions (Figure 5.14a). This may indicate that when there is a directional trend to growth, the infestation spreads over shorter distances than when there is no directional trend. When hot spot patches spread and have a smaller spatial extent in time period t_i than in t_{i-1}, the maximum spread distance tends to be small. Larger spread distances are associated with patches that increase in size. These trends support previous observations regarding aggregative behaviour in the mountain pine beetle. When populations decline, mountain pine beetles aggregate together to ensure successful attack of fewer trees (Safranyik *et al.*, 1989). However, more beetles may result in longer spread distances to ensure adequate food resources.

Directional trends in spread between hot spot patches with one intersection are shown in Table 5.6. Trends were not variable between years and a summary for all years is shown. In the North subarea, northwest directional trends are the most common; in the Middle subarea, the modal spread is southwest; and in the South subarea, the dominant spread directions are southwest and southeast. While observed southerly spread reflects either global provincial patterns or the influence of neighbouring beetle populations, a dominant northwest spread is difficult to interpret. Northwest spread may be the result of intense management that occurred early and continuously in the North subarea.

Table 5.6. The modal direction of leading edge spread between t_{i-1} and t_i for hot spots with one intersection stratified by Morice TSA subareas from 1995 to 2002.

	North	**Middle**	**South**	**All**
NE	14%	16%	0%	15%
SE	27%	27%	50%	29%
SW	27%	31%	50%	34%
NW	31%	25%	0%	22%

Hot spot patch intersection relationships were also explored in terms of the percentage of overlap between patches in previous and future time periods (Table 5.7).

Only a small proportion of patches intersect completely with hot spot patches in the previous year (Table 5.7a), yet many overlap entirely with locations having infestations in the previous year (Table 5.7b). The number of patches that intersect completely with infested locations in the previous year increases with the number of intersections; 80 percent of patches with no intersections and 100 percent of patches with greater than two intersections have 100 percent overlap with infestations in the pervious year. When hot spot patches have zero intersections, they are less often observed to intersect with patches in the future year than patches having at least one intersection (Table 5.7c). One hundred percent overlap with infested locations in the future year occurs for greater than 90 percent of all patches (Table 5.7d).

Table 5.7. Characteristics of hot spot patch overlap with patches and infested areas in t_{i-1} and t_{i+1} in the Morice TSA from 1995 to 2002.

	A	B	C	D
intersections between t_{i-1} and t_i	% of t_i patches that overlap 100% with t_{i-1} patches	% of t_i patches that overlap 100% with t_{i-1} infestation	% of t_i patches that overlap with t_{i+1} patches	% of t_i patches that overlap 100% with t_{i+1} infestations
0	0	80	40	94
1	28	96	66	91
≥ 2	0	100	91	91

Patterns in patch overlap may indicate that patches in t_i, which do not intersect patches in t_{i+1}, occur in locations that are sub optimal for the mountain pine beetle as they are the least likely to have future intersections with hot patches. One explanation may be related to the randomness of long-range dispersal. Hot spot patches occurring as a result of long-range dispersal may develop in locations sub-optimal for the mountain pine beetle. In these areas, intense mountain pine beetle infestations do not persist. During long-range dispersal some mountain pine beetles may also randomly disperse to locations that are highly suitable, and intense infestations will persist and experience processes associated with patches having one intersection. A more detailed view of overlap for patches having zero and one intersections shows that while the modal overlap is 100 percent other amounts of overlap are quite uniform.

5.5.3 Hot Spots and Age

Partitioned by subarea and year, box plots are used to display the relative frequency distributions of forest age for individual hot spot patches (Figure 5.15 to 5.18). There were too few hot spot patches in the South to warrant patch-based analysis. Using box plots we can investigate trends in the central tendency, variation, and skewness. Regardless of the year or size, median patch forest age is highly variable, and typically ranges from 50 to 200 years. In some years, variability in the forest ages associated with each hot spot patch appears related to patch size. Small hot spot patches appear to have lower internal variation, or more homogeneity, in terms of forest age. This trend is seen in the North subarea for 1996, 1997, 1998, and 2001 and in the Middle subarea for 1996, 1997, 1998, 1999, 2000, and 2002. In the North and to a lesser degree in the Middle subarea, long lower tails are more common than long upper tails; however, it is difficult to link trends in the skewness, to patch size or time.

In general, the forest age composition of hot spot patches remains relatively similar over time and is independent of patch size. The same overall trends were observed when percentage pine, elevation, and aspect were considered. Due to the large number of box plots (404 patches * 4 landscape characteristics = 1616 box plots), box plots associated with percentage pine, elevation, and aspect are not shown. Large patches appear to be bigger versions of small patches. This may indicate that the occurrence of hot spot patches is more related to the mountain pine beetle population than to landscape characteristics. For instance, microclimates and neighbouring mountain pine beetle populations may influence local population levels.

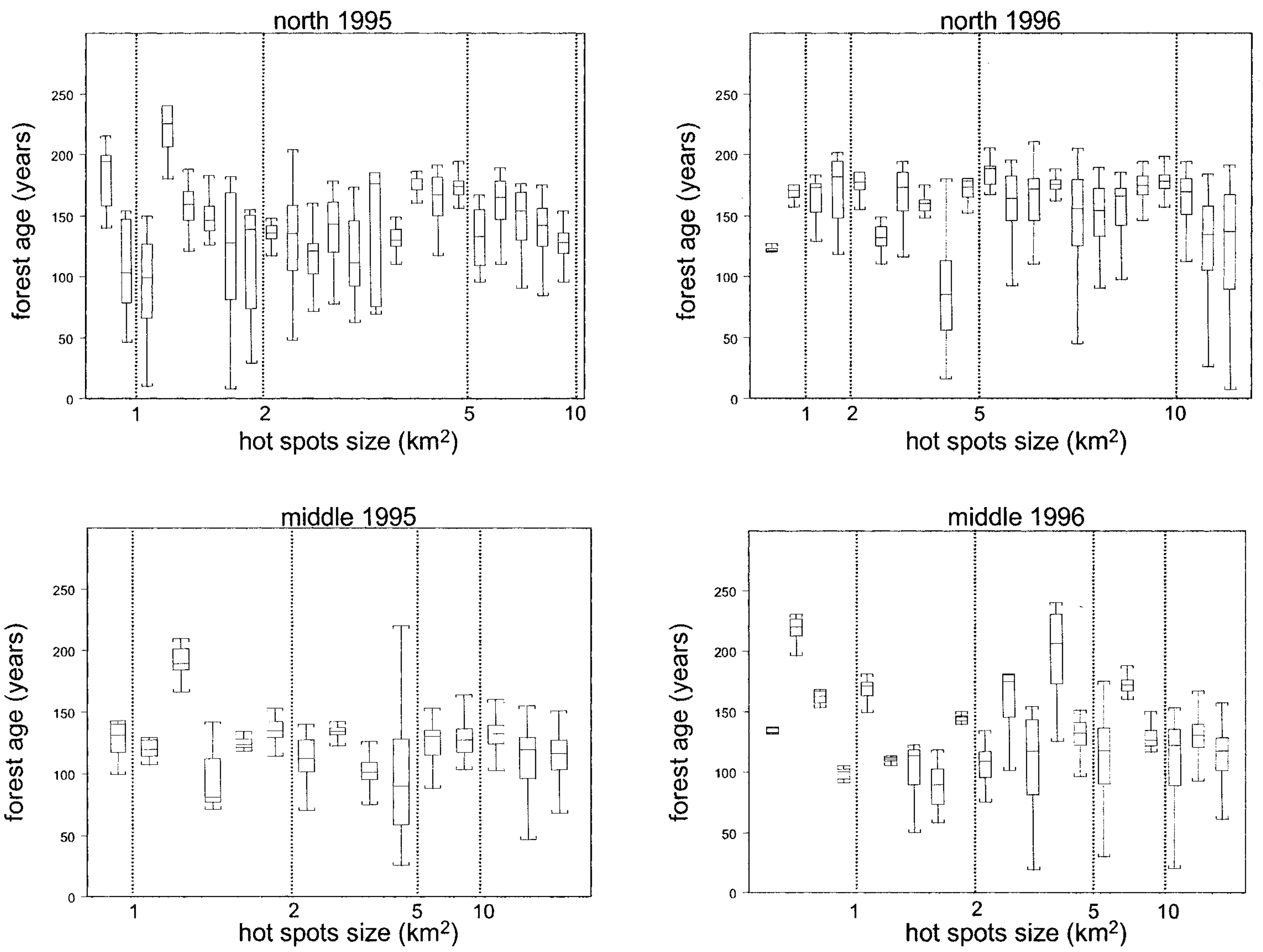


Figure 5.15. Distributions of forest age associated with hot spot patches in the North and Middle subareas of the Morice TSA in 1995 and 1996.

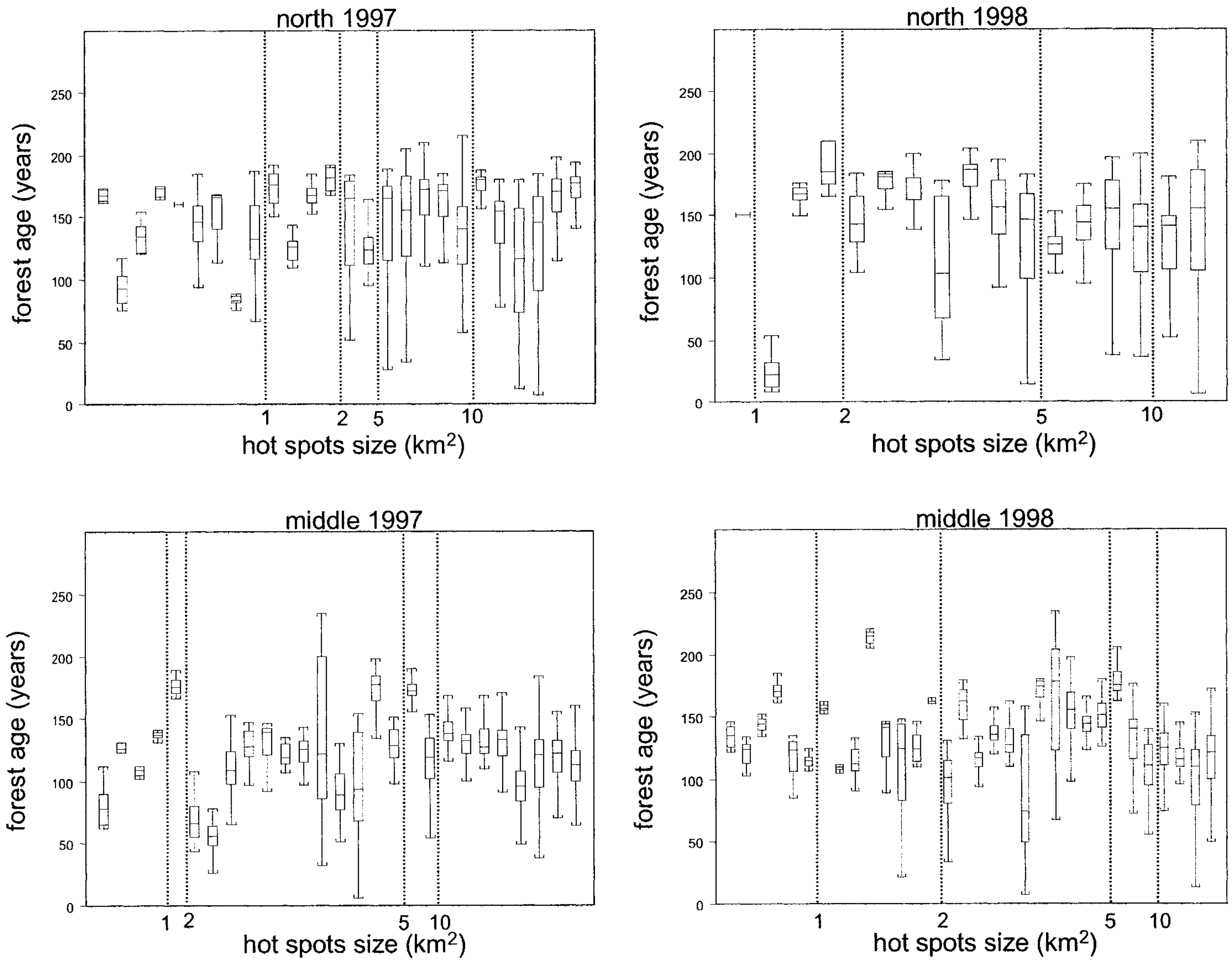


Figure 5.16. Distributions of forest age associated with hot spot patches in the North and Middle subareas of the Morice TSA in 1997 and 1998.

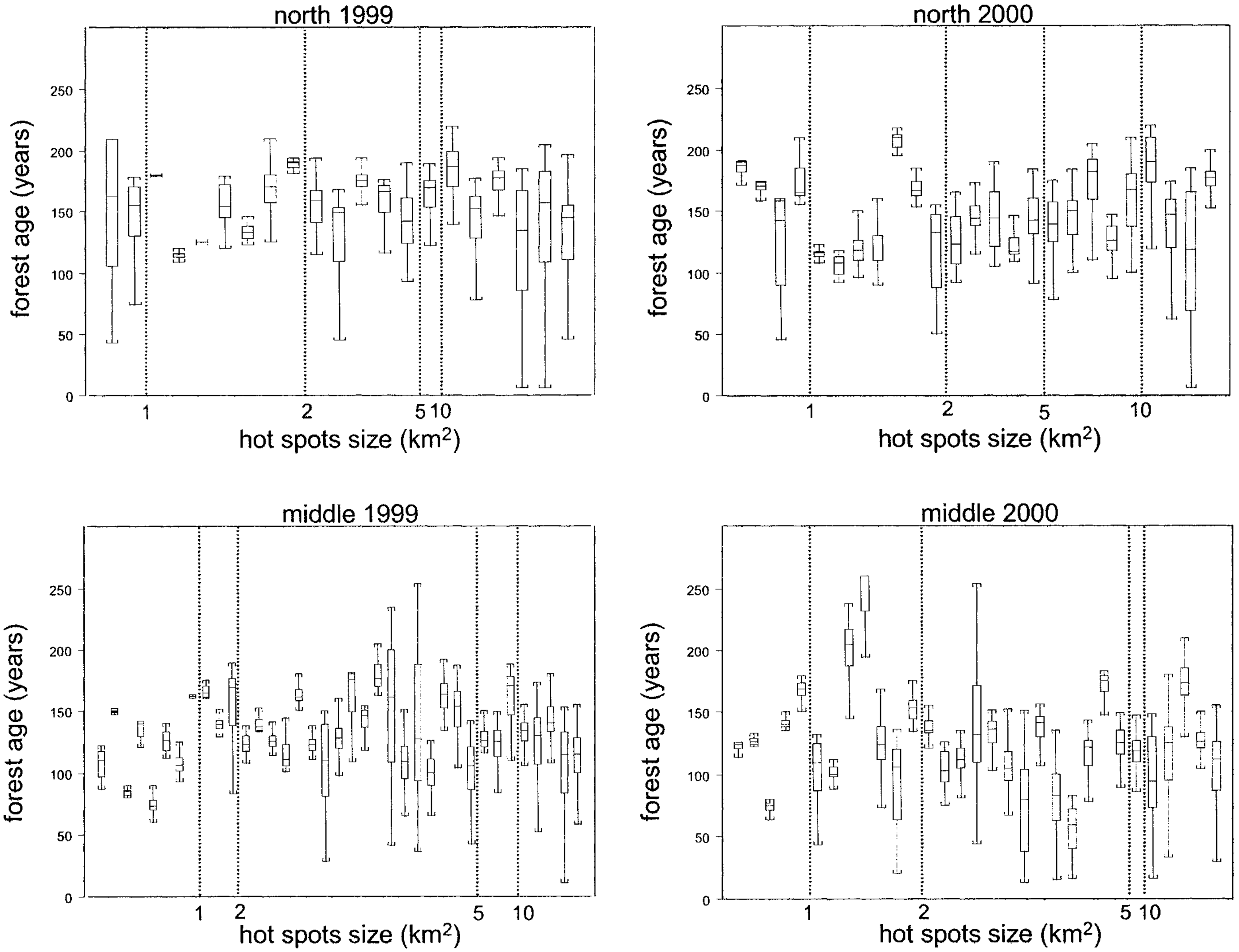


Figure 5.17Distributions of forest age associated with hot spot patches in the North and Middle subareas of the Morice TSA in 1999 and 2000.

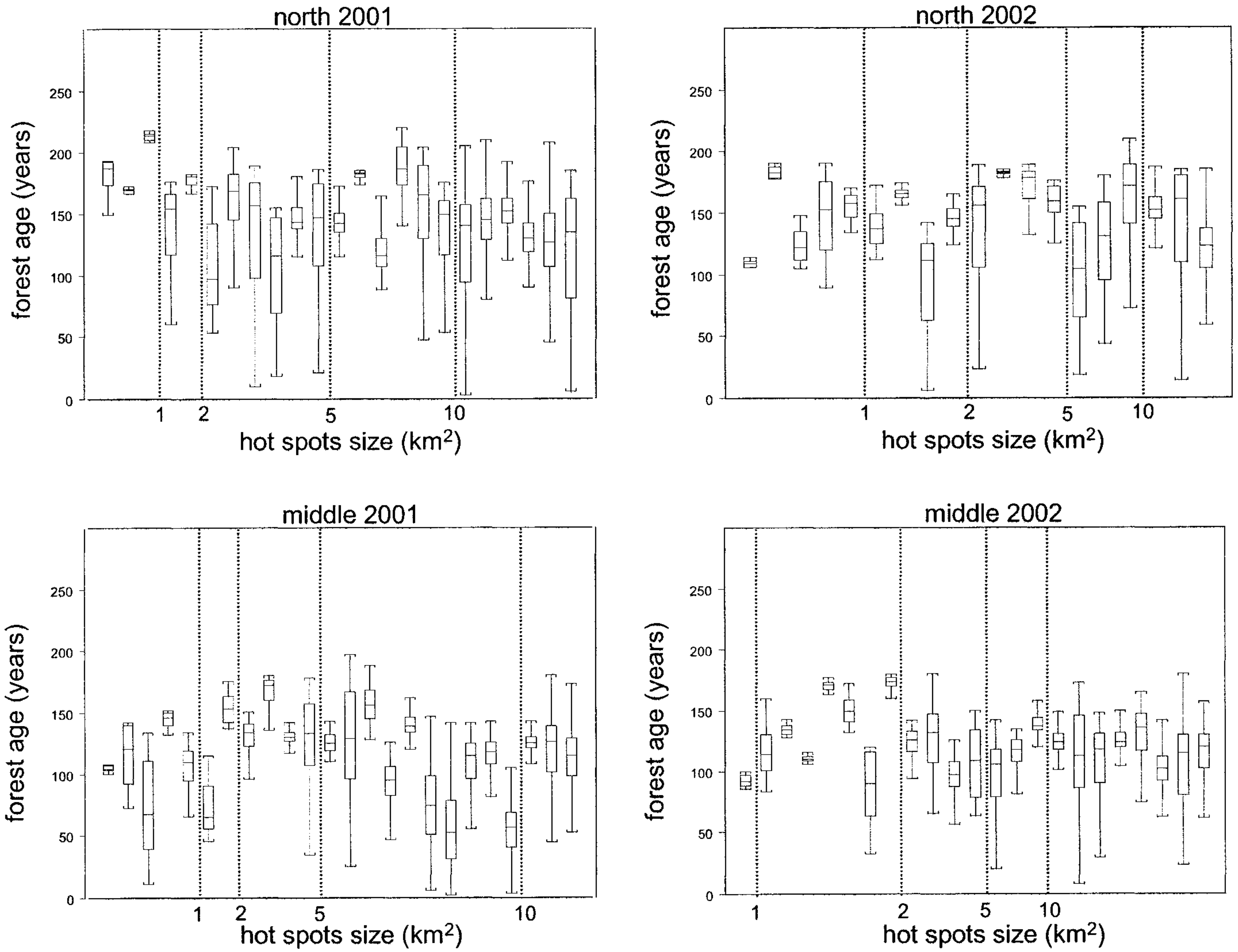


Figure 5.18. Distributions of forest age associated with hot spot patches in the North and Middle subareas of the Morice TSA in 2001 and 2002.

Relationships between intense infestations and the landscape were more clear when analysis was undertaken using hot spot pixels, rather than hot spot patches. Relative frequency distributions of landscape characteristics were composed from pixels associated with hot spots, and compared to relative frequency distributions generated from all pine pixels. When comparing the relative frequency distributions of pine age associated with single year hot spot pixels to the age relative frequency distributions for all pine locations, departures between distributions vary with each subarea (Figure 5.19). However, common trends emerge. In all subareas, few hot spot pixels are associated with forests less than 100 years old. Once the infestation is well established, hot spot pixels are located where the oldest trees occur in abundance (North 140 to 180 years; Middle 140 years; South greater than 180 years). In the North and South subareas, younger trees are infested over time and eventually the relative frequency distribution of forest age associated with hot spots becomes similar to the relative frequency distribution for all pine. One difference between the North and South subareas is the temporal scale with which the hot spot relative frequency distributions become similar to distributions for all pine. In the North, the hot spot relative frequency distribution of forest age changes over several years and likely reflects small, localized mountain pine beetle infestations and intensive management. In contrast, infestations in the South subarea are more intense and the relative frequency distribution of forest age associated with hot spots changes more quickly. In the Middle subarea the relative frequency distributions of forest age associated with hot spots do not change through time.

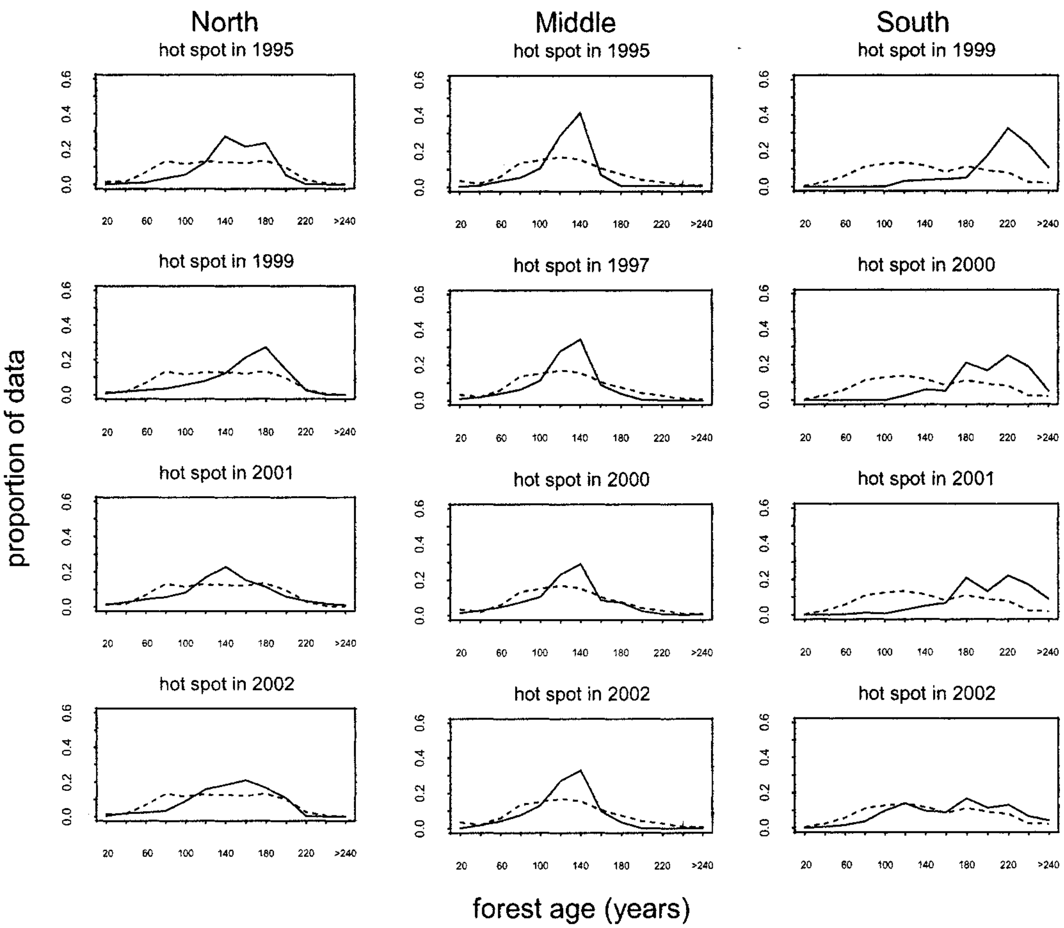


Figure 5.19. Relative frequency distributions of forest age for hot spot pixels (solid line) and all pine pixels (dotted line) in the Morice TSA.

Turning our attention to hot spot persistence, as the number of hot spot years increase, there is a greater difference between the relative frequency distribution of forest age associated with hot spots and age relative frequency distributions representing all pine (Figure 5.20). As seen in comparisons with single year hot spots, the forest age associated with persistent hot spots in each subarea differs. However, the more years a pixel is classified as hot, the more likely it is to be associated with the most mature, abundant age classes. Temporal persistence is greatest for hot spots that occur where the forest age is 180 years in the North, 140 years in the Middle, and 220 to 240 years in the South subarea.

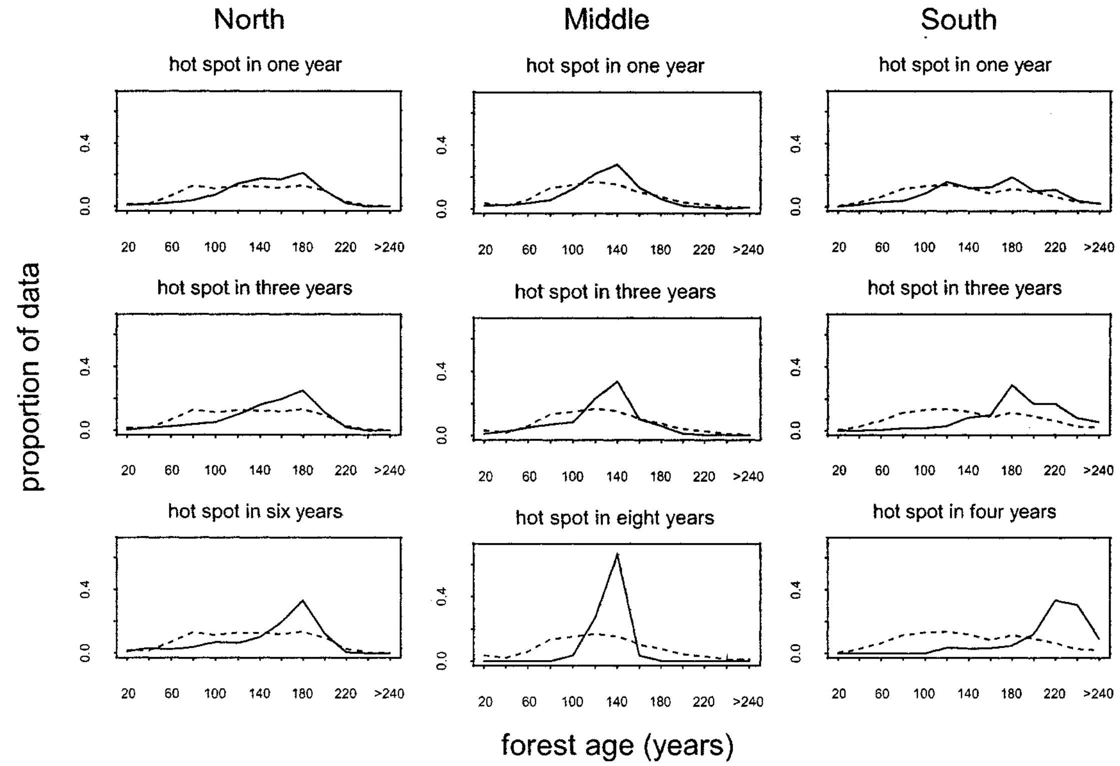


Figure 5.20. Partitioned by the number of years a pixel is a hot spot, the relative frequency distributions of forest age for hot spot pixels (solid line) in the Morice TSA. For comparison, the forest age relative frequency distributions for all pine pixels are also provided (dotted line).

Forest age relative frequency distributions associated with the first year a pixel is a hot spot are seen in Figure 5.21. Trends are similar to those found through comparisons with hot spots in single years. Essentially, over time, high intensity infestations shift from older to younger trees. In the South subarea, where the infestation is the most intense, hot spots are associated with younger forest conditions sooner than in other subareas.

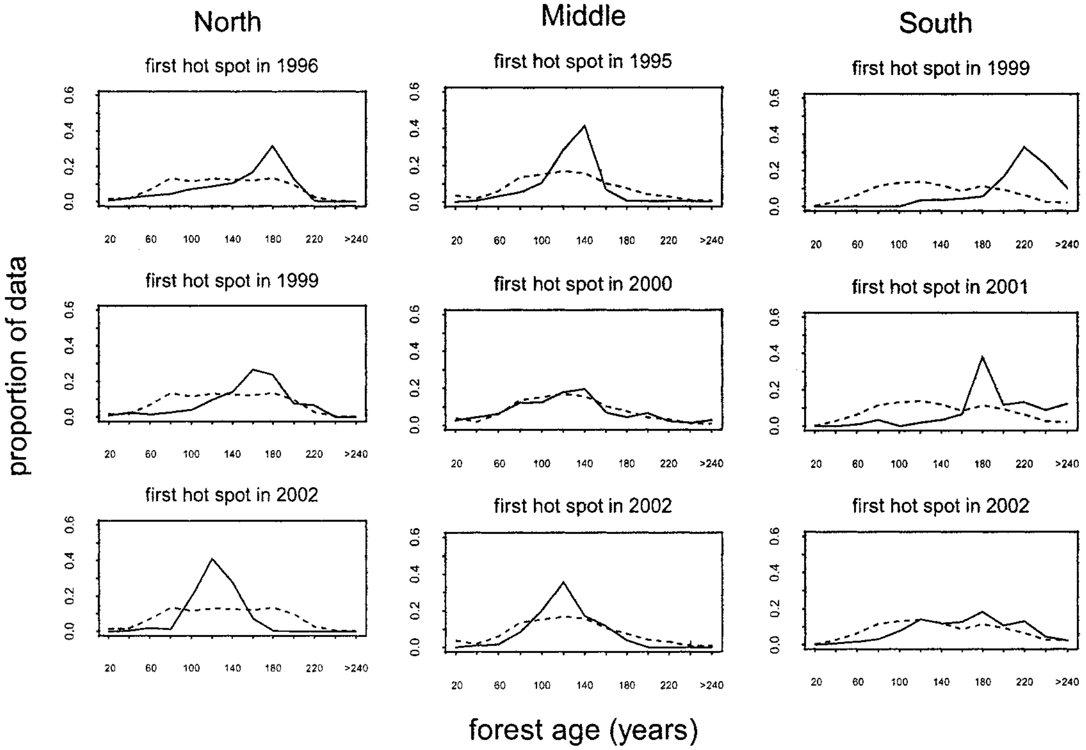


Figure 5.21. Partitioned by the first year a pixel is a hot spot, the relative frequency distributions of forest age for hot spot pixels (solid line) in the Morice TSA. For comparison, the forest age relative frequency distributions for all pine pixels are also provided (dotted line).

The number of years a pixel is found to be a hot spot is influenced by the length of time beetles were active in an area. To account for this influence, the proportion of active years that are hot spots were classified as zero, one to 25 percent, 26 to 50 percent, 51 to 75 percent, and greater than 75 percent. Similar to trends seen for persistence vectors categorized by the number of hot years, the lower the proportion of hot spot years, the greater the similarity between the hot spot relative frequency and distributions of forest age for all pine locations (Figure 5.22). Pixels that are never hot have an age relative frequency distribution similar to the distribution of all pine; this trend is the same through time and between subareas. The higher the proportion of hot spot years, the larger the proportion of pixels that are associated with mature forest ages. It is interesting that pixels having hot spots for greater than 75 percent of active years are primarily associated with the mature trees, as well as trees 20 years younger. For instance, in the North, infestations are associated with trees 160 to 180 years, in the Middle 120 to 140 years, and in the South 220 to 240 years.

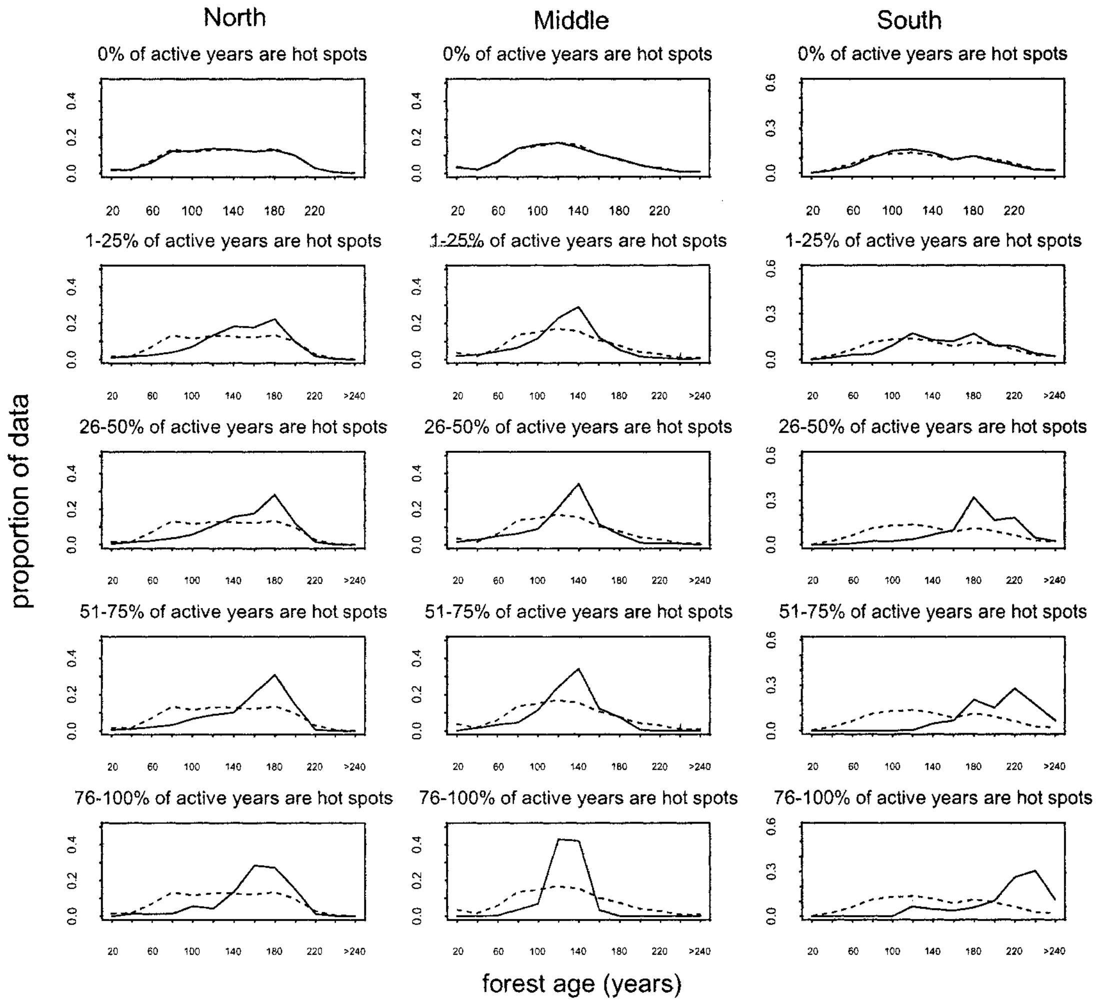


Figure 5.22. Partitioned by the percentage of active years a pixel is a hot spot, the relative frequency distributions of forest age for hot spot pixels (solid line) in the Morice TSA. For comparison, the forest age relative frequency distributions for all pine pixels are also provided (dotted line).

Repeatedly, hot spots occur most commonly in forests older than 100 years. This is consistent with published findings that mountain pine beetle prefer mature trees (Safraynik *et al.*, 1974). At the landscape level, the intensity and duration of mountain pine beetle infestations is greatest when trees are mature. These results are in line with mountain pine beetle population dynamic studies, which demonstrate that at a more local scale, pine mortality is the highest in mature stands, due to higher beetle magnitude and longer duration of beetle infestations (Safranyik *et al.*, 1999).

Visualization of temporal variations in forest age relative frequency distributions associated with hot spots, are related to initial forest conditions and the magnitude of the infestations. In all subareas, through time the mountain pine beetle infests younger trees and the relative frequency distribution of forest age associated with hot spots becomes more similar to the relative frequency distribution for all pine; in other words, the location of high magnitude infestations become more random over time. This can be explained by research that suggests that mountain pine beetle epidemics initiate in mature trees, but once the infestation is established the beetles will randomly attack younger trees (Safranyik *et al*, 1974; Mitchell and Priesler, 1991). Large numbers of successfully brooded mountain pine beetles result in an ability to infest a range of hosts that are typically considered unsuitable. When infestations are very intense, as in the Southern subarea, changes to the relative frequency distribution of forest age associated with hot spots occur quickly. Forest age relative frequency distributions associated with less intense (but still epidemic) infestations that are heavily managed (North subarea) appear to change more slowly, and little change is found when lower magnitude infestations receive modest treatment (Middle subarea). It should be mentioned that compared to endemic levels of attack, all subareas have large rates of mountain pine beetle infestation.

5.5.4. Hot Spots and Percent Pine

Investigation of the percent pine relative frequency distributions associated with hot pixels also revealed interesting trends. In the North, single year hot spot pixels are most frequently associated with 30 to 40 percent pine and in the mid 1990s, it was uncommon for hot spots to be located in pixels with more than 60 percent pine (Figure 5.23). The Middle subarea also shows little change through time in the percent pine relative frequency distributions associated with hot pixels, and cells with 60 to 80 percent pine are most frequently associated with hot spots. In the South, once the infestation established, hot spots occur in pixels where pine percent is 40 to 70, but by 2002 the relative frequency distribution of percentage pine associated with hot spots is nearly the same as the percent pine relative frequency distribution for all pine cells.

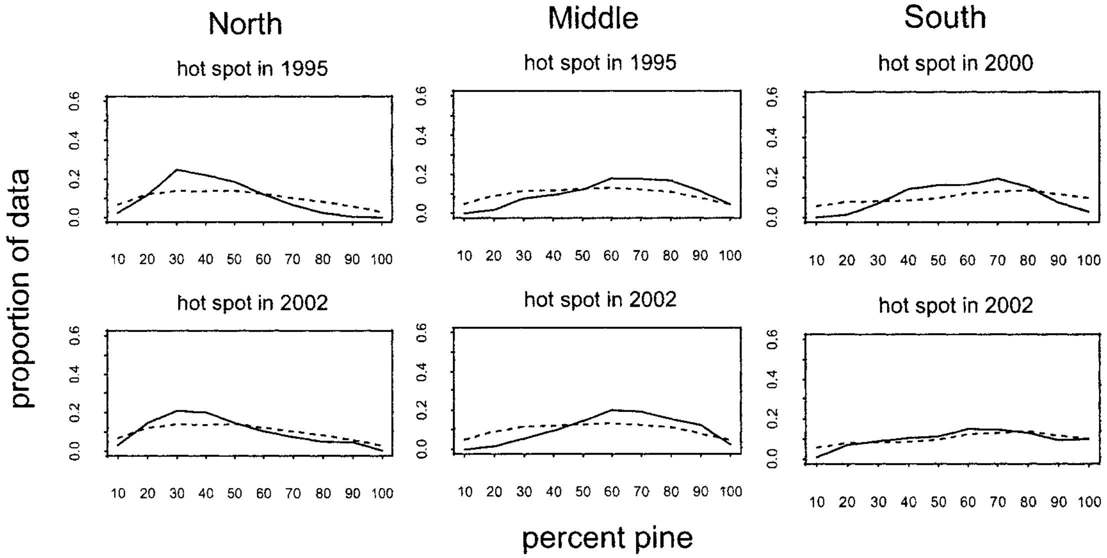


Figure 5.23. Relative frequency distributions of percent pine for hot spot pixels (solid line) and all pine pixels (dotted line) in the Morice TSA.

Typically, when the number of hot spot years are few, the relative frequency distributions for percent pine associated with hot spots are similar to the relative frequency distributions for all pine locations (Figure 5.24). As the number of hot spot years increase, pixels are more likely to have percent pine values associated with cells hot for a single year (North 30 to 40 percent, Middle 60 to 80 percent, and South 40 to 70 percent).

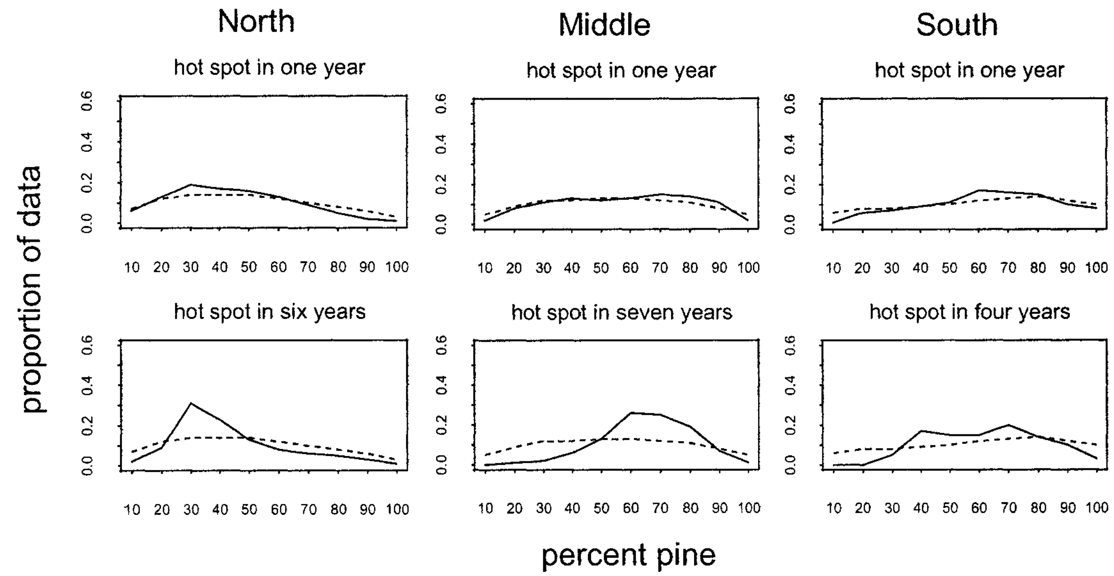


Figure 5.24. Partitioned by the number of years a pixel is a hot spot, the relative frequency distributions of percent pine for hot spot pixels (solid line) in the Morice TSA. For comparison, the percent pine relative frequency distributions for all pine pixels are also provided (dotted line).

The relationship between the percentage of years a pixel is a hot spot and percent pine, indicates that pixels hot for the longest time periods are often associated with higher percent pine cells (Figure 5.25). In the North subarea, the dominant percent pine associated with pixels where hot spots are persistent for less than 75 percent of years is 30 to 40 percent, however this increases to between 40 and 50 percent when a pixel is hot in greater than 75 percent of active years. In the Middle subarea, the dominant percent pine is consistently 60 to 80 percent. Yet, when hot for greater than 75 percent of active years, a larger portion of hot spots occur in high percent pine pixels. In the South this trend is also noted. While hot spots usually occur where percent pine falls between 40 and 70, pixels hot for greater than 75 percent of active years most often have 70 to 80 percent pine. As with age, pixels that are never hot have a similar percent pine relative frequency distribution to all pine cells.

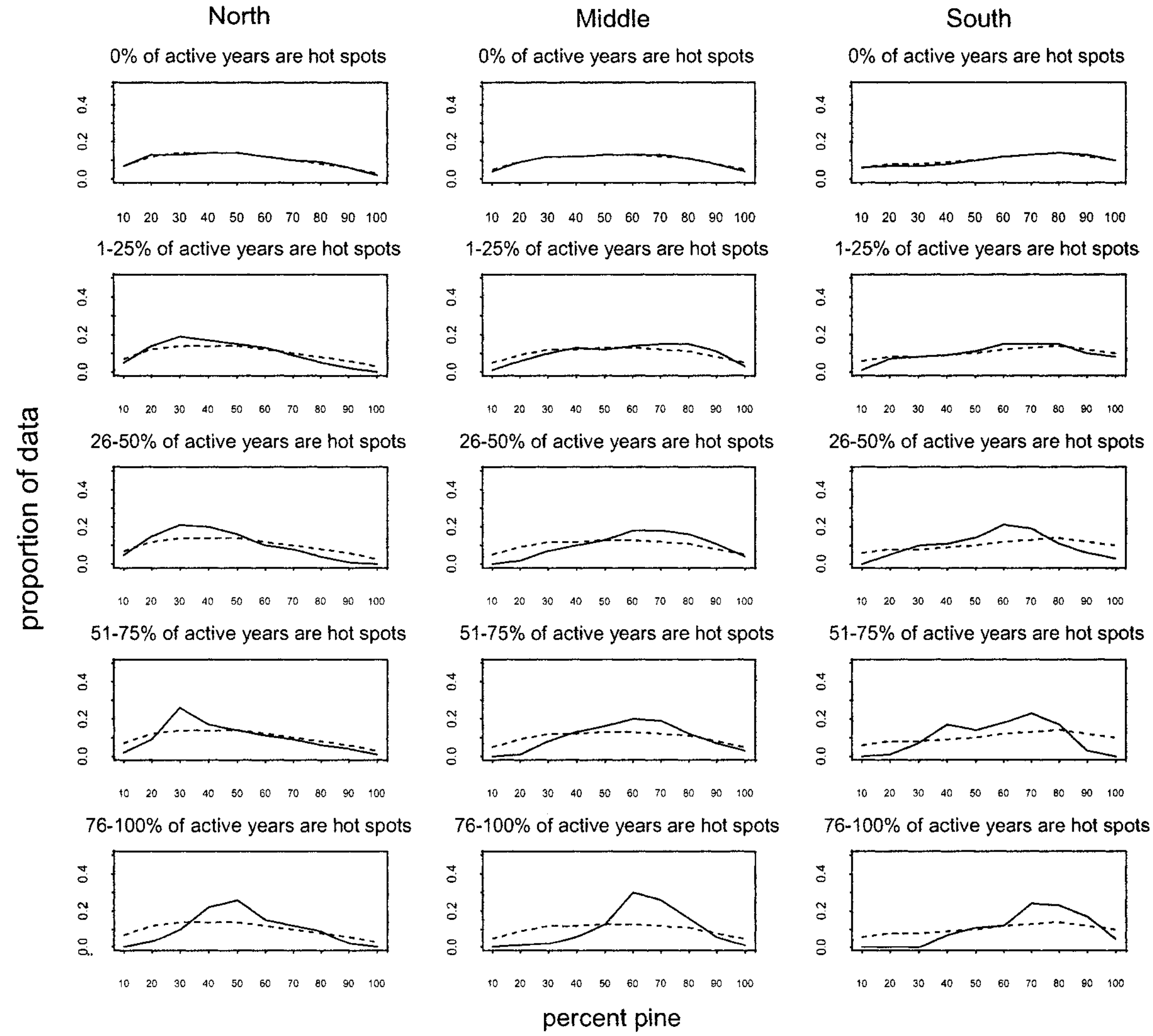


Figure 5.25. Partitioned by the percentage of active years a pixel is a hot spot, the relative frequency distributions of percent pine for hot spot pixels (solid line) in the Morice TSA. For comparison, the percent pine relative frequency distributions for all pine pixels are also provided (dotted line).

The mountain pine beetle is observed to initially infest low to moderate percent pine pixels. This is counter to stand scale observations that mountain pine beetles typically infested pure stands (Safranyik *et al.*, 1974). In part, the preference for medium percent pine stands may be partly explained by the inverse relationship between forest age and percent pine (Figure 5.26). The highest percent pine locations typically host younger trees and mature trees are found where percent pine is low to moderate (30 to 80 percent). The preference for low to moderate percent pine pixels may also indicate that, at a landscape scale, pine trees experience more stress and greater susceptibility when they grow in marginal conditions that result in lower percentages of pine. It is interesting to note that while low to moderate percent pine areas appear to be preferred sites for mountain pine beetles initially, infestations persist longer in locations where the percentage pine is higher. Perhaps pixels with higher percentages of pine, have an increased number of stems available for infestation and the smaller trees at these locations may slow the infestation as fewer beetles emerge (Safranyik *et al.*, 1974).

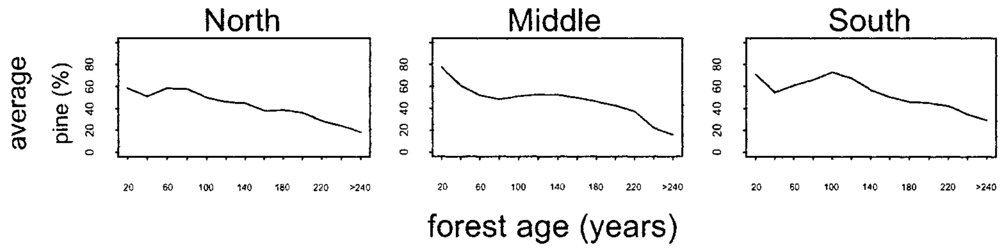


Figure 5.26. Average percent pine versus forest age by subarea in the Morice TSA.

5.5.5 Hot Spots and Elevation

Elevations at which hot pixels were detected may also provide insight into mountain pine beetle preferences. In the North subarea relative frequency distributions of elevation associated with single year hot spots, deviate from the relative frequency distribution for all pine at a single elevation class (Figure 5.27). In 1995 and 1996, 900 metre elevations were most frequently associated with hot spots. In 1999 and 2000 the dominant elevation was 1000 metres, and in 2001 this changed to 700 metres. In other years, strong preferences are not clear. In the Middle subarea hot spots are typically associated with pixels having elevations of 800 metres, and this does not change with time. Similarly, in the South subarea 900 metres is always the preferred elevation for hot spots, and elevations greater than 1,000 metres are under represented in comparison to the relative frequency distribution of elevation for all pine pixels. Over time, the relative frequency distribution of elevations associated with hot spots becomes more similar to the relative frequency distribution for all pine cells.

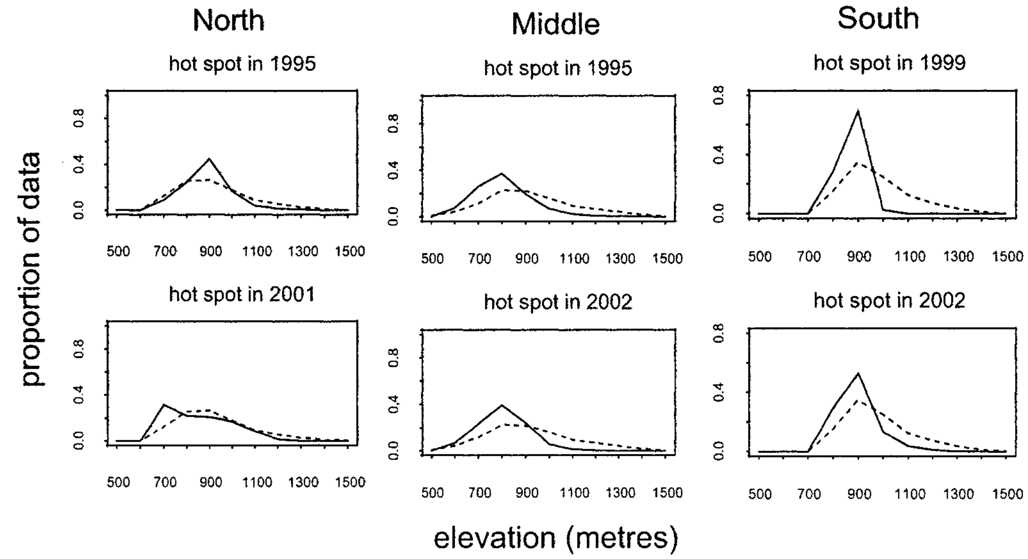


Figure 5.27. Relative frequency distributions of elevation for hot spot pixels (solid line) and all pine pixels (dotted line) in the Morice TSA.

As with other landscape characteristics, relative frequency distributions of elevations associated with hot spots are most similar to the relative frequency distributions for all pine when the number of hot spot years is few (Figure 5.28). As the number of hot spot years increase so do deviations from the elevation relative frequency distributions for all pine pixels. The dominant elevations associated with hot spots are: 900 to 1,000 metres in the North subarea, 800 metres in the Middle subarea, and 900 metres in the South subarea.

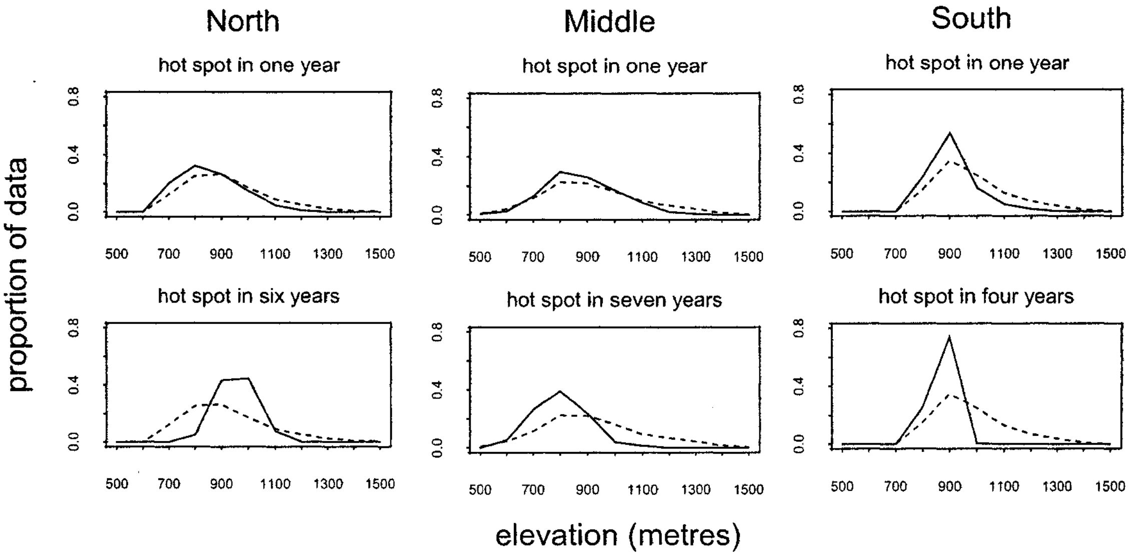


Figure 5.28. Partitioned by the number of years a pixel is a hot spot, the relative frequency distributions of elevation for hot spot pixels (solid line) in the Morice TSA. For comparison, the elevation relative frequency distributions for all pine pixels are also provided (dotted line).

Comparisons between the percentage of hot spot years versus elevation, demonstrates that in the North, as the proportion of hot spot years increases, the proportion of pixels with elevations between 900 and 1000 metres also rises (Figure 5.29). In the Middle and South subareas, once the percentage of hot spot years is greater than 25 percent, relative frequency distributions of elevations associated with hot spots have a consistent shape. The most prevalent elevations associated with hot spots are 800 metres in the Middle subarea and 900 metres in the North subarea. Although similar to the relative frequency distribution for elevations associated with all pine cells in the North and South subareas, locations that are never hot spots tend to occur slightly more often in low elevations.

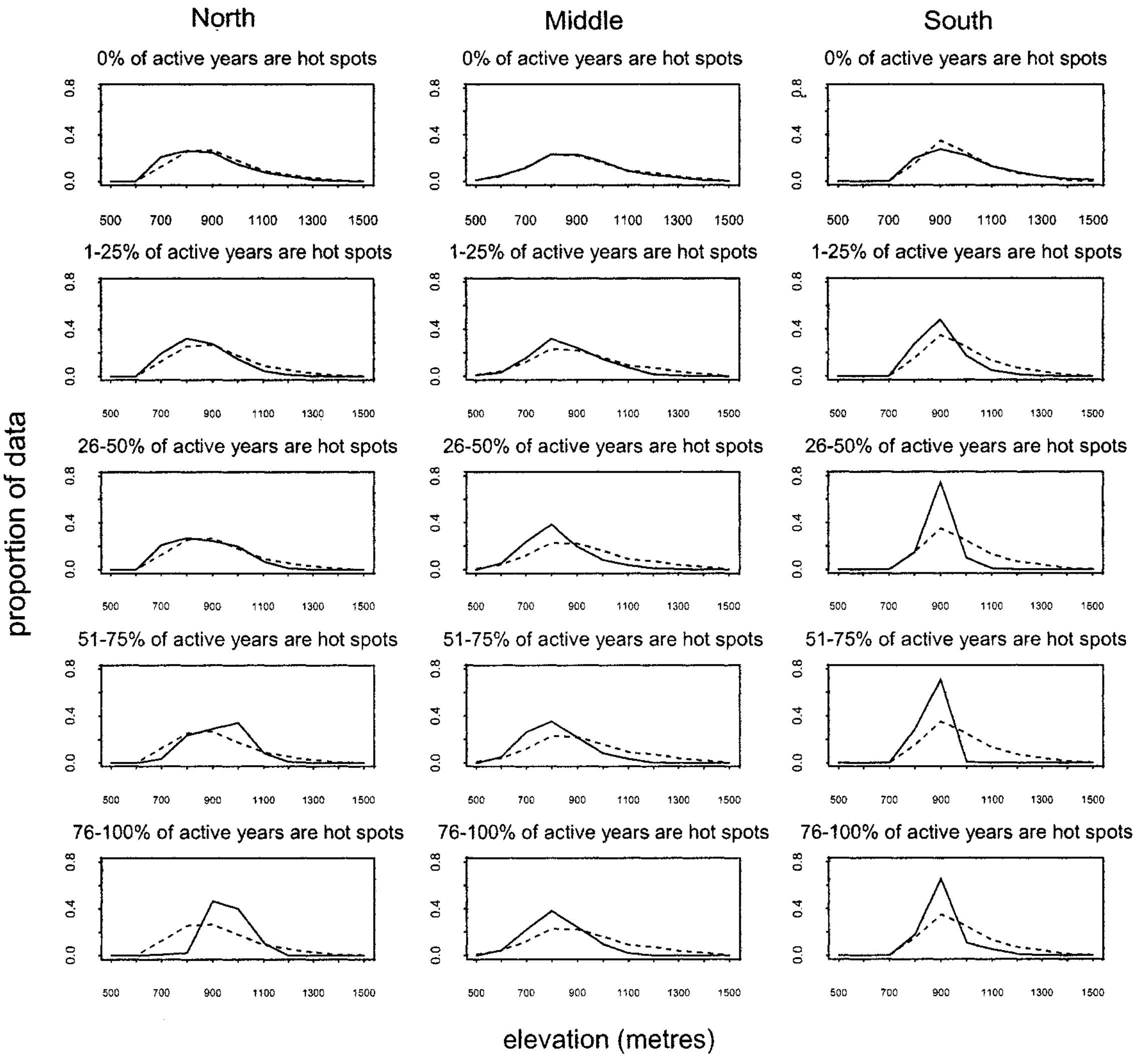


Figure 5.29. Partitioned by the percentage of active years a pixel is a hot spot, the relative frequency distributions of elevation for hot spot pixels (solid line) in the Morice TSA. For comparison, the elevation relative frequency distributions for all pine pixels are also provided (dotted line).

Elevations associated with hot spots are constrained by the range of elevations suitable for pine growth, which in Morice is 600 to 1400 metres. While elevations associated with hot spots change through time, hot spots primarily occur at elevations ranging from 800 to 1000 metres. In Morice, this may indicate that mitigation and treatment will be most effective if applied within this range. In past research, associations between elevation and mountain pine beetle infestations are typically linked to climate (Amman, 1973; Safranyik *et al.*, 1974). Cool temperatures, related to elevations greater than 1900 metres (near the Grand Teton National Park) have been shown to delay mountain pine beetle development and increase mortality (Amman, 1973). In the more northern location of Morice, the mountain pine beetle is limited to lower elevations, and the majority of intense infestations occur below 1000 metres.

5.5.6 Hot Spots and Aspect

For exploration of aspects associated with hot spots, only results for the South subarea are shown, as in the North and Middle subarea aspect distributions were always similar to the distributions for all pine cells. Hot spots are most commonly located on south facing slopes (Figure 5.30). The dominance of south facing slopes decreases through time, and by 2002 the relative frequency distribution of aspects associated with hot spots approximates the relative frequency distribution for all pine pixels.

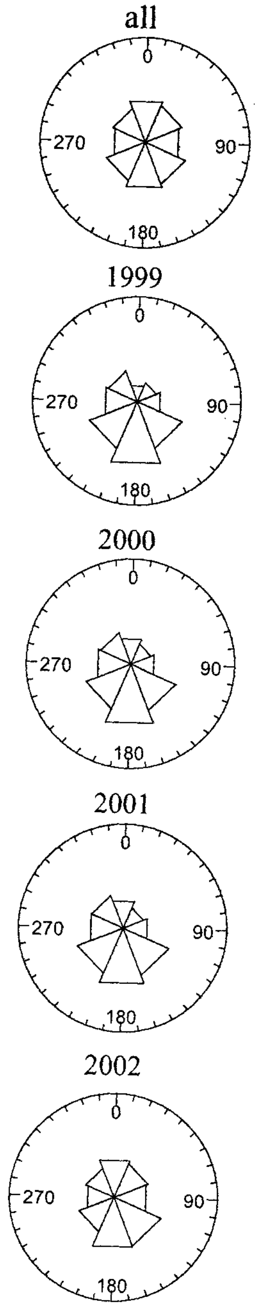


Figure 5.30. For the South subarea circular plots showing aspects (degrees) for hot spot pixels and all pine pixels in the Morice TSA.

Relationships between aspect and the number of hot spot years or the initial hot spot year are more difficult to interpret. In the North and Middle subareas, deviations from the relative frequency distributions of aspect for all pine pixels are few and inconsistent. In the South subarea there are more deviations (Figure 5.31). Pixels that are hot for one and two years are most commonly associated with south-westerly slopes. Pixels hot for longer, three and four years, are increasingly found on south facing slopes.

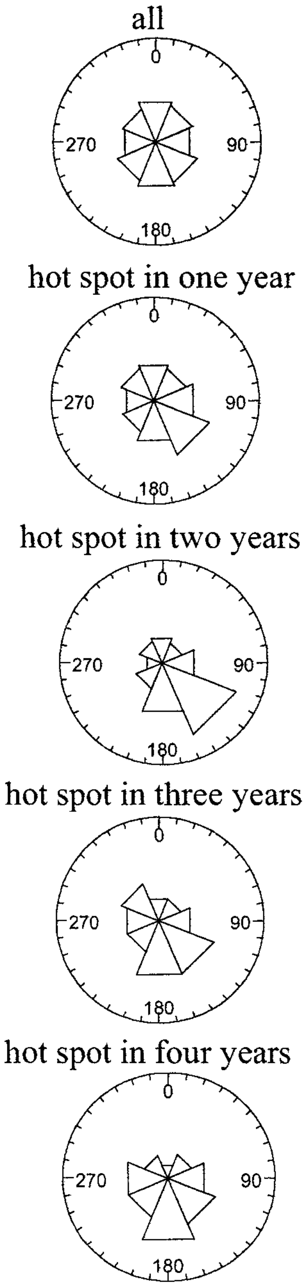


Figure 5.31. Partitioned by the number of years a pixel is a hot spot circular plots showing aspects (degrees) for hot spot pixels and all pine pixels for the South subarea of the Morice TSA.

The relative frequency distributions of aspect generated for pixels categorized by the percentage of hot spot years are inconsistent between study areas; yet, within subareas temporal trends emerge (Figure 5.32). In all subareas, pixels that are never hot have aspect relative frequency distributions that approximate the aspect distribution for all pine cells. In the North, pixels having hot spots in greater than 75 percent of active years are typically associated with western slopes. In the Middle subarea, east and south-eastern slopes are most commonly associated with cells hot for greater than 75 percent of active years. In the South, the largest deviation from the relative frequency distribution generated from all pine pixels occurs when cells are hot for 51 to 75 percent of years. In this case south facing slopes are dominant.

At a stand scale, south and west facing slopes have been shown to be important for outbreak initialization (Safraynik *et al.*, 1974), and newly emergent beetles prefer spot sources of light (Safranyik *et al.*, 1989). At a landscape scale, west and south facing slopes appear favourable in locations where the mountain pine beetle are intense for a number of years. The relationship between aspect and mountain pine beetle infestations is most clear during the initiation of a widespread infestation in the South subarea, during which southern slopes appear preferentially infested.

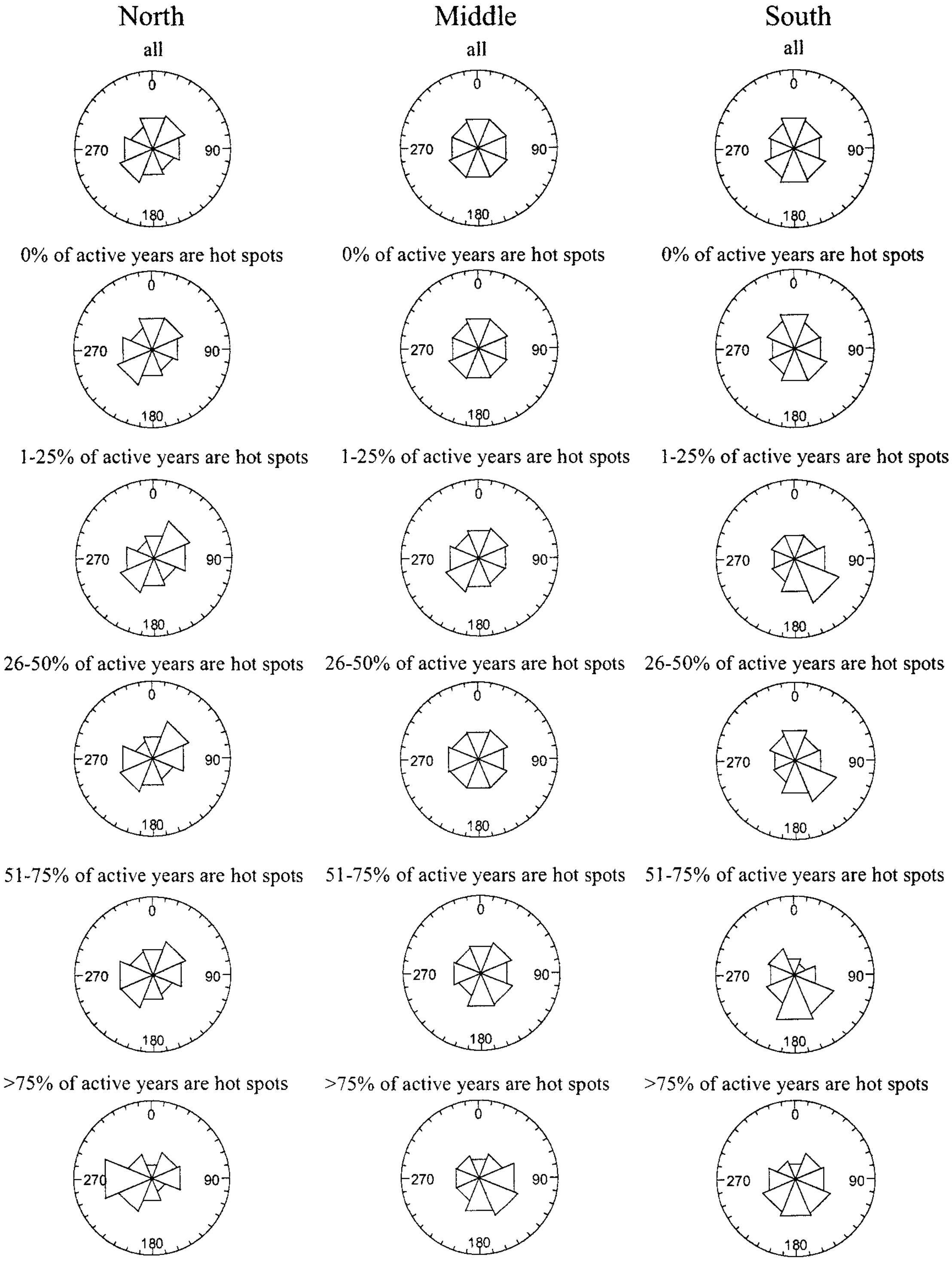


Figure 5.32. Partitioned by the percentage of active years a pixel is a hot spot, the circular plots showing aspects (degrees) for hot spot pixels and all pine pixels in the Morice TSA.

5.6 SUMMARY

In part, due to the technical limitations of large area data collection, past studies of mountain pine beetle dispersal have focused on stand or finer spatial scales. Hot pixels and patches can be used to explore the spatial-temporal interactions of intense mountain pine beetle infestations at a landscape level. Identifying and visualizing hot spots provides a mechanism for exploring spatial and spatial-temporal variation in locations that are intensely attacked. Hot pixels tend to cluster spatially, even though the definition of a hot spot used in this research is aspatial. Therefore, spatial-temporal analysis was undertaken on both hot spot pixels and hot spot patches.

While there are many possible definitions for hot spots, using the 90th percentile of infestation intensity has several benefits. For instance, this definition identifies infested pixels associated with landscape characteristics that are different from general characteristics found for all pine locations. A second benefit of defining hot spots using the 90th percentile of infestation intensity is that a practical amount of area for mountain pine beetle management within a TSA, is identified. Over large areas, and under epidemic conditions, treating greater than ten percent of an infestation is likely impractical. The hot spot definition used in this research is helpful for understanding epidemic mountain pine beetle populations within the context of applied management. While the definition of hot spot used for this analysis proved useful for spatial-temporal analysis, all relationships identified are tied to hot spot delineation. In future work, the impact of alternate definitions of hot spots should be examined.

Pixel-based analysis indicates that intense infestations persist in a 200 by 200 metre pixel for a number of years. The observed patterns also suggest that intense infestations typically occur within two to four kilometres of the previous year's hot spots and dispersal distance are approximately exponential in form. Pixel-based analyses differ from patch analyses, as trends associated with a few large patches dominate pixel-based results.

Hot spots are useful for investigating dispersal. Exploratory analyses of hot spot patches suggest the presence of three processes of dispersal: coalescence, short-range dispersal (spreading), and long-range dispersal. When hot spot patches are very large there is evidence that infestations result from hot spot coalescence. However, coalescence is observed in only 4.5 percent of hot spot patches. More commonly, hot spot patches intersect with one patch in the previous time period (47 percent of patches). For such patches, the modal distance of maximum leading edge spread is near zero (0.3 metres), suggesting that dispersal is a result of beetles spreading short distances, as they move from one suitable location to the next. The remainder of hot spot patches occur where no patches were previously (48 percent of patches). In these cases, the modal minimum distance between patches is 1.8 kilometres and distances of six kilometres are more common than those near zero. Further minimum distances between patches suggest that long-range processes may be operating.

From the perspective of large area mountain pine beetle modelling, it is interesting that 53 percent of hot patches overlap with one or more patches in the previous year, while 47 percent of hot patches are found at some distance (most commonly 1.8 kilometres) from the most intense infestations of the previous year. This gives some indication as to why temporal modelling of mountain pine beetle infestations can be complex. Intense infestations occur at distances that are both near and far from hot spot patches in the previous year.

Hot spot patches with one intersection are more likely to shrink than to grow. For patches that do expand, spread occurs over longer distances when growth is in all directions. The more intersections a patch has, the more likely it is to overlap future patches. This may indicate that well-established infestation sites are more likely to persist than those having no intersections and resulting from long-range dispersal. The random component of wind driven long-range dispersal results in mountain pine beetles infesting both optimal and sub-optimal locations. When beetles infest a sub-optimal location, resources are inadequate to sustain long-term high intensity infestations.

The finding that hot spot patches having no intersections with patches in the previous time period, are less likely to be intensely infested in the future than those with intersections, may have management implications. Mountain pine beetle mitigation activities may be best directed towards established hot spot patches (*i.e.* those having pervious intersections), as beetle populations in other hot spot patches are more likely to decline naturally.

Investigation of landscape characteristics suggests that patch characteristics are relatively consistent regardless of size or time. However, pixel-based analyses demonstrate that landscape scale relationships between mountain pine beetle infestations and the physical environment change through time and impact the duration of intense infestations. Temporal variability in relationships between hot spots and the physical environment may indicate increasing randomness in mountain pine beetle host selection over the duration of an infestation; it may also be indicative of a reduction in host availability over an epidemic cycle.

Typically, the shape of relative frequency distributions for landscape characteristics associated with hot spot pixels deviate from the relative frequency distributions of all pine locations. Departures between the relative frequency distributions seem to be impacted by initial landscape conditions and infestation magnitude. Usually, pixels identified as hot earlier, or for longer periods of time, have relative frequency distributions that are the most different from those associated with all pine pixels. Relationships between hot spot pixels and age characteristics show that high intensity mountain pine beetle infestations tend to occur earliest and persist the longest in mature forests. As well, hot spots initially occur in mature forests, but over time they shift to younger trees.

While we anticipated hot spots would be associated with pixels that have the highest percentages of pine, results indicate that they are typically found in cells with low to moderate percentages of pine (30 to 80 percent pine). However, hot spots have the longest temporal duration when percent pine is high. This suggests that conditions most favourable for infestation establishment are different than those required for maximum infestation duration.

By restricting lodgepole pine growth, elevation limits the location of mountain pine beetle infestations. In Morice, hot spot pixels typically have elevations between 800 and 1000 metres. It is at these elevations that mountain pine beetle treatments and silivicultural efforts are likely to have the most impact.

Finally, when an area hosts a high magnitude infestation for several years, south and west facing slopes appear to be preferred by mountain pine beetles. Such slopes also have an important role in the initialization of outbreaks in new locations. During the latter phase of an epidemic, aspects associated with warmer conditions are less essential.

Relationships between intense infestations and the landscape provide a starting point for further investigations into characteristics that enable the development of epidemic populations, and the conditions that support such populations over long time periods. It is interesting that landscape scale, pixel-based relationships between mountain pine beetle infestations and the physical environment appear similar to those observed at finer scales. While further research is needed, these results might suggest that spatial processes observed at finer scales could be useful for modelling coarser, landscape level processes. In future work it may be beneficial to take a multivariate approach to investigating the relationship between hot spots and landscape characteristics as physical factors, such as forest age and percentage of pine, are interrelated. Another important consideration in future studies is the impact of the spatial structure of the landscape on spatial and spatial-temporal patterns of hot spots. For instance, knowing the impact of landscape pattern on the distances between hot spot patches could add further insights into processes of dispersal.

6 EXPLORING SPATIAL-TEMPORAL CHANGE IN MOUNTAIN PINE BEETLE INFESTATIONS

6.1 INTRODUCTION

In spatial analysis the term "change" has several meanings. Change may occur through space or both space and time, and can be either gradual or abrupt (*e.g.*, Gong and Xu, 2003). As well, change may refer to the creation and/or disappearance of events (*e.g.*, Sadahiro and Umemura, 2001) or the relative differences in high and low attribute values (*e.g*,. Anselin, 1995). Like hot spots, change may be used as a mechanism for characterizing variations in spatial patterns and by detecting change it is possible to investigate processes. For instance, large changes in spatial patterns may suggest dynamic process(es), while locations with little or no change reveal processes more static in nature (Barbujani *et al.,* 1989; Sokal *et al.,* 1998).

Investigating change for the purpose of understanding spatial processes requires a definition of meaningful change. From the perspective of spatial processes, it is likely that some changes in spatial pattern are inconsequential. For instance, if a forested area was digitally imaged on two consecutive days (assuming that all imaging parameters were held constant), many differences in digital values would occur. In the absence of a catastrophic event or harvesting, differences would not provide meaningful information regarding forest processes. This example highlights the importance of considering the nature of processes, and the research question, when defining change. While the amount of change is often important, the type of change (*e.g.*, normal/abnormal) should also be considered when generating a change definition (Oden *et al.,* 1996; Rogerson, 2002).

The change definition may also be impacted by practical considerations such as data uncertainty and representation.

Few descriptions are available to guide development of a definition of meaningful change in mountain pine beetle populations. Although population dynamics, or change in populations through time, are considered important, most studies on the topic do not define meaningful change (*e.g.*, Safranyik *et al.*, 1999). Research typically focuses on the continuous temporal response of mountain pine beetle populations, indicated by pine mortality, to variables such as forest age, climate, and treatment of mountain pine beetles (Safranyik *et al.*, 1999). One exception is a stand scale study by Cole (1981), which uses variation in infestation intensity to define pre-epidemic, epidemic, and post-epidemic mountain pine beetle populations. Pre- and post-epidemic conditions are defined as zero to 10 percent annual tree mortality of susceptible trees in an area, whereas epidemic conditions are defined by 10 to 45 percent annual tree mortality.

In this chapter our goal is to explore spatial-temporal change in mountain pine beetle populations. Meeting this goal requires consideration of several objectives. First, we consider an appropriate definition of change and select a suitable method for change detection and visualization. Secondly, we explore multi-temporal representations of spatial change through time. Thirdly, we investigate temporal trends in change. Finally, locations of change are compared with underlying landscape characteristics.

6.2 DEFINING AND VISUALIZING CHANGE BETWEEN TWO YEARS

Spatial-temporal change in mountain pine beetle infestation magnitude can occur in a variety of ways. Over a landscape, infestation magnitude may significantly increase and decrease, only decrease significantly, only increase significantly, or have no significant change. Change is likely a response to climate, management, forest conditions, and is dependent on the state of the mountain pine beetle population. As with many forest processes, the amount and nature of change in infestation magnitude is likely to vary throughout a forest. To adequately reflect the nature of mountain pine beetle processes, a method for detection must allow all possible change scenarios to be identified, including no change, and should assess local variations or heterogeneity in change over space.

In spatial analysis, the definition of change is inextricably linked to the process under investigation, data representation, and the change detection method. Data in this study are modelled as a continuous surface and are represented by a raster grid with cell values equal to estimates of infestation density (see Chapter 4 for descriptions of kernel density estimated surfaces). Most methods for detecting change in raster data were developed for use with remotely sensed imagery. The effectiveness of common remote sensing change detection methods, such as image differencing and ratioing, has been widely demonstrated (Gong and Xu, 2003). However, application of such methods hinge on the user's ability to identify meaningful change. Typically, meaningful change is determined by applying thresholds, such as two standard deviations, to a frequency distribution of change. Although such methods could be applied to the mountain pine beetle infestation surfaces, the utility of these methods for detecting change in mountain pine beetle attack levels is limited, as they do not allow for the possibility that no change has occurred.

A method designed specifically for use with kernel density estimated surfaces is well suited to this application, as it allows all types of change in mountain pine beetle populations to be detected (Bowman and Azzalini, 1997 pg 112-117). While positive and negative change may be detected, the presence of no change is also a possibility. This method is essentially a square root variance stabilizing transformation of the difference between two kernel density estimated surfaces. The main benefit of this technique is that the difference between the square root kernel density estimates is measured, at any point, in terms of pooled standard deviations by applying

$$change_{t_i t_{i+1}} = \frac{\sqrt{\hat{\lambda}_{t_i}} - \sqrt{\hat{\lambda}_{t_{i+1}}}}{\sqrt{se_{t_i}^{\,2} + se_{t_{i+1}}^{\,2}}} \qquad 6.1$$

$\hat{\lambda}_{t_i}$ is the kernel density estimate at given location in a year, and $\hat{\lambda}_{t_{i+1}}$ is the kernel density estimate at the same location in the following year. se_{t_i} and se_{t_i+1} are standard errors in the first and second year, respectively (Bowman and Azzalini, 1997).

The standard error is a measure of the variance of the kernel function. Kernel density variance is dependent on the shape or curvature of the kernel, the search radius, and the total sample size. For traditional kernel density estimators, these parameters are invariable over space. Therefore, the standard error is constant and defined as

$$se = \sqrt{\frac{\left[\int (k(\mathrm{z}))^2 \,\mathrm{dz}\right]^2}{4n\tau^2}} \qquad 6.2$$

where $k(z)$ is the Gaussian kernel with mean of zero and a standard deviation of $\sqrt{2}$ (Bowman and Azzalini, 1997).

For this study, change is identified when $change_{t_i t_{i+1}}$ is greater than two or less than negative two. Calculating $change_{t_i t_{i+1}}$ does not produce an exact measure of statistically significant change. As suggested by their name, kernel density estimators produce estimates and the standard error or variance can be thought of as a confidence envelope around that value. Therefore, significant change is also estimated and most appropriately considered exploratory, rather than confirmatory, analysis (Bowman and Azzalini, 1997 pg 116; Fotheringham *et al.*, 2002 pg 205).

The kernel used for this study is quartic. The main benefit of the quartic kernel, relative to the normal kernel, is the increased speed of calculations (Silverman, 1986). The quartic kernel has about half the width, or half the standard deviation, of the normal kernel (Silverman, 1986). Therefore, a normal kernel with radius $\tau / 2$ will produce approximately the same results as a quartic kernel with radius τ. In this study the quartic standard error was approximated using equation 6.2, with a standard deviation equal to $\sqrt{1}$.

Two variations of equation 6.2 were explored for detecting change. The variable *n* can be defined as the number of points or the sum of the attribute values. Choice of definition of *n* is primarily conceptual. If the points are considered unique entities, then *n* should be defined as the number of points. However, if points are clusters of phenomena, it may be better to define *n* as the sum of the attribute values. This requires consideration of whether mountain pine beetle point data represent infestation entities or clusters of smaller entities (infested trees). In this study, *n* may be conceptualized as either the number of points or the sum of point attributes. While points represent clusters of trees infested by the mountain pine beetle, the attributes represent individual trees. Therefore, change was calculated using both definitions of *n*. Operationally, the larger the value of *n*, the smaller the standard error and the more change detected. A more conservative estimate of change is obtained when *n* is defined by the number of points.

6.3 REPRESENTING AND VISUALIZING SPATIAL CHANGE IN MULTIPLE TIME PERIODS

Change between two years provides a short-term view of mountain pine beetle processes. A longer-term perspective may be gained by investigating temporal patterns in spatial-temporal change. Exploring the temporal pattern of change may provide insights for prediction and modelling. For this analysis, multi-temporal change was represented as the number of positive or negative changes between the two kernel density estimated surfaces, over the eight year period for which data were available.

It is worth mentioning additional efforts made to represent the temporal pattern of change. Vectors of change were investigated as a mechanism to explore temporal patterns of change. For each cell in the kernel density surfaces, a vector was generated representing changes that occurred over an eight year period. Vectors of change were categorized based on persistence of change (*e.g.*, the number of consecutive increases) and directional shifts in the change (*e.g.*, positive change followed by negative change). Categories of change were compared to infestation levels in order to determine if a relationship between these variables existed. Unfortunately, change vectors did not relate meaningfully to temporal variation in mountain pine beetle infestation magnitude. However, the concept may have utility for other applications.

6.4 INVESTIGATING TEMPORAL TRENDS IN CHANGE

To better understand patterns of change in mountain pine beetle infestations, spatial-temporal relationships of change were explored using both pixels and patches of change. Patches of change are defined as spatially contiguous positive change pixels or spatially contiguous negative change pixels. Spatial contiguity is determined using the queen's definition.

Pixel-based analysis was used to determine if change occurring between two years was useful for predicting future change in a pixel. For cells with positive and negative change, we determined the proportion of pixels having positive, negative, or no change in the next time period. Spatial-temporal interactions between change pixels were also explored. The nearest Euclidean distances, and associated directions, between change pixels in consecutive years were determined. Restricting analysis to locations within 10 kilometres of a given pixel served to control edge effects.

Further insights into change trends were gained from spatial-temporal analysis of change patches. Temporal variation in patch characteristics, including patch size, the number of patches, the average patch size, and variability in patch sizes were investigated. Change patch properties were also compared with the total number of change pixels, in order to determine if temporal variation in patch characteristics could be associated with global levels of change.

Spatial-temporal patterns in change patches were also investigated by exploring intersections between patches of change in two change periods. Intersections between positive-positive patches, negative-negative patches, positive-negative patches, and negative-positive patches were considered. The sizes of patches with and without intersections were assessed using a *t*-test (Burt and Barber, 1996) and coefficients of variations compared. Differences in patch shape were determined using the simple index:

$$S = \frac{4\pi A}{P^2} \qquad 6.3$$

where A and P are polygon area and perimeter, respectively. S ranges from zero to one. A patch is circular when S equals one and becomes more elongated as S approaches zero (Bogaert *et al.*, 2000).

When patches had no intersections, the minimum Euclidean distance, and associated direction, between patches in consecutive time periods was explored. Only positive-negative patches had a substantial number of intersections and for these the maximum distance of leading edge spread (see Figure 5.3b for defintion) and percentage of patch area overlap was also characterized.

6.5 EXPLORING CHANGE AND THE UNDERLYING LANDSCAPE

To investigate the relationship between changes in mountain pine beetle infestations and the landscape, relative frequency distributions of forest age, percentage pine, elevation, and aspect were generated for pixels having significant change. The procedure for this investigation is the same as discussed in Chapter 5 when the landscape underlying hot spot locations was investigated. Essentially, for each of the three subareas relative frequency distributions of landscape characteristics underlying change locations were compared to the relative frequency distribution generated for all pine cells.

Relationships between change and landscape characteristics are presented using a sample of relative frequency distributions selected to aid the visualization of general trends. As less than one percent of pixels had more than two significant positive or negative changes, investigations of landscape characteristics focused on cells with one or two significant positive or negative changes. Landscape associations with pixels that never experienced significant change were also investigated, but are not presented as the associated relative frequency distributions were consistently the same as the relative frequency distributions for all pine cells.

6.6 RESULTS AND DISCUSSION

6.6.1 Visualizing Change

Pixels identified as having statistically significant change in kernel density estimated surfaces are shown in Figures 6.1 through 6.7. When *n* in the standard error calculation (equation 6.2) is defined as the sum of the points, the amount of meaningful change detected is quite small (Table 6.1). A less conservative definition of change is obtained when *n* is equal to the sum of point attributes (Table 6.2). Confidence in this representation of change is reinforced by general trends observed in Morice from 1995 to 2002. Initially, the infestation was largest in the North and Middle subareas. Cool temperatures in 1998 lead to an overall decline in mountain pine beetle populations. In 1999, large infestations occurred in the South subarea and the mountain pine beetle population grew exponentially in 2002.

Table 6.1. The percentage area in the Morice TSA that changed when *n* equals the number of points. Columns represent change periods.

	9596	**9697**	**9798**	**9899**	**9900**	**0001**	**0102**
positive	0.54	0.19	0.08	0.02	0.04	0.03	1.05
negative	0.00	0.43	0.06	0.06	0.01	0.00	0.12
no change	99.46	99.38	99.86	99.92	99.96	99.97	98.83

Table 6.2. The percentage of the study area that changed annually when *n* equals the sum of attribute values. Columns represent change periods.

	9596	**9697**	**9798**	**9899**	**9900**	**0001**	**0102**
positive	4.95	2.09	0.29	0.95	0.87	0.50	5.23
negative	0.25	2.46	2.41	0.29	0.37	1.07	2.14
no change	94.80	95.46	97.30	98.76	98.76	98.42	92.63

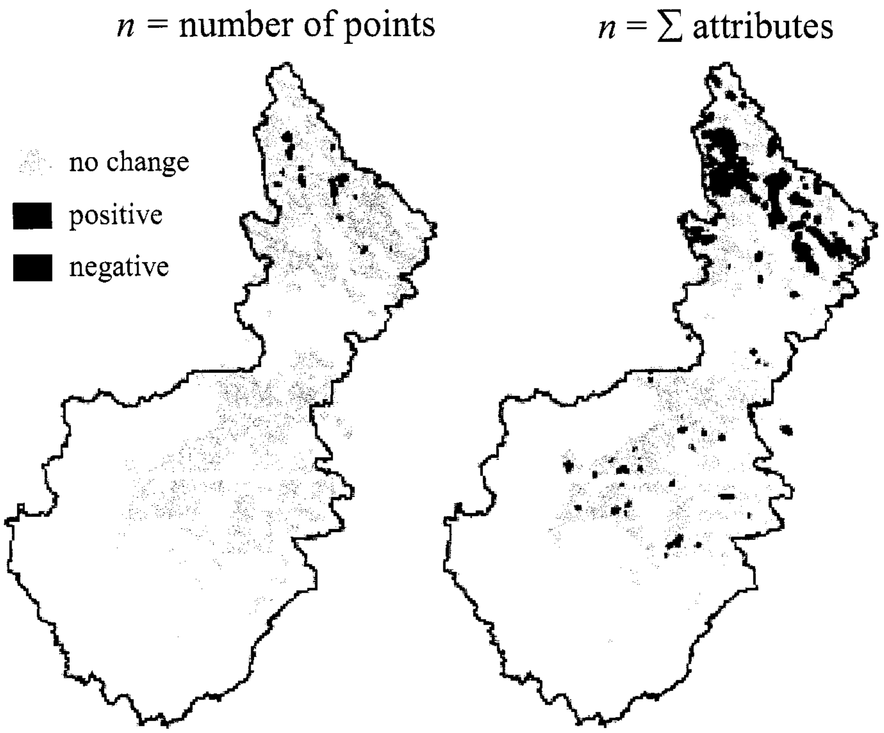

n = number of points
$n = \sum$ attributes

Figure 6.1. Change in infestation magnitude from 1995 to 1996 in the Morice TSA.

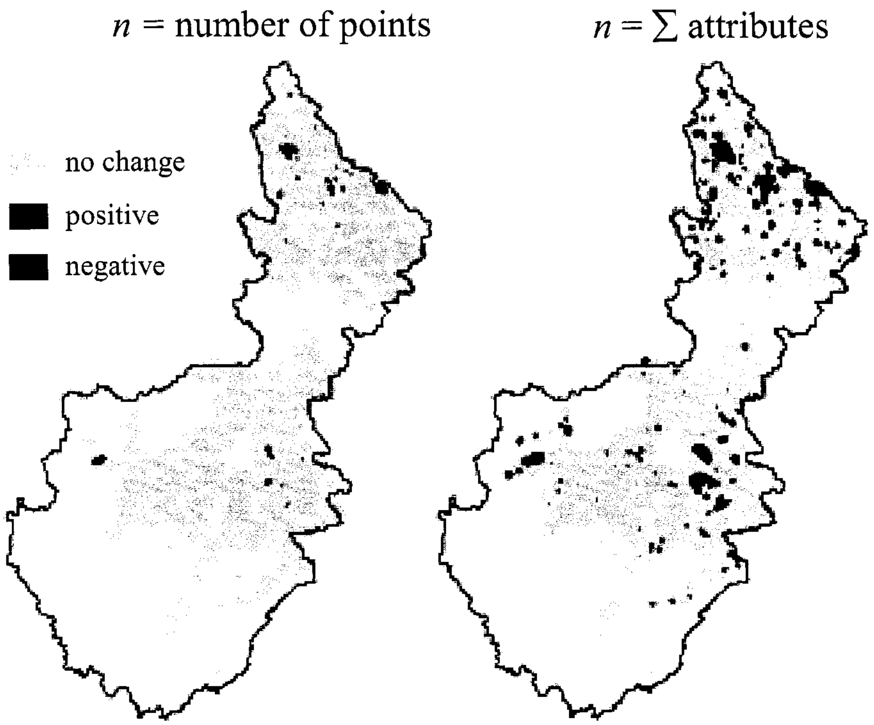

n = number of points
$n = \sum$ attributes

Figure 6.2. Change in infestation magnitude from 1996 to 1997 in the Morice TSA.

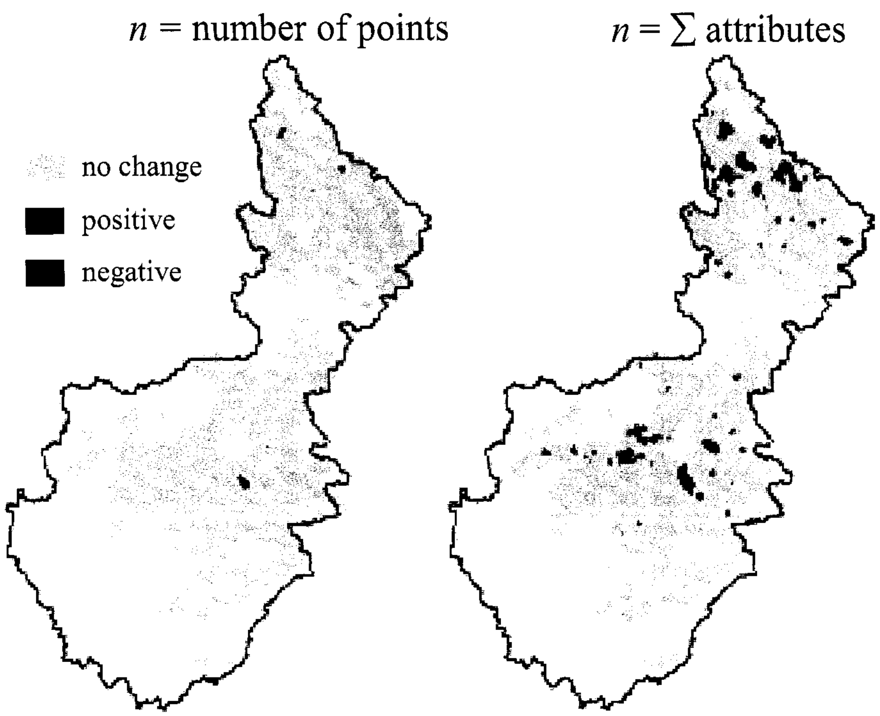


Figure 6.3. Change in infestation magnitude from 1997 to 1998 in the Morice TSA.

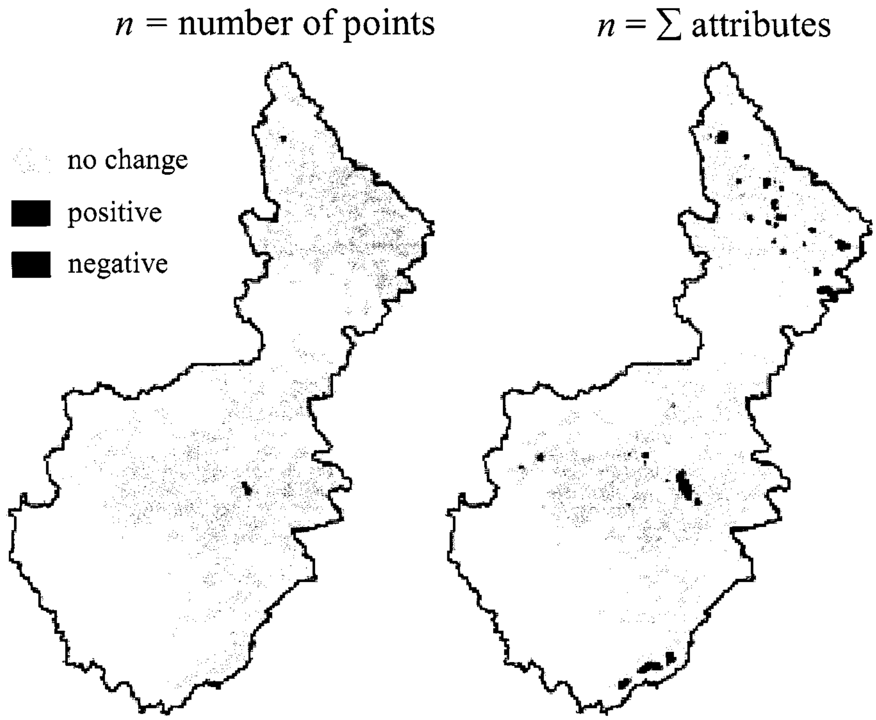


Figure 6.4. Change in infestation magnitude from 1998 to 1999 in the Morice TSA.

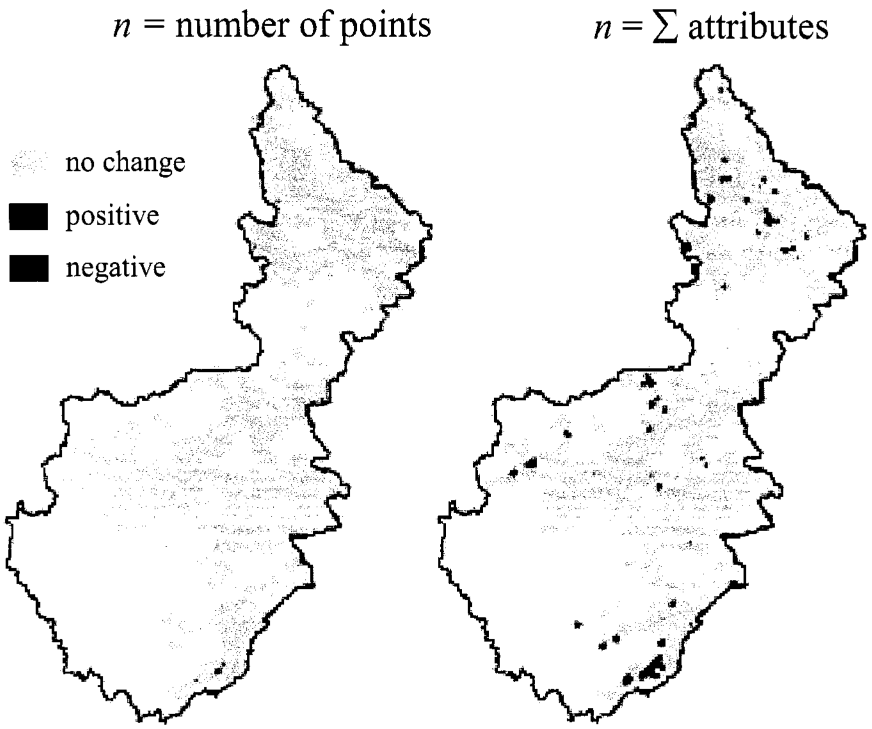


Figure 6.5. Change in infestation magnitude from 1999 to 2000 in the Morice TSA.

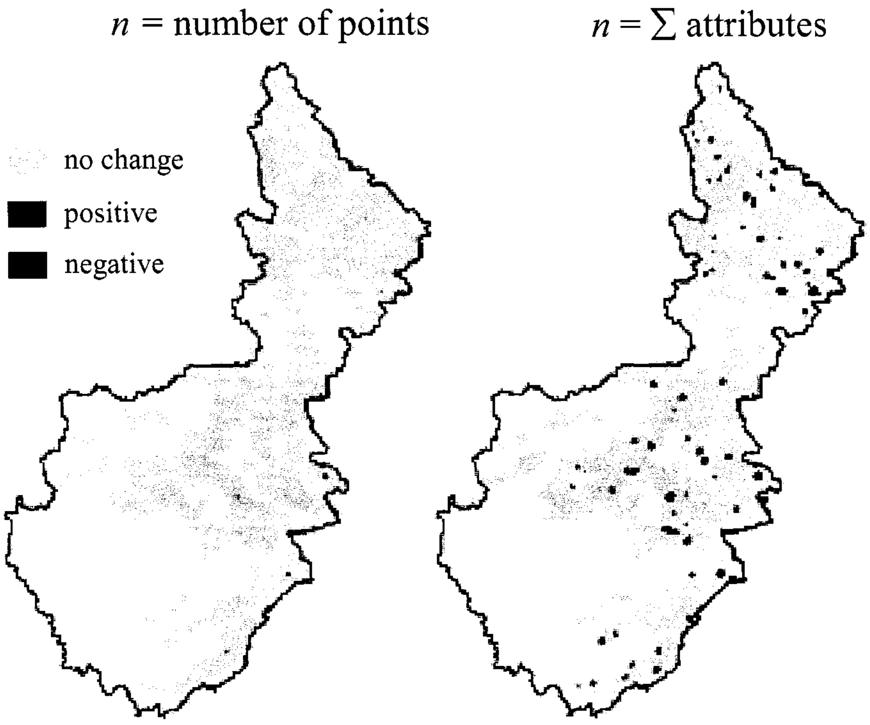
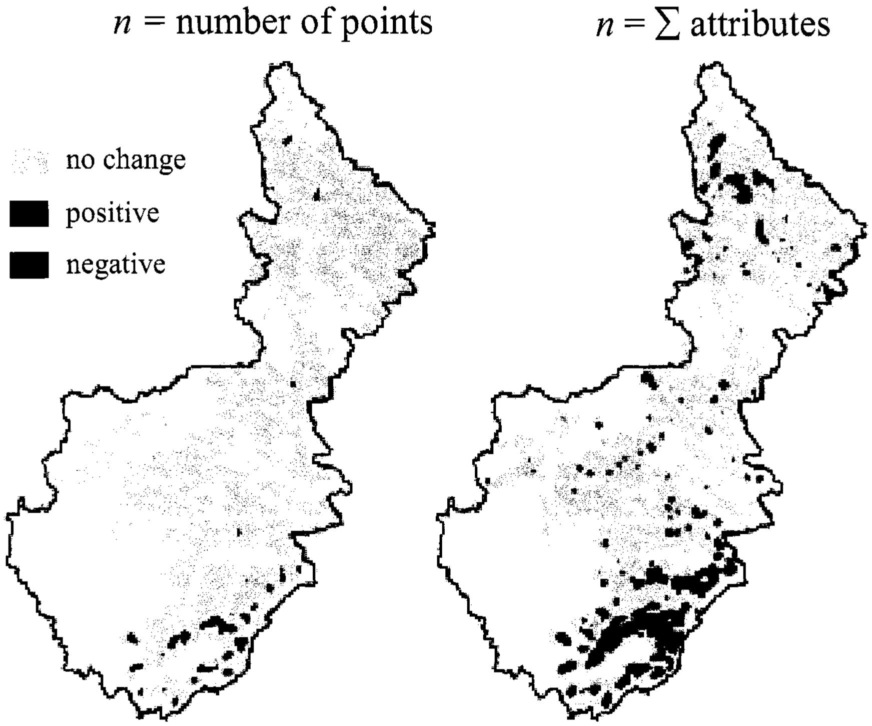


Figure 6.6. Change in infestation magnitude from 2000 to 2001 in the Morice TSA.


n = number of points

$n = \sum$ attributes

Figure 6.7. Change in infestation magnitude from 2001 to 2002 in the Morice TSA.

Multi-temporal change is represented in Figure 6.8. The maximum number of years that a location has positive change is three, and the maximum number of negative changes is four. There are nearly twice as many positive change pixels as there are negative change pixels (Table 6.3.). Of pixels with change, 57 percent of pixels have only positive change, 18 percent have only negative change, and 25 percent have both positive and negative change. As Figures 6.1 to 6.7 show, the North and Middle subareas have more pixels with both positive and negative change than the South (subarea boundaries are shown in Chapter 3). In the South subarea, the infestation is younger and negative changes should be anticipated in the future.

Only 7.9 percent of pixels with change have more than one significant positive change and only 1.0 percent of pixels have positive change in two consecutive years. Six percent of pixels have more than one significant negative change, and 1.2 percent of pixels have two consecutive years of negative change. No pixels have greater than two consecutive years of positive or negative change.

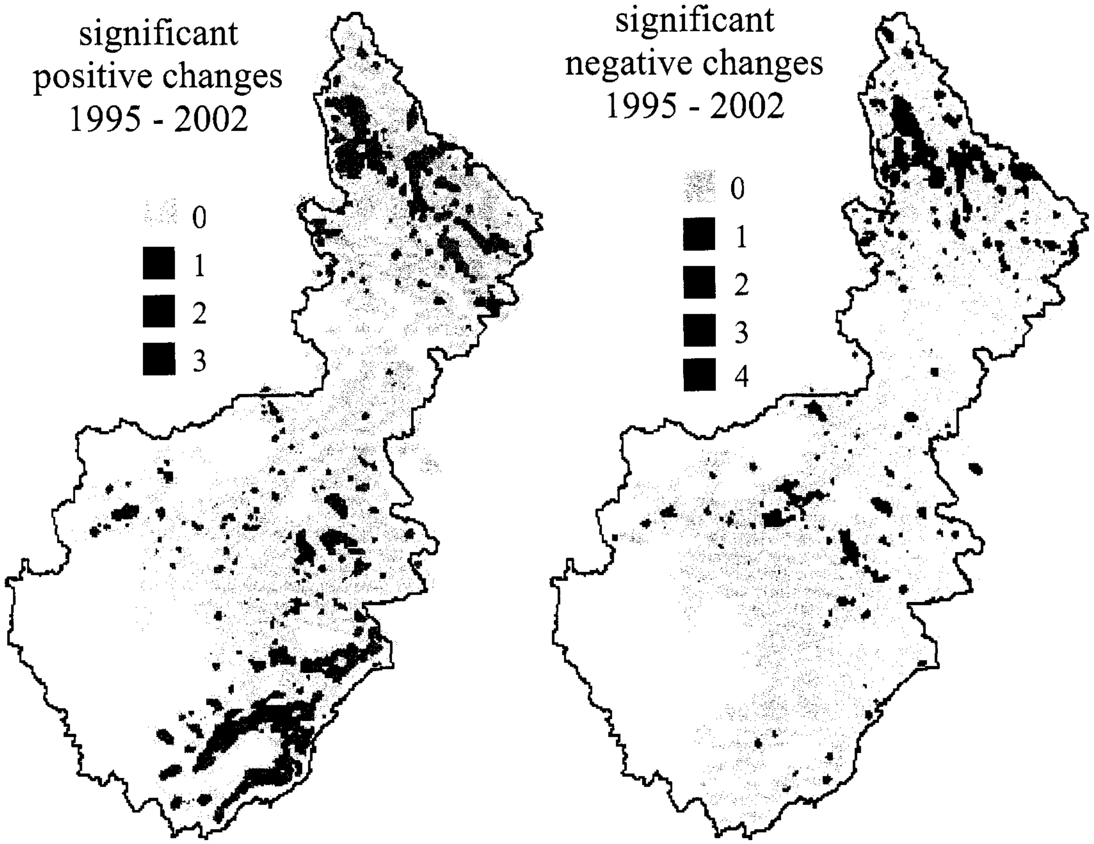


Figure 6.8. In the Morice TSA, the number of significant positive or negative changes in infestation intensity that occurred between 1995 and 2002.

Table 6.3. The number of pixels having significant change in one or more years between 1995 and 2002 in the Morice TSA.

number of years having significant changes	positive change pixels	negative change pixels
1	47598	23582
2	4851	3308
3	225	451
4	0	22

6.6.2 Pixel-Based Temporal Investigation of Change

The temporal sequence of change at a given location suggests patterns in states of change through time. Sequences of change over three years can be seen in Tables 6.4 and 6.5. Based on the definition of change applied in this study, significant positive change was typically followed by no significant change (annual average = 77.12%) and sometimes by negative change (annual average = 21.82%). Positive change followed by negative change may be the result of harvesting treatments used for mountain pine beetle management. Intensely infested locations that experience a sudden decline in attack levels have likely been exposed to harvesting as, typically, untreated mountain pine beetle populations will gradually increase and decrease with time (Carroll, pers com). A significant negative change in mountain pine beetle populations was typically followed by no significant change (annual average = 87.99 %) and sometimes by positive change (10.10%). The tendency for negative change to be followed by no significant change may suggest that a large decline in population signals a reduced ability to support mountain pine beetle activity. However, negative change followed by positive change may result when treatment or local climate conditions reduce the mountain pine beetle population. The remaining forests are still susceptible and future increases in attack magnitude are possible. Rarely is positive change followed by positive change (annual average = 1.06%) or negative change followed by negative change (annual average = 1.93%), suggesting little temporal persistence of any type of change.

Table 6.4. In the year following a positive change, the percentage of pixels that have negative change, no change, or positive change in the Morice TSA.. Columns represent change periods.

positive change followed by	**95-97**	**96-98**	**97-99**	**98-00**	**99-01**	**00-02**	**all**
negative	28.92	17.82	14.73	NA	17.22	30.41	21.82
no change	70.90	81.28	85.27	NA	81.16	67.01	77.12
positive	0.18	0.91	0.00	NA	1.62	2.58	1.06

Table 6.5. In the year following a negative change, the percentage of pixels that have negative change, no change, or positive change in the Morice TSA. Columns represent change periods.

negative change followed by	**95-97**	**96-98**	**97-99**	**98-00**	**99-01**	**00-02**	**all**
negative	0.00	8.13	0.00	0.00	0.00	3.45	1.93
no change	83.68	91.19	100.00	98.25	91.76	62.97	87.98
positive	16.32	0.68	0.00	1.75	8.24	33.58	10.10

Nearest neighbour distances between change pixels in consecutive years vary depending on the type of change (Figure 6.9). Relative frequency distributions of nearest neighbour distances are approximately uniform, except between positive and negative change pixels. The dominance of zero distances, confirms earlier observations that pixels with positive change often have negative change in the following year. Nearest neighbour distances of zero are uncommon between positive-positive and negative-negative changes (indicating little temporal persistence of change) and distances of two to four kilometres are more common.

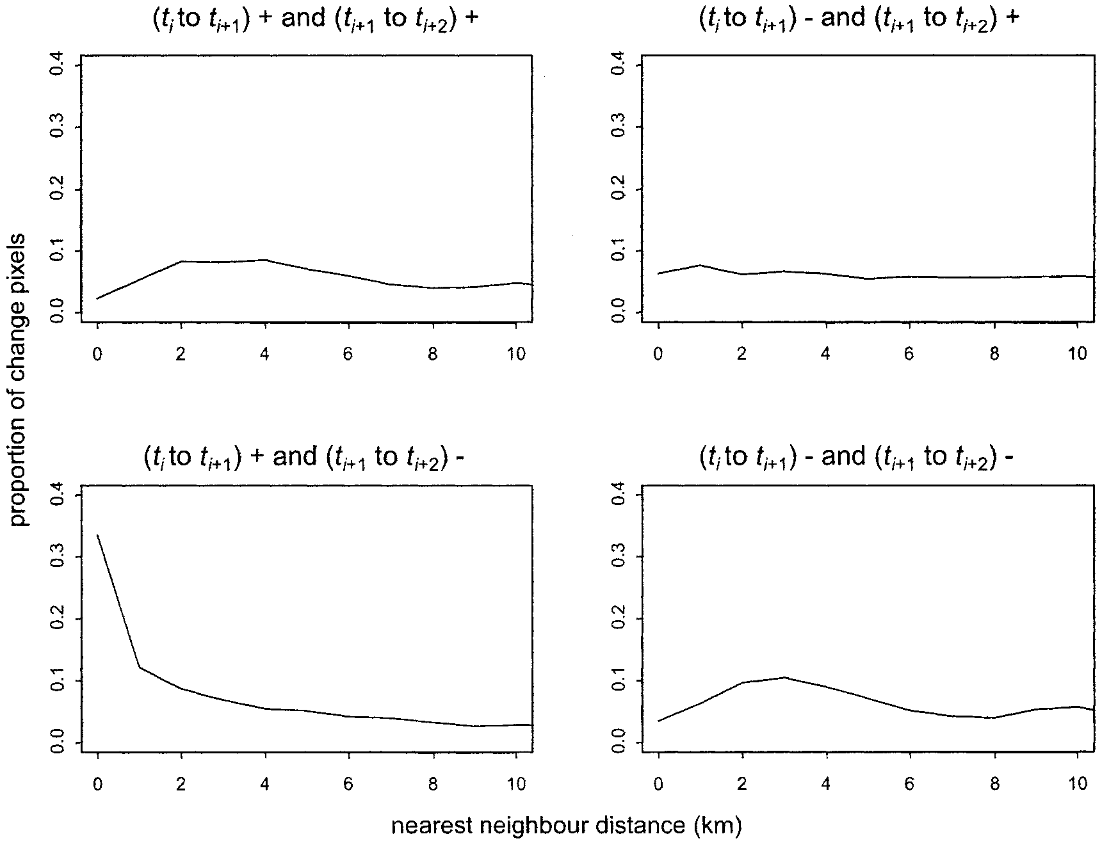


Figure 6.9. Nearest neighbour distance between change pixels in t_i and t_{i+1}, and change pixels in t_{i+1} and t_{i+2}. Values are summarized over all years and subareas.

The directions between nearest neighbouring change pixels, in consecutive time periods, are difficult to interpret (Tables 6.6). Between positive change locations, there is a trend whereby change in t_{i+1} occurs to the northeast of change in t_i. Negative pixels in t_{i+1} are found either south-east or north-west of negative pixels in t_i. Nearest neighbour distances between negative change pixels in one year and positive change pixels in the next, or vice versa, (positive change in t_i and negative change in t_{i+1}) have a tendency to occur in a north-western direction. Northern directional trends are counter to what we might expect, as globally mountain pine beetle infestations in British Columbia appear to be moving in a south-easterly direction (Carroll, pers com). In the absence of meteorological information, it is difficult to understand why these directional trends are occurring. However, it does suggest that local factors are influential.

Table 6.6. Directional trends between change pixels in t_i and t_{i+1}, and change pixels in t_{i+1} and t_{i+2} in the Morice TSA from 1995 to 2002..

	Pos to Pos	Neg to Neg	Neg to Pos	Pos to Neg
NE	34%	21%	26%	26%
SE	18%	31%	18%	20%
SW	19%	17%	24%	19%
NW	30%	31%	32%	35%

6.6.3 Patch-Based Temporal Investigation of Change

Annual variability in the characteristics of positive and negative patches of change demonstrate how the spatial pattern of positive and negative change varies through time (Tables 6.7 and 6.8; Figure 6.10 and Figure 6.11). The number of positive change patches ranges from five to 68; similarly, the number of negative change patches ranges from six to 65. When change is positive, the mean patch size tends to be larger and more variable than the mean size of negative change patches, however the minimum size of patches is similar. Relationships between the number and size of patches are unclear, yet larger mean patch sizes are associated with higher coefficients of variation. Mean patch size does not appear related to the global infestation levels. The median size of negative change patches may be related to population decline, as the largest patches occur from 1996 to 1997 and from 1997 to 1998 when infestation levels decrease generally. As well, the number of negative change patches seems to be highest in years when infestations decline globally (1996 to 1997 and 1997 to 1998) or in years with a large amount of mountain pine beetle activity (2001 to 2002).

Table 6.7. Characteristics of positive change patches in the Morice TSA from 1995 to 2002. Columns represent change periods.

Positive Change	**9596**	**9697**	**9798**	**9899**	**9900**	**0001**	**0102**
mean size (km2)	10.96	4.64	8.69	4.57	4.36	3.72	13.36
median size (km2)	2.92	1.80	2.52	2.00	3.16	3.24	2.56
minimum size (km2)	0.04	0.04	0.20	0.16	0.04	0.04	0.04
maximum size (km2)	242.48	47.56	34.56	20.48	36.44	10.12	352.72
cv of size	2.98	1.75	1.68	1.20	1.52	0.68	3.55
number of patches	68	65	5	31	29	42	59
global infestation	⬆	⬇	⬇	⬆	⬆	⬆	⬆

Table 6.8. Characteristics of negative change patches in the Morice TSA from 1995 to 2002. Columns represent change periods.

Negative Change	**9596**	**9697**	**9798**	**9899**	**9900**	**0001**	**0102**
mean size (km2)	3.06	5.76	7.06	7.22	2.94	1.15	4.92
median size (km2)	0.68	2.34	2.36	1.74	1.76	0.56	1.76
minimum size (km2)	0.16	0.04	0.04	0.75	0.08	0.04	0.04
maximum size (km2)	12.92	59.20	55.84	34.16	11.56	6.40	53.08
cv of size	1.53	1.91	1.56	1.84	1.12	1.27	1.71
number of patches	7	62	51	6	19	34	65
global infestation	⬆	⬇	⬇	⬆	⬆	⬆	⬆

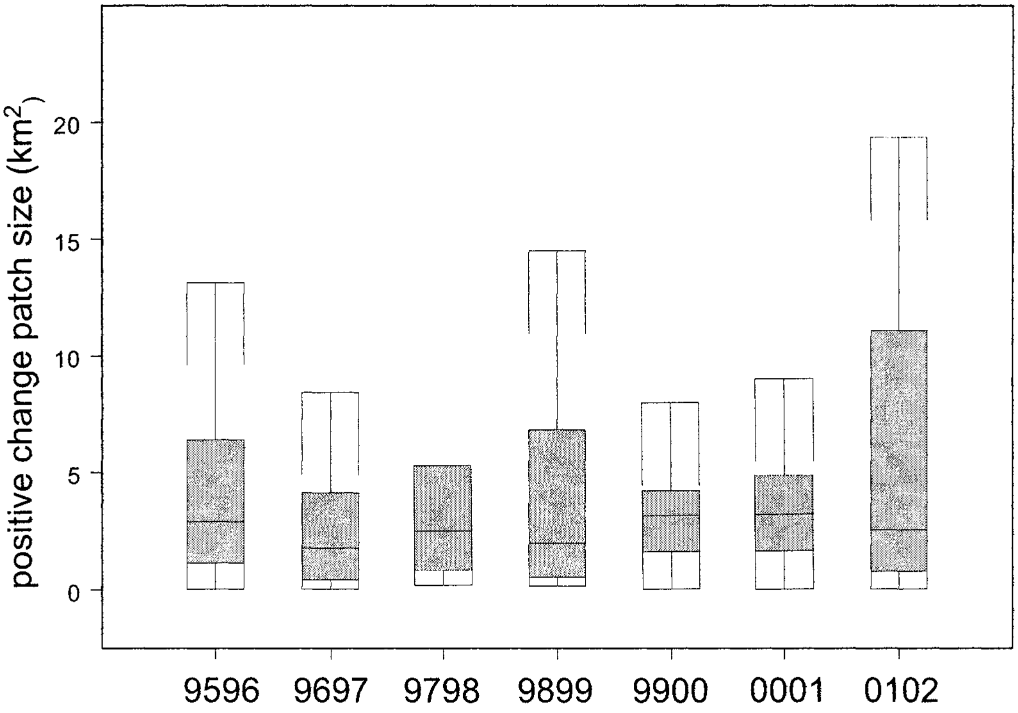


Figure 6.10. Distributions of positive change patch sizes for different change periods in the Moirce TSA.

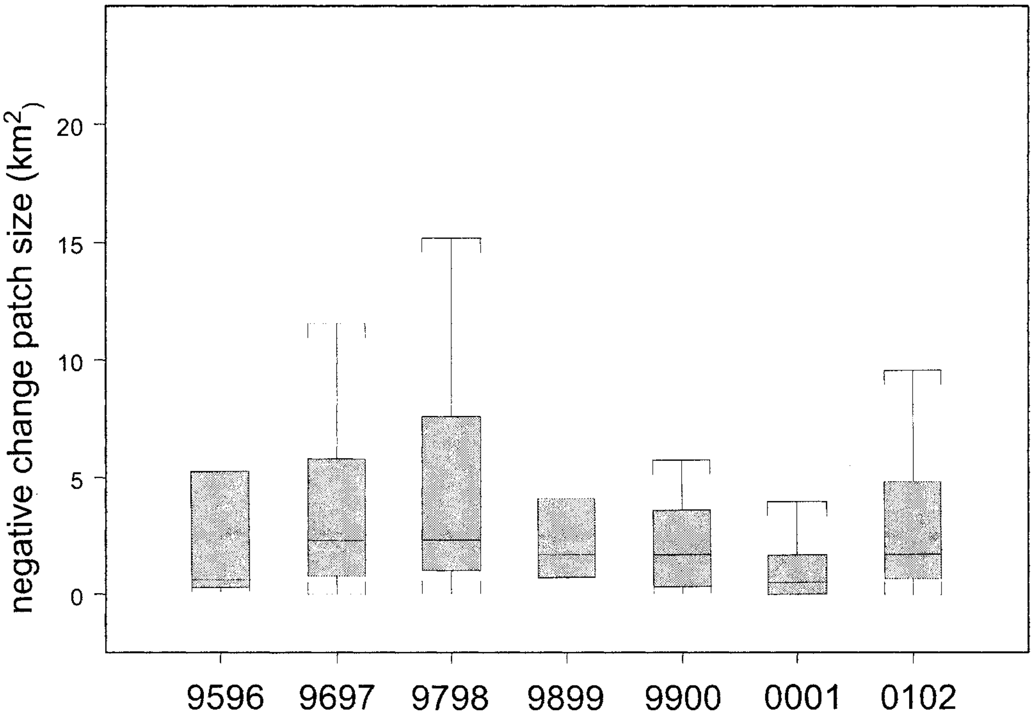


Figure 6.11. Distributions for negative change patch sizes for different change periods in the Moirce TSA.

Differences in the size of positive and negative change patches may indicate that positive change processes operate at a coarser spatial scale than negative change processes. Generally positive change in infestation growth seems driven by broader scale trend than negative change, which seems to result from more local processes. The main processes that lead to a sudden decline in mountain pine beetle populations are either climatic events or management activities. While climatic events played a role in population reduction during 1997 and 1998, most localized population decline is likely related to treatment. Due to practical constraints, treatment efforts tend to occur at a finer spatial scale than the spread of epidemic mountain pine beetle populations, perhaps explaining why negative change patches tend to be smaller.

Change patch characteristics appear associated with the global amount of change in the study area. Generally, as the number of positive or negative change pixels increase globally, the number, size, and variability in patch size also increases (Figure 6.12). These trends are stronger for positive change than for negative change.

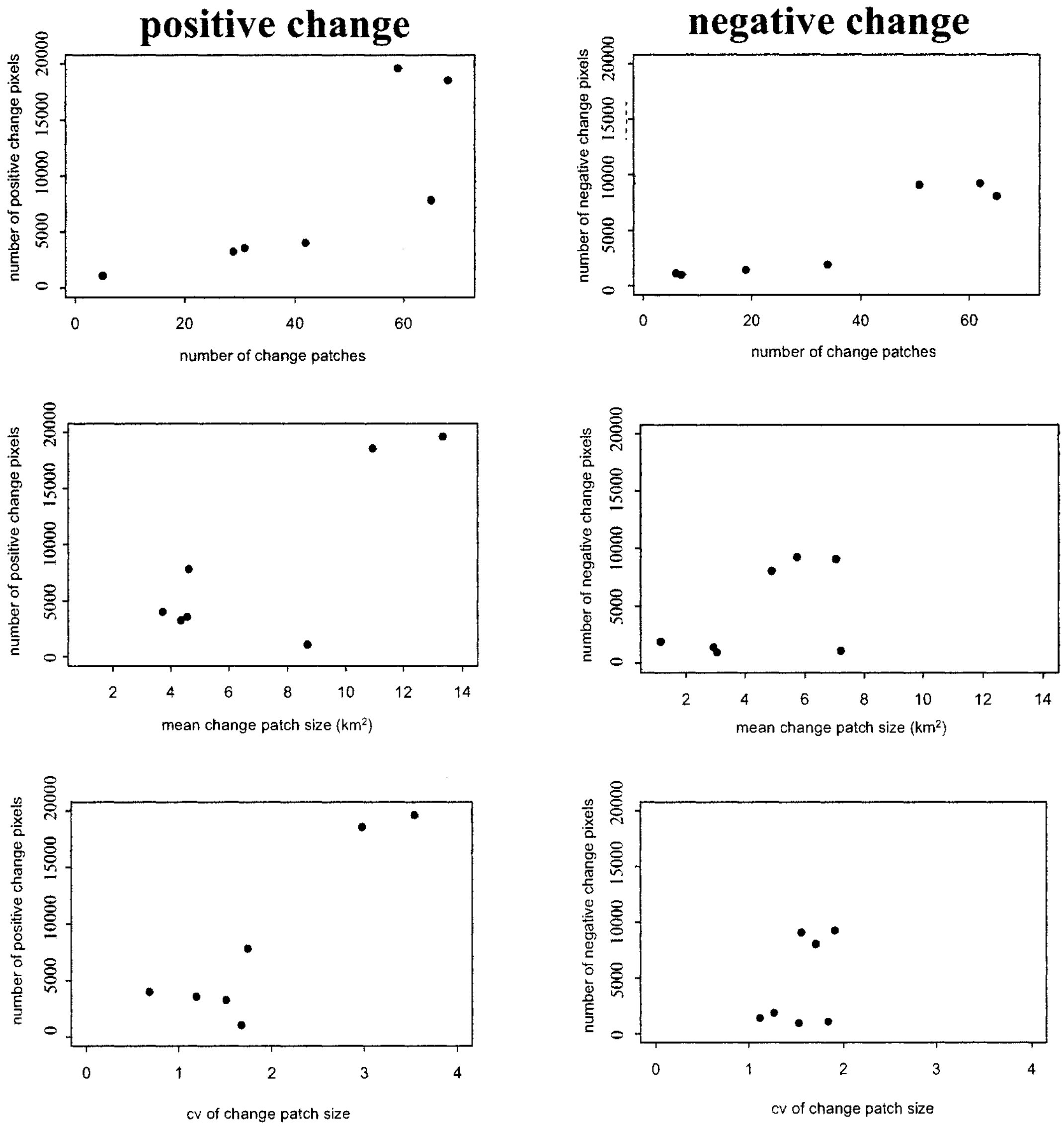


Figure 6.12. Relationships between change patch characteristics and the number of change pixels. Figures are a summary of trends for all years and subareas in Morice TSA. (cv = coefficient of variation)

Positive-Positive Patches

Analysis of the spatial-temporal relationships between positive patches of change revealed that only 6.8 percent of positive patches in t_i intersect with positive patches in t_{i-1}. Positive patches that intersect positive patches in the previous time period are smaller than those that do not intersect positive patches; average sizes are 6.58 and 7.23 square kilometres respectively. Using a *t*-test to assess statistical difference in mean size we must accept the null hypothesis of similarity between sizes regardless of the presence of intersections ($\alpha = 0.05$). Positive patches with positive patch intersections also have less variance than those without positive patch intersection; the coefficient of variation is 1.73 for patches with intersections and 3.68 for patches without intersection. A *t*-test ($\alpha = 0.05$) allowed us to reject the null hypothesis that the average shapes of positive patches with (average $S = 0.58$) and without positive patch intersections in t_{i-1} (average $S = 0.55$) were similar.

Additional analysis focused on those positive patches having no positive patch intersections in the previous year, as this was the most typical scenario for positive patches. In most years, the relative frequency distribution of the minimum distance between positive patches appears uniform; an example is shown for positive change patches from 1998 to 2000 (Figure 6.13). Non-uniform trends in the minimum distance between non-intersecting positive patches are observed from 1995 to 1997 and from 2000 to 2002 (Figure 6.14 and 6.15). These trends may result from the large amounts of positive change that occur in the North from 1995 to 1996 and in the South between 2001 and 2002. Random or uniform patterns are more common if the amount of change in all years is sparse. When the relative frequency distributions of minimum distances between positive change patches are non-uniform, the modal minimum distance is near two kilometres.

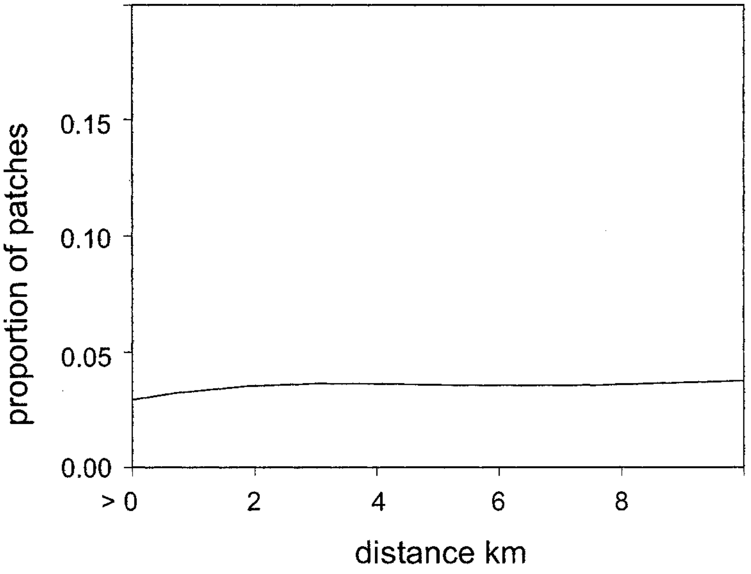


Figure 6.13. The relative frequency distribution of minimum distances between positive change patches in 1998-1999 and 1999-2000 in the Morice TSA. Positive patches from 1999 to 2000 have no intersections with positive patches from 1998 to 1999.

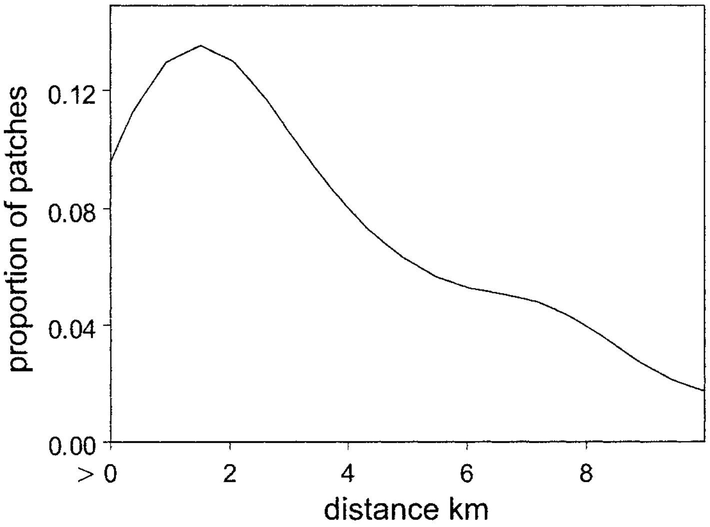


Figure 6.14. The relative frequency distribution of minimum distances between positive change patches in 1995-1996 and 1996-1997 in the Morice TSA. Positive patches from 1996 to 1997 have no intersections with positive patches from 1995 to 1996.

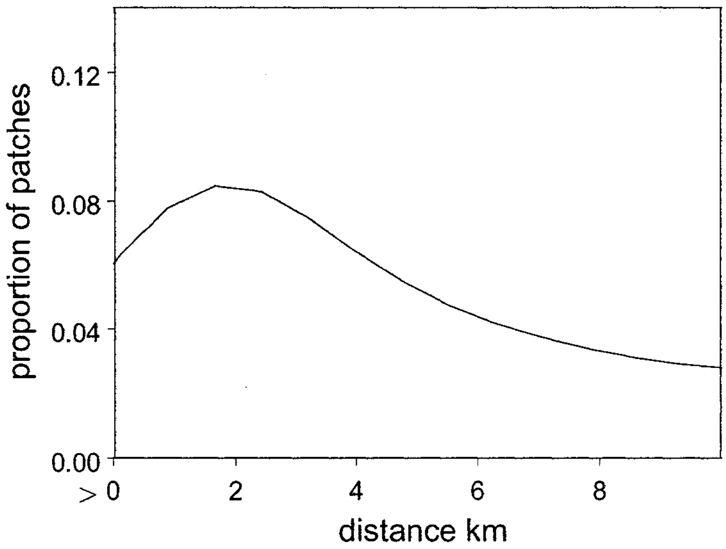


Figure 6.15. The relative frequency distribution of minimum distances between positive change patches in 2000-2001 and 2001-2002 in the Morice TSA. Positive patches from 2001 to 2002 have no intersections with positive patches from 2000 to 2001.

When positive patches in t_i do not intersect with positive patches in t_{i-1} and distance trends are non-uniform, directional trends associated with the minimum distance between positive patches are uniform, (Table 6.9). The most common direction from 1995 to 1997 was southerly. From 2000 to 2002 north-easterly directions dominated, perhaps indicating the influence of the large mountain pine beetle population to the south-east.

Table 6.9. Examples of directional trends in the minimum distances between positive change patches having no intersections with positive change patches in the previous year in the Morice TSA. Columns represent change periods.

	9596 to 9697	**0001 to 0102**
NE	17.65%	48.48%
SE	29.41%	12.12%
SW	33.33%	24.24%
NW	19.61%	15.15%

Negative-Negative Patches

Spatial-temporal investigations demonstrate that only in 5.1 percent of cases do negative patches in t_i intersect with negative patches in t_{i-1}. Negative patches that intersect negative patches in the previous year are larger than those that do not, with respective mean patch sizes equalling 22.37 and 4.26 square kilometres. A *t*-test enabled us to reject the null hypothesis that patches with and without intersections are similar in size ($\alpha = 0.05$). The coefficient of variation for patch sizes is 0.67 when negative patches intersect negative patches in the previous year and 5.86 for negative patches with no t_{i-1} negative patch intersections. Also, negative patches having no negative patch intersections are more circular (average $S = 0.56$) than negative patches with negative patch intersections (average $S = 0.36$), and a *t*-test allows us to reject the null hypothesis that average shape indices are similar ($\alpha = 0.05$).

As with positive patches, the relative frequency distribution of minimum distances between negative patches, when negative patches do not have intersections with negative patches in the previous year, tends to be approximately uniform. This may be related to the fact that few years have large amounts of negative change. A typical relative frequency distribution of minimum distances between negative patches, when t_i negative patches have no intersections with negative patches in t_{i-1}, is represented using data from 1995 to 1997 (Figure 6.16). Exceptions to the uniform trend occur from 1996 to 1998 and from 2000 to 2002 when there is at least one year having a substantial amount of negative change (Figure 6.17 and Figure 6.18). In these cases an abundance of negative change is found from 1996 to 1997, 1997 to 1998, and 2001 to 2002. From

1996 to 1998, the modal minimum distance between patches is two kilometres and from 2000 to 2002 the modal minimum distance between patches is 3.5 kilometres. Directional trends are uniform except from 1996 to 1998, where south-westerly directions are most common between negative patches (Table 6.10).

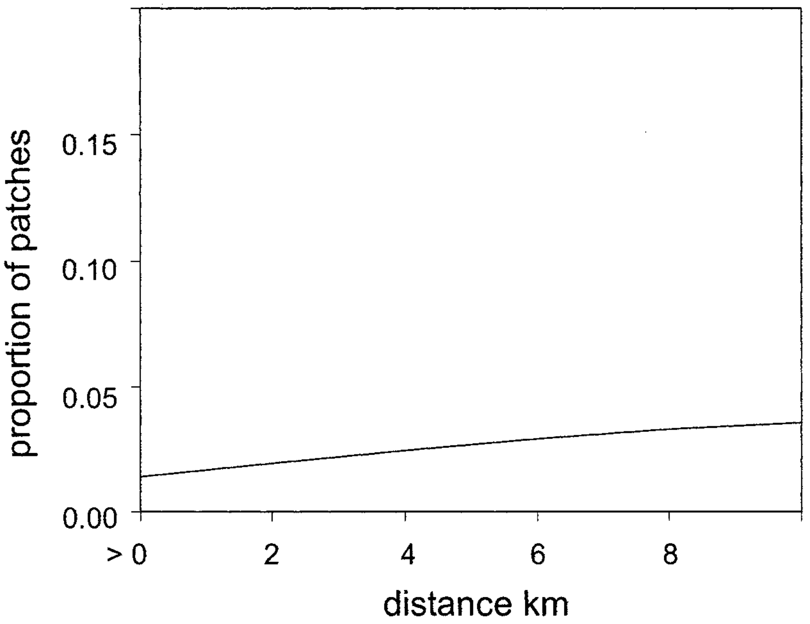


Figure 6.16. The relative frequency distribution of minimum distances between negative change patches in 1995-1996 and 1996-1997 in the Morice TSA. Negative patches from 1996 to 1997 have no intersections with negative patches from 1995 to 1996.

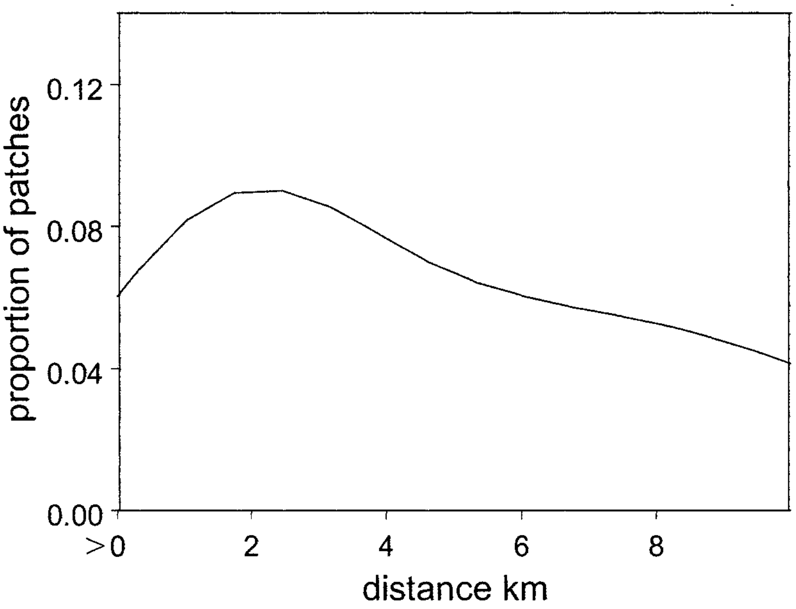


Figure 6.17. The relative frequency distribution of minimum distances between negative change patches in 1996-1997 and 1997-1998 in the Morice TSA. Negative patches from 1997 to 1998 have no intersections with negative patches from 1996 to 1997.

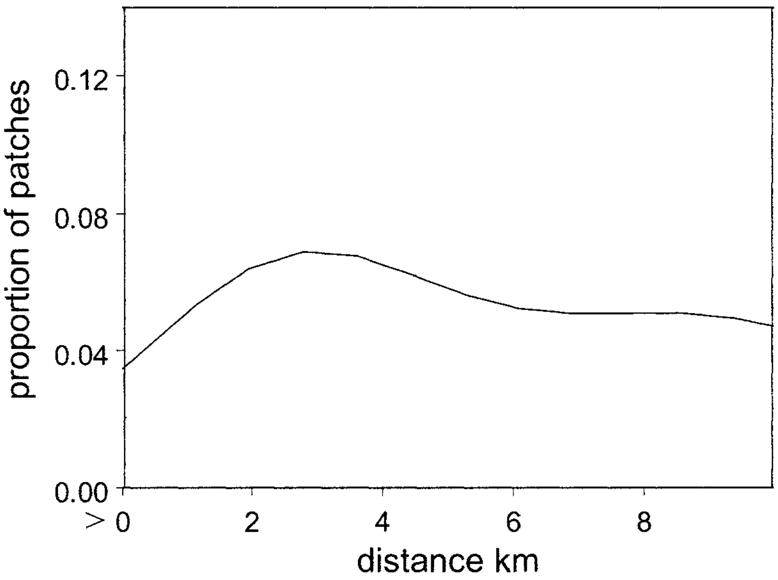


Figure 6.18. The relative frequency distribution of minimum distances between negative change patches in 2000-2001 and 2001-2002 in the Morice TSA. Negative patches from 2001 to 2002 have no intersections with negative patches from 2000 to 2001.

Table 6.10. Directional trends in the minimum distances between negative change patches having no intersections with negative change patches in the previous year in the Morice TSA. Columns represent change periods.

	9697 to 9798
NE	9.38%
SE	15.63%
SW	46.88%
NW	28.13%

Negative-Positive Patches

Only 8.7 percent of positive patches in t_i had intersections with negative patches in t_{i-1}. Although on average positive patches in t_i with no negative patch intersections in t_{i-1} were larger than those that did not intersect negative patches in t_{i-1} (7.41 versus 5.81 square kilometres). A null hypothesis of similarity in patch sizes could not be rejected using a *t*-test ($\alpha = 0.05$). Positive patches with no negative patch intersections had more size variability (coefficient of variation = 3.69) than positive patches with negative patch intersections (coefficient of variation = 0.85). The average shape index for positive patches was 0.55 regardless of intersections with negative patches in the previous year. In all years, when positive patches have no intersections with negative patches in the previous year, the relative frequency distributions of the minimum distance and direction between negative patches in t_{i-1} and positive patches in t_i are approximately uniform. An example of a uniform distance distribution is shown for 1999 to 2001 (Figure 6.19).

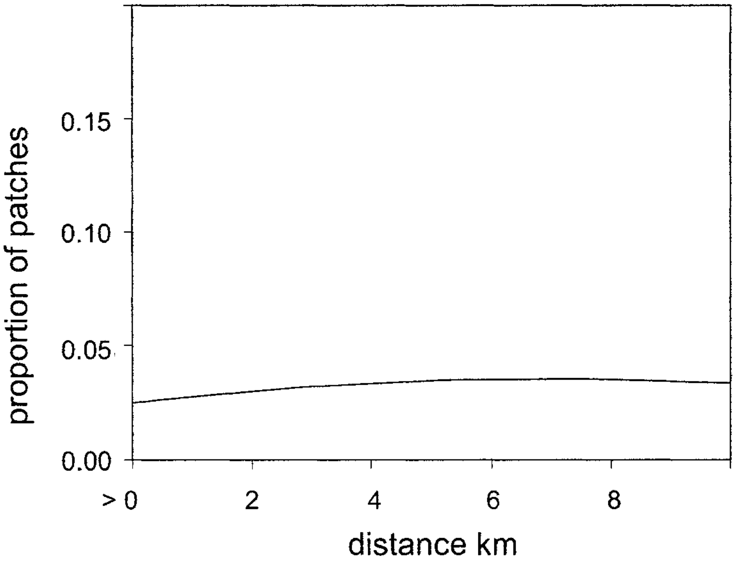


Figure 6.19. The relative frequency distribution of minimum distances between negative change patches in 1999-2000 and positive change patches in 2000-2001 in the Morice TSA. Positive change patches in 2000-2001 have no intersections with negative patches from 1999-2000.

Although it is uncommon that positive patches in t_i intersect negative patches in t_{i-1}, it is perhaps surprising that this scenario ever occurs. There are two possible scenarios that may explain why a location having a significant decrease in infestation magnitude, may have an increase in the future. The first is related to climate. If the decline in mountain pine beetle activity is the result of local climatic factors, the forest at that location is still susceptible. Therefore, under favourable climatic conditions the population may increase again. Secondly, if the decrease in mountain pine beetle population levels is related to a treatment that does not remove all the trees, neighbouring populations may infest the remaining trees in future years.

Positive-Negative Patches

The most common type of intersection occurs between positive patches in t_{i-1} and negative patches in t_i. Thirty-seven percent of negative patches in t_i intersect with positive patches in t_{i-1}. The average size of negative patches that have no intersections with positive patches in t_{i-1} is larger than the average size of patches that do intersect positive patches in t_{i-1} (3.08 and 8.75 square kilometres, respectively). Comparison of means using a *t*-test resulted in a rejection of the null hypothesis that patches with and without positive patch intersections are similar in size ($\alpha = 0.05$). The coefficient of variation for patch size did not vary substantially and was 1.60 for negative patches with positive patch intersections and 1.48 for those without. The average shape index is 0.51 for negative patches with no positive patch intersections and 0.58 for negative patches with positive patch intersections. A *t*-test leads us to reject the null hypothesis that the average shape indices were similar ($\alpha = 0.05$).

As 37 percent of negative patches in t_i intersect with positive patches in t_{i-1}, the percentage of overlap was investigated. The relative frequency distribution of percentage areal overlap is shown in Figure 6.20, and the modal areal overlap is 100 percent. This may indicate that, in most cases, patches of significant negative change are the result of harvesting or other treatment methods that affect all trees in an infestation cluster.

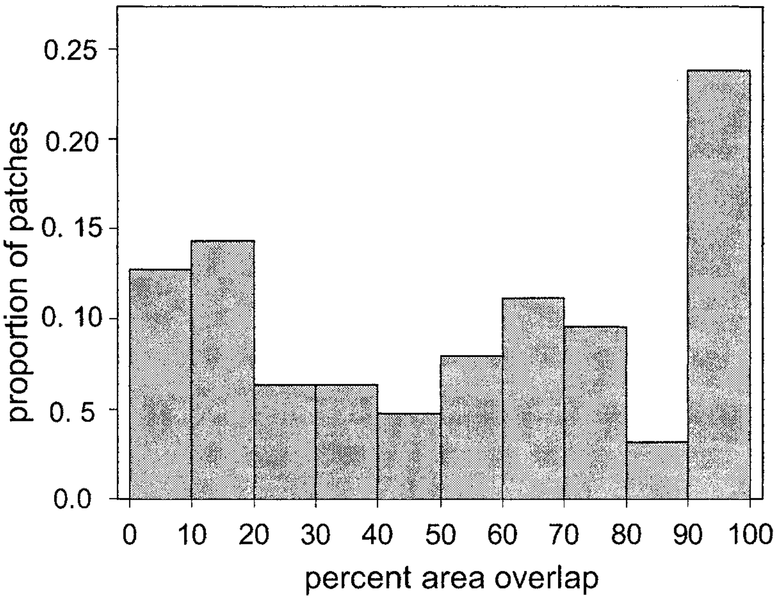


Figure 6.20. Percent overlap for positive patches in t_{i-1} that intersect negative patches in t_i in the Morice TSA from 1995 to 2002.

For negative patches in t_i having no intersections with positive patches in t_{i-1}, the relative frequency distribution of minimum distances to positive patches in t_{i-1} was typically uniform. For instance, the relative frequency distribution of minimum distances between positive patches from 1999 to 2000 and negative patches from 2000 to 2001 can be seen in Figure 6.21. An exception occurs between positive change patches found from 1996 to 1997 and negative change located from 1997 to 1998 (Figure 6.22). In these years, four kilometres is the modal minimum distance from positive to negative patches and the modal directional between patches is north-east (Table 6.11).

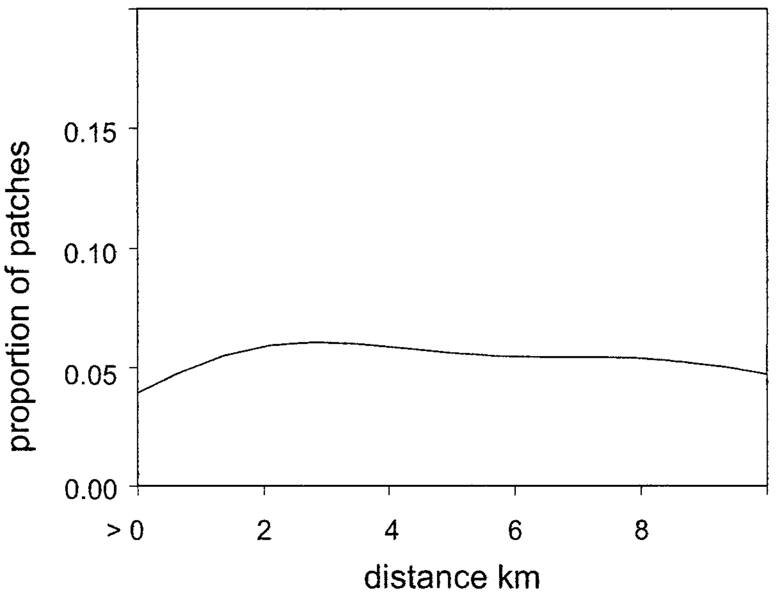


Figure 6.21. The relative frequency distribution of minimum distances between positive patches in 1999-2000 and negative change patches in 2000-2001 in the Morice TSA. Negative change patches in 2000-2001 have no intersections with positive patches from 1999-2000.

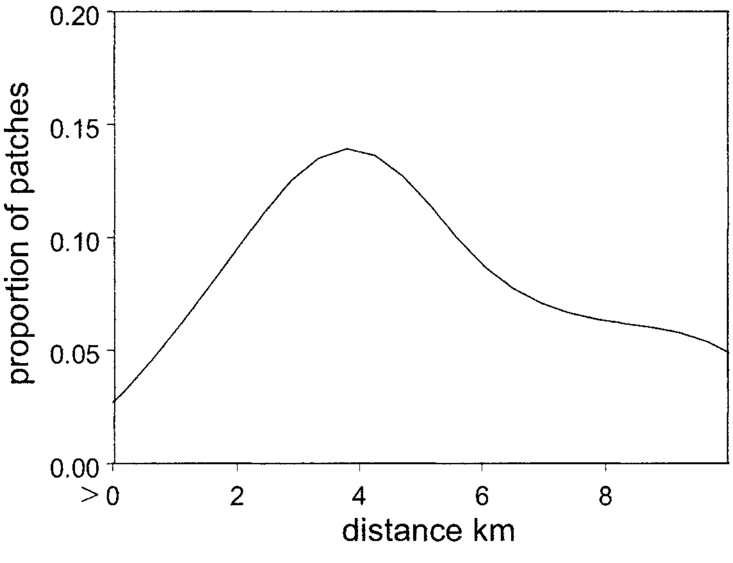


Figure 6.22. The relative frequency distribution of minimum distances between positive patches in 1996-1997and negative change patches in 1997-1998 in the Morice TSA. Negative change patches in 1997-1998 have no intersections with positive patches from 1996-1997

Table 6.11. Directional trends in the minimum distances between negative change patches having no intersections with positive change patches in the previous year in the Morice TSA.

	9697 to 9798
NE	28.13%
SE	18.75%
SW	21.88%
NW	31.25%

Most change patches in t_i are unlikely to intersect patches with the same type of change in the previous year. When a considerable area undergoes a particular type of change, either positive or negative, distance relationships associated with that type of change (either positive-positive or negative-negative) are non-random and the modal minimum distance between change patches is near two kilometres. When positive or negative change is limited, the minimum distance relationships between change patches of a similar type in t_{i-1} and t_i are random.

Patches having positive change in t_i rarely intersect with patches of negative change in t_{i-1}. Relationships in the minimum distance between negative change in t_{i-1} and positive change in t_i appear random. This trend is perhaps expected as locations with significant negative change likely had high levels of infestation in the past and are less apt to have large infestations in the following year.

The most common intersection occurs between negative change t_i and positive change in t_{i-1}. When negative patches intersect patches of positive change in the previous year, the areal overlap is often 100 percent. Negative patches that intersect positive patches in the previous year are on average less than half the size of negative patches having no intersection with positive patches in the previous year. Such a trend may indicate that negative patches that intersect positive patches in the previous time period result from treatment. The average size of negative patches (three square kilometres) could indicate the spatial scale of treatment. For negative patches having no intersections, minimum distances from positive change patches in t_{i-1} typically exhibit a random relationship.

6.6.4 Change and Age

Relative frequency distributions of forest age were generated for pixels having one and two years of positive or negative change (Figure 6.23). Typically, locations with two significant changes, regardless of whether the change is positive or negative, are more often associated with older forests than locations with less change. In the North subarea, change is most frequently associated with forests that are 180 years old; in the Middle subarea, change is most associated with trees 120 to 160 years; and in the South subarea, trees 180 years or older are most often associated with change. Different trends in the Middle subarea likely reflect the larger proportion of trees that are 120 to 140 years old.

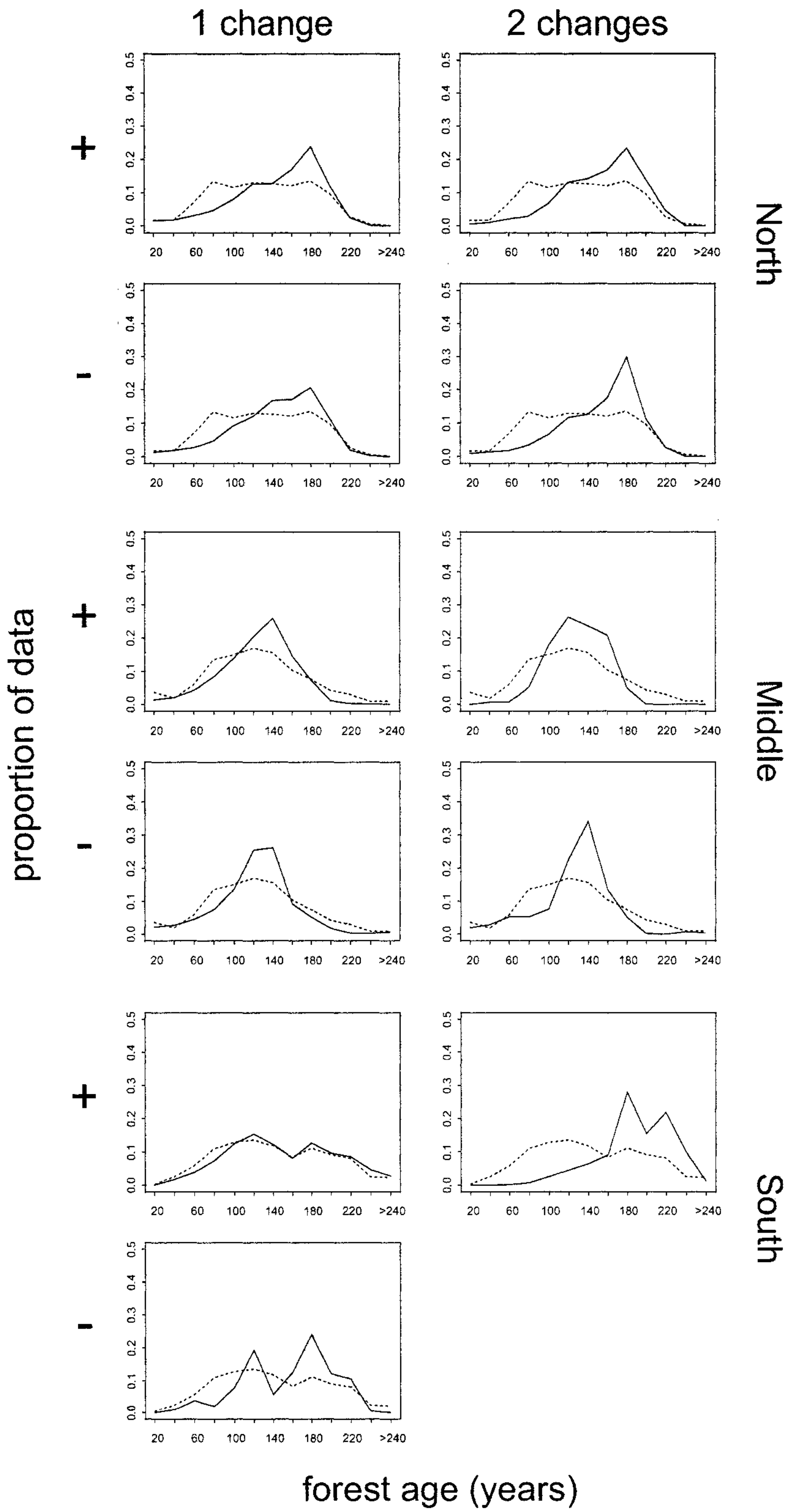


Figure 6.23. Partitioned by Morice TSA subareas, relative frequency distributions of forest age associated with change pixels (solid line) and all pine pixels (dotted line). Change is categorized as occurring once or twice between 1995 and 2002.

6.6.5 Change and Pine

The percentage of pine associated with change pixels does not appear to vary over time (Figure 6.24). However, locations with two changes have relative frequency distributions more different from the distribution of all pine than locations with only one significant change. Generally, there is a preference for changes, both positive and negative, to occur in cells with 30 percent pine in the North subareas, between 70 and 90 percent pine in the Middle subarea, and between 30 and 70 percent pine in the South subarea. It is unclear why the Middle subarea had change in stands with higher percentages of pine than in other areas. One possible explanation is that although the North and Middle subareas had similar levels of infestation, the Middle had relatively little management. Although further investigation is required, this may indicate that management in the North successfully reduced the impact of the mountain pine beetle in high percentage pine areas.

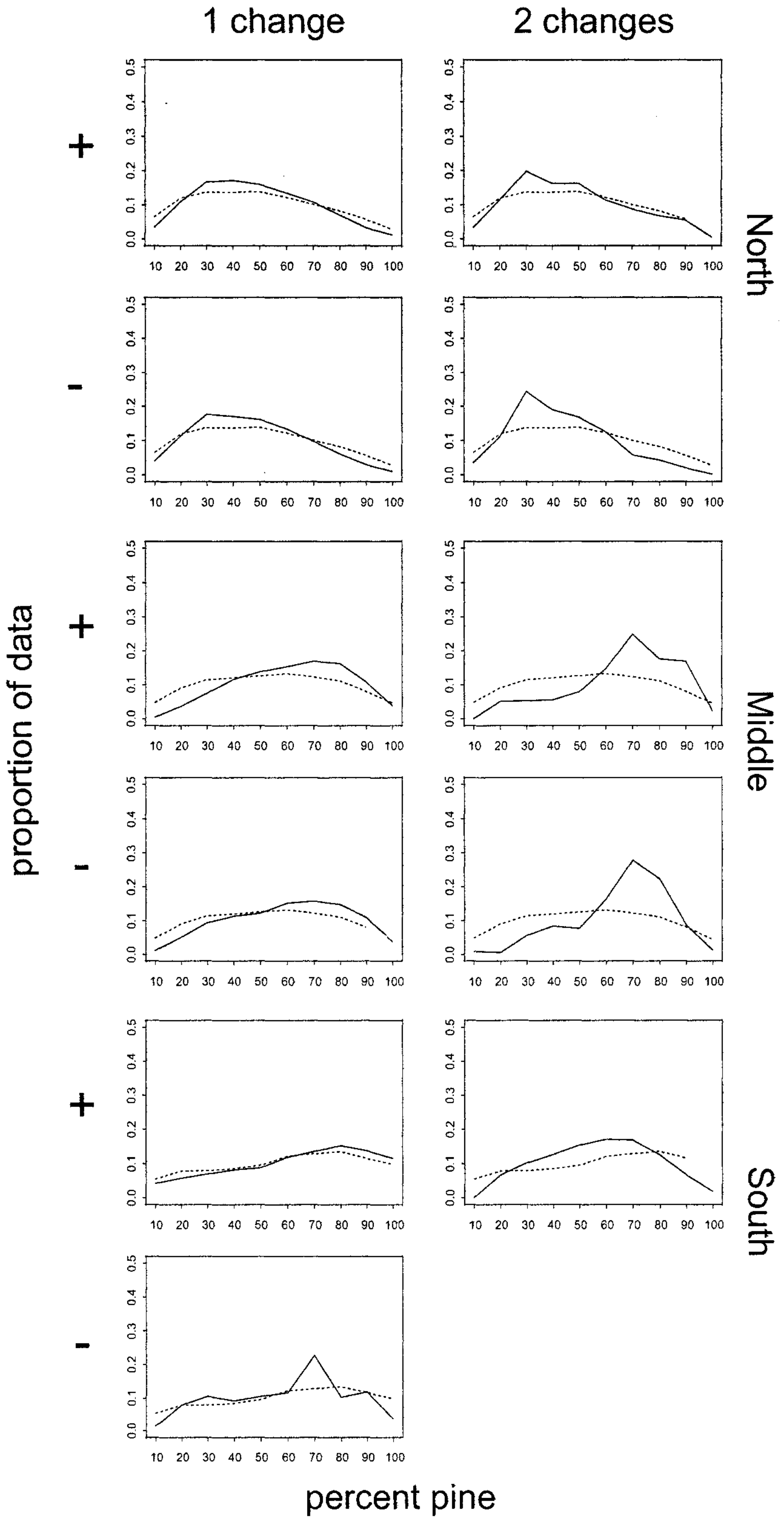


Figure 6.24. Partitioned by Morice TSA subareas, relative frequency distributions of percent pine associated with change pixels (solid line) and all pine pixels (dotted line). Change is categorized as occurring once or twice between 1995 and 2002.

6.6.6 Change and Elevation

Relative frequency distributions of elevation generated from pixels with two significant changes differ more from relative frequency distributions of elevations associated with all pine pixels than cells associated with only one change (Figure 6.25). In the North, increased change is associated with elevations of 700 metres; the relationship with negative change is similar, yet weaker. A stronger trend is apparent in the Middle subarea, with elevations of 800 metres being most commonly associated with change pixels. In the South, elevations of 900 metres are most associated with positive change cells, and elevations of 800 and 900 metres are associated with negative change pixels. As latitude increases, significant change is spatially constrained to lower elevations. This trend may indicate the impact of climate on change.

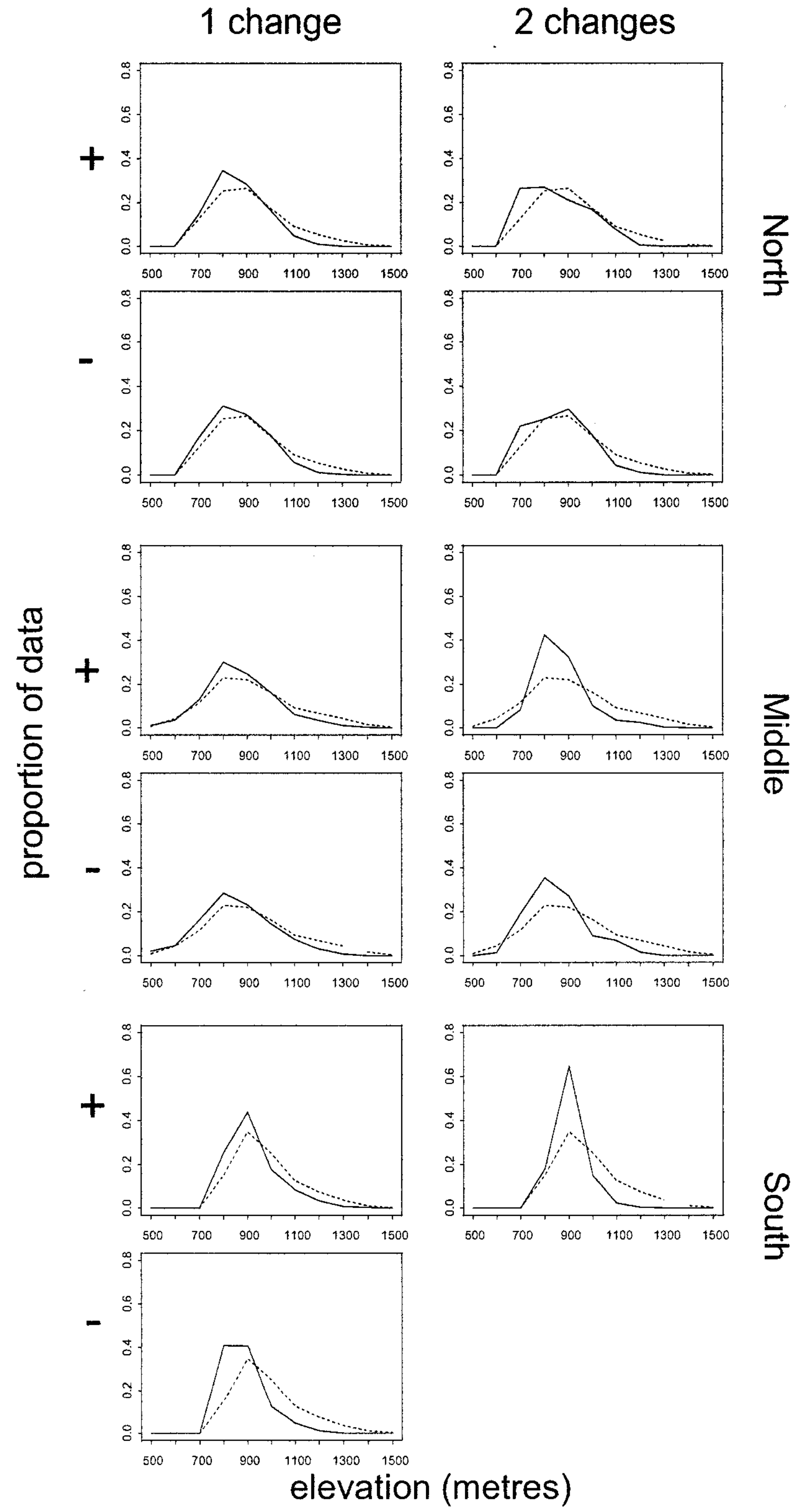


Figure 6.25. Partitioned by the Morice TSA subareas, relative frequency distributions of elevation associated with change pixels (solid line) and all pine pixels (dotted line). Change is categorized as occurring once or twice between 1995 and 2002.

6.6.7 Change and Aspect

Relative frequency distributions of aspects associated with change pixels are shown in Figure 6.26. In the North subarea, the relationship between change and aspect is unclear. In the Middle subarea western aspects were associated with locations that have two positive changes, but there does not appear to be a strong relationship with negative change. In the South subareas, southern slopes were most associated with change. When change is positive, the preference of southern slopes was strongest when two changes occur. Trends in the south are likely related to infestation initialization, which has been shown to occur preferentially on southern slopes (Safranyik *et al.*, 1974).

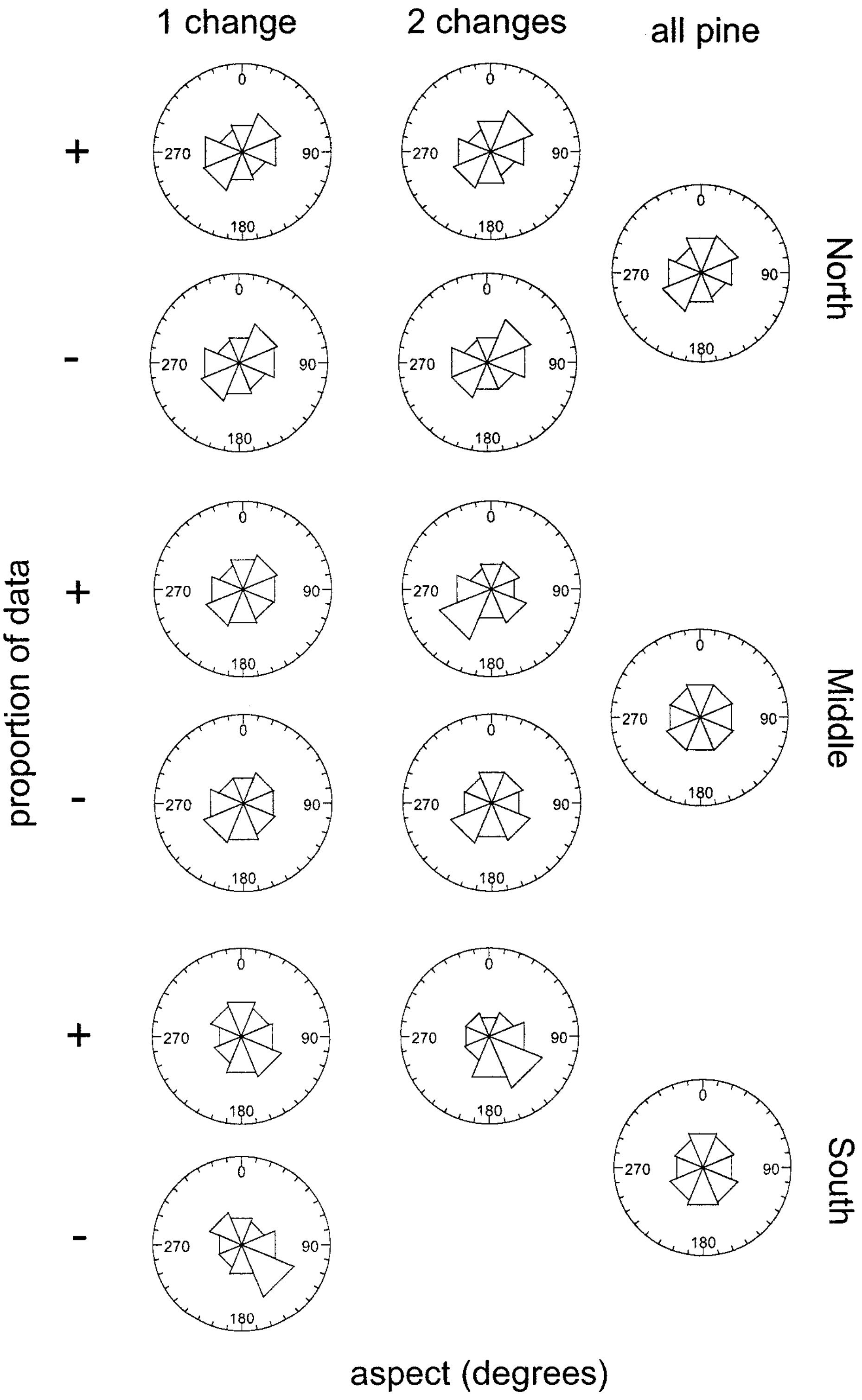


Figure 6.26. Partitioned by Morice TSA subareas, circular plots showing aspects associated with change pixels and all pine pixels. Change is categorized as occurring once or twice between 1995 and 2002.

6.7 SUMMARY

All trends associated with spatial-temporal change are linked to the definition of meaningful change in a mountain pine beetle population. We have defined meaningful change using the differences in kernel density estimated surfaces representing the magnitude of mountain pine beetle infestations. This approach provides a mechanism for detecting significant positive and negative change, as well as no significant change, which is also sensitive to spatial heterogeneity. Visualizing locations of significant change provides confidence that the change definition is appropriate, as the amount and locations of change reflect general observations; the North and Middle subareas were infested first and the South subarea impacted later.

We found that significant change of either a positive or negative type is never common with less than six percent of the landscape, and often much less, being impacted at any time. Neither type of change is consistently more common and there is considerable variation in the levels of both over time, reflecting global trends in the infestation. Similarly, while there are no obvious trends in the relative magnitudes of the numbers and sizes of positive and negative patches of change, both of these characteristics are related to changes in global levels of infestation.

Analysis of spatial-temporal relationships of change demonstrates that as the global level of infestation increases, more patches of positive and negative change are observed rather than existing patches growing larger. This interpretation is also consistent with the finding that, whether positive or negative, change patches rarely intersect with patches of the same change type in the previous change period. Thus, it appears that significant change does not persist for long at any given location, nor is continuous spatial diffusion of a given type of change over time the norm.

Our results suggest that it would be difficult to predict where new change patches will occur since the distances between change patches that do not intersect with those of the same kind in the previous time period only exhibit non-random trends when at least one time period has an abundance of the change type being investigated. When there is considerable change of a particular type (either positive or negative), the modal minimum distance between change patches of the same type is near two kilometres suggesting that change moves to nearby locations.

Positive change patches in t_i rarely intersect negative change patches in t_{i-1} and distance relationships between non-intersecting patches of these types are random. This suggests that, spatially, large decreases in mountain pine beetle populations are rarely followed by a sudden increase in levels. This finding is expected, as locations with significant negative change likely had high levels of infestation in the past and are less likely to have large infestations in the following year.

The strongest spatial coincidence occurs for negative change patches in t_i and positive changes patches in t_{i-1}. Thirty-seven percent of negative change patches overlap with positive change patches in the previous time period with overlaps of 100 percent being common. One possible explanation for the complete overlap is that the decrease in infestation magnitude is the result of some form of treatment. If this is correct, the mean negative change patch size of three squared kilometres, which is less than half that of patches without intersections, may indicate the spatial scale for effective treatment.

Locations of change are difficult to interpret in terms of mountain pine beetle biology, as few change studies have been carried out at any spatial scale. Both types of change occur most frequently in locations where the forest is mature. Positive change occurs first and most commonly in older, and likely more susceptible, stands. Negative change, in contrast, occurs initially in younger stands and through time becomes more associated with older stands. Although trends differ between subareas, change occurs most frequently at locations with 30 and 80 percent pine. Elevations associated with significant change in infestation magnitude typically range from 700 metres to 900 metres, and decrease with increasing elevation. Finally, it appears that western or southern aspects are most associated with locations of change, particularly in the early stages of infestation.

7 RELATING HOT SPOTS AND CHANGE IN MOUNTAIN PINE BEETLE INFESTIONS

7.1 INTRODUCTION

Thus far, the spatial and spatial-temporal patterns of landscape level pine mortality during a mountain pine beetle epidemic have been investigated using hot spots and change. Identifying hot spots allows exploration of the most intensely infested locations on the landscape, whereas change detection provides a mechanism for studying areas where mountain pine beetle infestations increase or decrease with statistical significance.

The goal of this chapter is to investigate the correspondence between hot spots and change. There are several benefits to using multiple approaches for spatial pattern analysis. For instance, each method for characterizing spatial pattern summarizes information differently, thus providing the analyst with unique perspectives to aid interpretation. As well, particularly when working with large area data sets, results may be influenced by data uncertainty and the exploratory nature of many spatial analysis methods. When similar trends are obtained from different spatial analysis approaches, users may have more confidence in results.

7.2 INVESTIGATING SPATIAL-TEMPORAL RELATIONSHIPS

In this chapter, relationships between change and hot spot pixels and patches were explored in a number of ways. All comparisons are made between change from t_i and t_{i+1} and hot spots in t_{i+1}. In the first analysis, spatial-temporal relationships were visualized by mapping change patches and hot spot patches. Secondly, a pixel-based analysis was used to determine the rate at which change and hot spot pixels overlap. A third, patch-based analysis, explored the rate of intersection between change and hot spot patches. For patches with intersections, the percentage of areal overlap was characterized. Finally, for patches without intersections, the minimum distances and directions between patches were investigated.

7.3 RESULTS AND DISCUSSION

7.3.1 Visualizing Spatial-Temporal Relationships

Visualizations of hot spot patch and change patch intersections are seen in Figures 7.1 to 7.7. Hot spots correspond more often with positive change than with negative change. This is not surprising as the definitions of both hot spots and positive change focus on abundance in mountain pine beetle infestations. By definition, hot spots always cover 10 percent of the infested area, whereas the amount of change varies annually. Consequently, in years with little change, for instance positive change from 1997 to 1998, the maximum possible correspondence between the two types of pattern is limited.

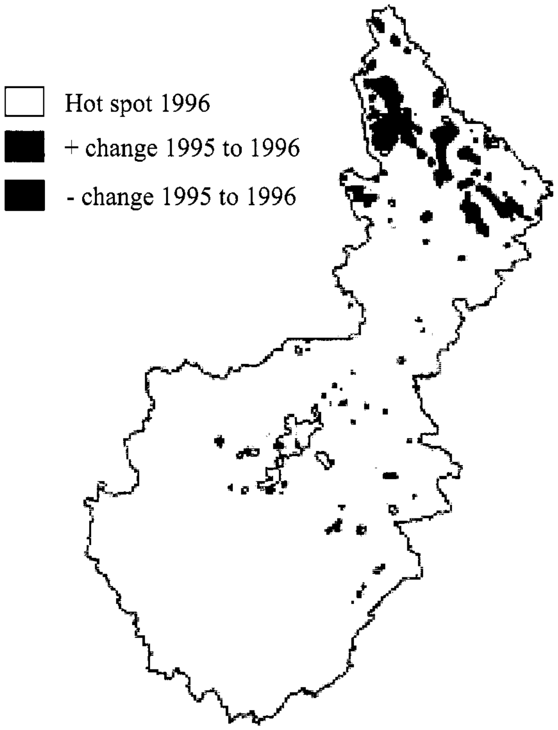


Figure 7.1. 1996 hot spot patches and 1995 to 1996 change patches in the Morice TSA.

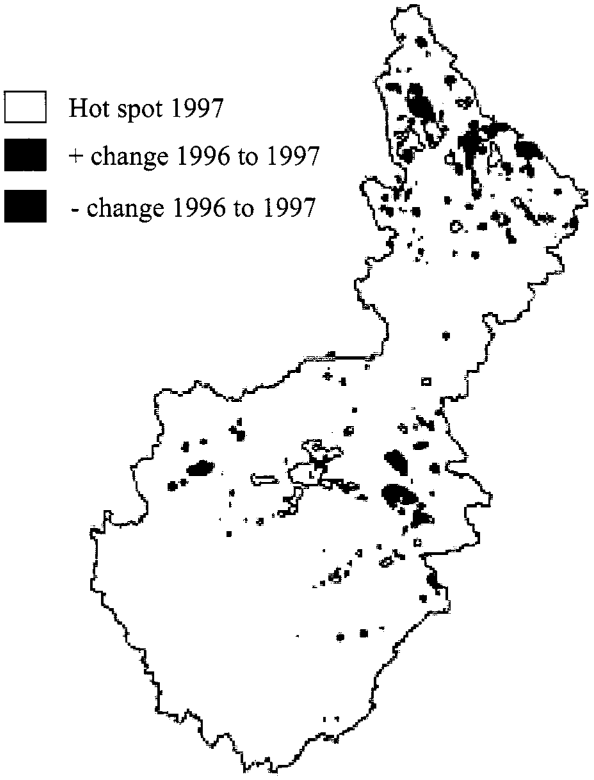


Figure 7.2. 1997 hot spot patches and 1996 to 1997 change patches in the Morice TSA.

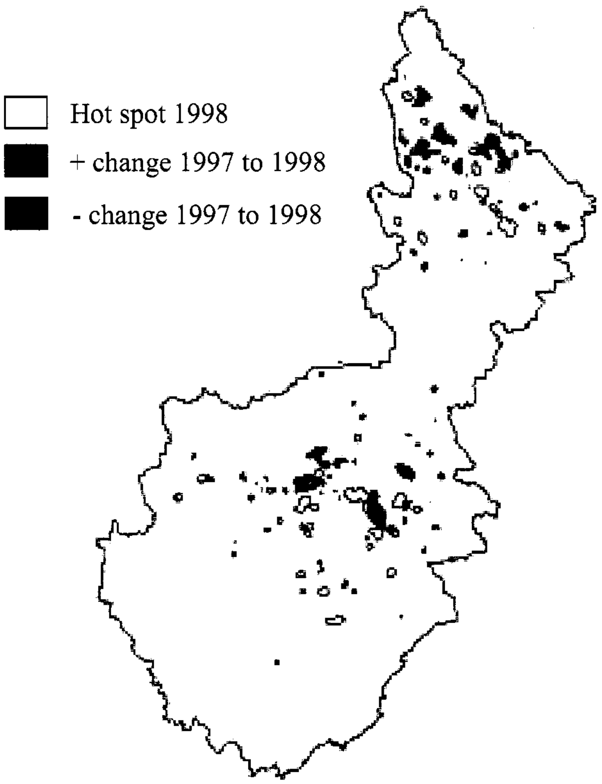


Figure 7.3. 1998 hot spot patches and 1997 to 1998 change patches in the Morice TSA.

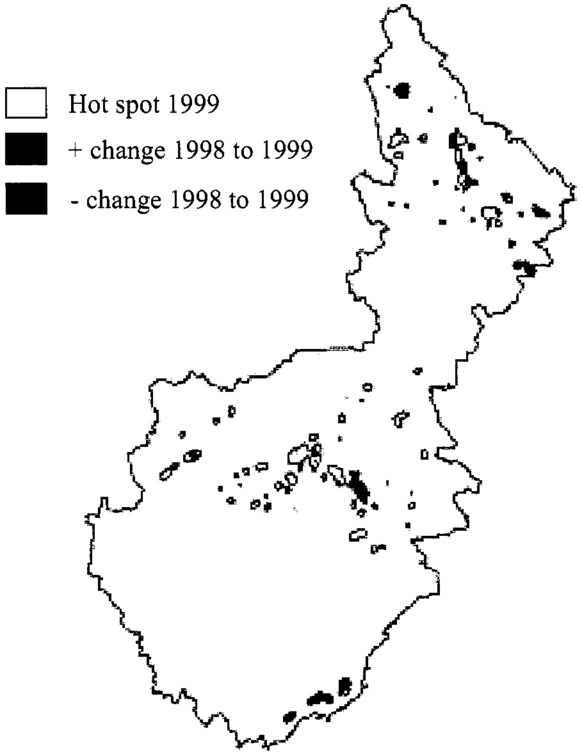


Figure 7.4. 1999 hot spot patches and 1998 to 1999 change patches in the Morice TSA.

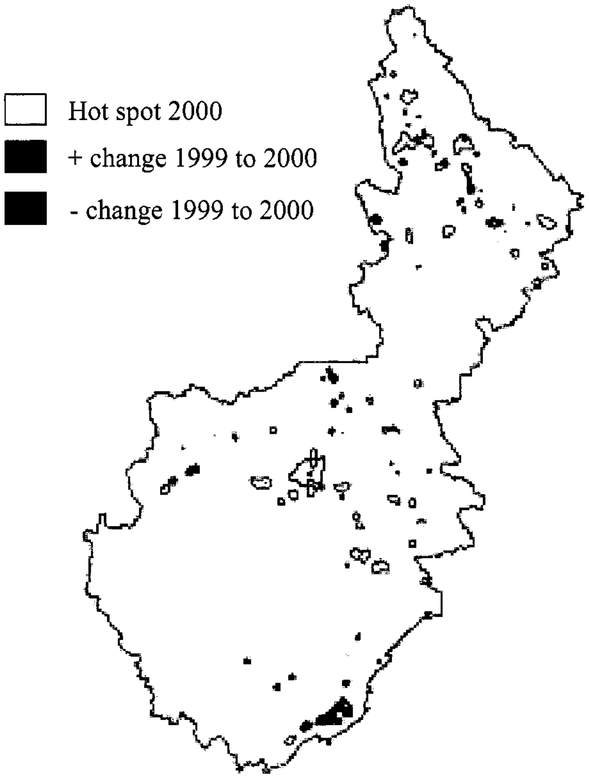


Figure 7.5. 2000 hot spot patches and 1999 to 2000 change patches in the Morice TSA.

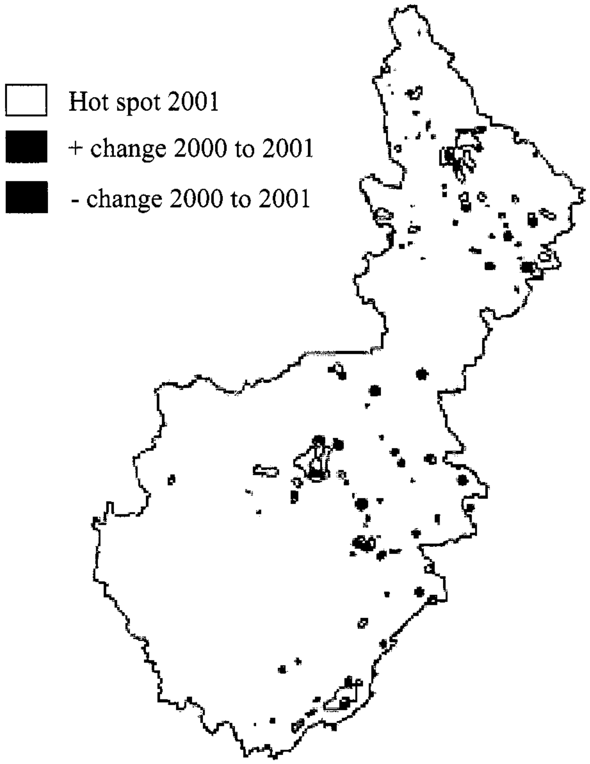


Figure 7.6. 2001 hot spot patches and 2000 to 2001 change patches in the Morice TSA.

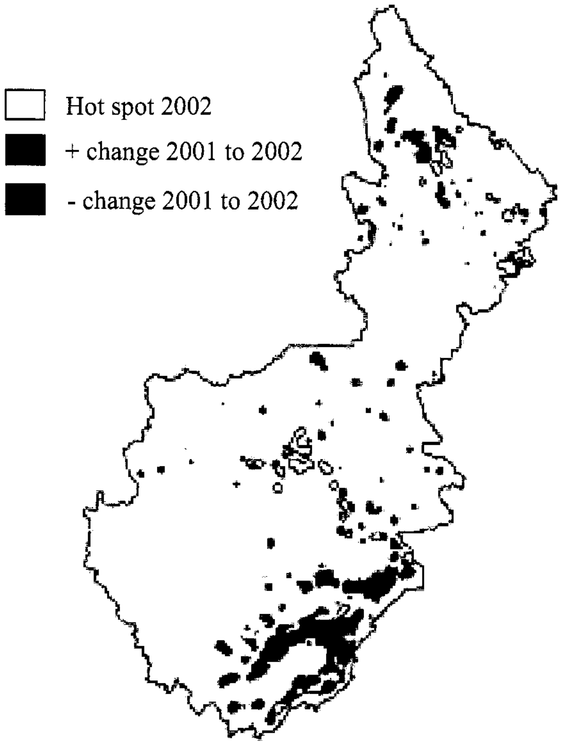


Figure 7.7. 2002 hot spot patches and 2001 to 2002 change patches in the Morice TSA.

7.3.2 Pixel-Based Investigations

A pixel-based analysis of change and hot spots was used to investigate the rate of correspondence between change pixels and hot spots. On an annual basis, the number of positive change pixels, hot spot pixels, and pixels that are both hot and have positive change are listed in Table 7.1. Annual percentages of hot spot pixels that overlap with positive change, and vice versa, are also provided.

In the two change periods with the largest numbers of positive change pixels (2001 to 2002, 1995 to 1996), the greatest numbers of pixels that have both positive change and are hot are observed, but the percentages of change pixels that are hot are relatively low. These same years have the largest percentages of hot spot pixels that have positive change. In the time period with the smallest number of positive change pixels, 1997 to 1998, the percentage of positive change pixels that are hot is the highest, and the percentage of hot pixels also having positive change is the lowest. When the number of hot spot pixels is the highest (2001 to 2002) the percentage of hot spot pixels that have positive change is also the highest. Similarly, when the number of hot spot pixels is the lowest (1997 to 1998) the percentage of hot pixels that have positive change is the lowest.

Table 7.1. Partitioned by periods of change, the number of positive change pixels, hot pixels, and pixels that have both positive change and are hot in the Morice TSA.

change t_i to t_{i+1}	**positive**	**hot spot t_{i+1}**	**positive & hot spot t_{i+1}**	**positive change overlapping hot spot (%)**	**hot spots overlapping positive change (%)**
1995 to 1996	18566	10373	4847	26.11	46.73
1996 to 1997	7830	12345	2323	29.67	18.82
1997 to 1998	1086	7761	1070	98.53	13.79
1998 to 1999	3569	9783	2408	67.47	24.61
1999 to 2000	3270	9806	1435	43.88	14.63
2000 to 2001	4032	10924	2377	58.95	21.76
2001 to 2002	19622	15456	7529	38.37	48.71

Overall, there are significant positive relationships between the number of positive change pixels and the number of hot spot pixels and between the number of positive pixels and the number of pixels that are both positive and hot (Kendall's Tau = 0.715, $p = 0.024$ in both cases). However, the relationship between hot spot pixels and the number of pixels that are both positive and hot is not significant (Kendall's Tau = 0.429, $p = 0.177$).

The annual number of negative change pixels, hot spots, and pixels that have both negative change and are hot, are listed in Table 7.2. Percentages of negative change pixels that are hot, and hot pixels that have negative change are also shown. Compared to positive change, there are fewer negative change pixels over the entire time period. The number of hot spot pixels also having negative change is lower and the percentages of overlaps are smaller. The number of pixels that are categorized as being both hot and having negative change seems influenced by the total number of negative change pixels. For instance, three of the four time periods with the fewest negative change pixels also have the lowest numbers of pixels that are both hot and have negative change. When the number of negative change pixels is the highest (1996 to 1997), the number of pixels in both categories is largest, and the percentages of both negative change and hot pixels having overlaps are the highest. When the number of hot spot pixels is largest (2002) the second largest number of pixels in both categories is observed.

Table 7.2. Partitioned by years of change, the number of negative change pixels, hot pixels, and pixels that have both negative change and are hot in the Morice TSA.

change t_i to t_{i+1}	**negative**	**hot spot t_{i+1}**	**negative & hot spot t_{i+1}**	**negative change overlapping hot spot**	**hot spots overlapping negative change**
1995 to 1996	956	10373	0	0.00	0.00
1996 to 1997	9224	12345	1151	12.48	9.32
1997 to 1998	9052	7761	344	3.80	4.43
1998 to 1999	1083	9783	7	0.01	0.00
1999 to 2000	1396	9806	148	10.60	1.51
2000 to 2001	1885	10924	6	0.00	0.00
2001 to 2002	8043	15456	487	6.05	3.15

Overall, relationships between negative pixels and hot spot pixels differ from those observed between positive pixels and hot spot pixels. There is no significant relationship between the number negative and hot spot pixels (Kedall's Tau = 0.238, p =

0.453) or between hot spot pixels and those that are both negative and hot (Kedall's Tau = 0.652, $p = 0.143$). There is, however, a significant positive relationship between the number of negative pixels and pixels that are both negative and hot (Kedall's Tau = 0.7142, $p = 0.024$).

7.3.3 Patch-Based Investigations

The annual numbers of hot spot patches, positive change patches, and negative change patches are shown in Table 7.3. Percentages of intersections, also reported on an annual basis, are listed in Table 7.4. The percentages of hot spot patches that intersect positive patches range from 12 to 64 percent. Intersections with negative hot spot patches range from 0 to 25 percent. The higher percentage of hot spot patches having intersections with positive change patches is likely related to the definitions of spatial patterns. Both hot spots and positive change focus on patterns of infestation abundance. The cause of annual variability in the percentages of hot spot patches that intersect with change patches is unclear. Unlike pixel-based correlation analysis, there were no significant relationships found, using Kendall's test, between the number of hot spot patches, positive patches, and negative patches.

Table 7.3. Partitioned by years of change, the number of change and hot spot patches in the Morice TSA.

change t_i **to** t_{i+1}	**hot spot patches in** t_{i+1}	**positive change patches**	**negative change patches**
1995 to 1996	44	68	7
1996 to 1997	55	65	62
1997 to 1998	52	5	51
1998 to 1999	65	31	6
1999 to 2000	65	29	19
2000 to 2001	55	42	34
2001 to 2002	55	59	65

Table 7.4. Partitioned by years of change, the percentage of patches with intersections in the Morice TSA.

change t_i **to** t_{i+1}	hot spot patches intersecting positive patches	hot spot patches intersecting negative patches	positive patches intersecting hot spots	negative patches intersecting hot spots
1995 to 1996	63.64	0.00	30.88	0.00
1996 to 1997	32.73	25.45	27.69	20.97
1997 to 1998	11.54	11.54	100.00	9.80
1998 to 1999	32.31	0.00	74.19	16.67
1999 to 2000	21.54	7.69	48.28	31.58
2000 to 2001	40.00	3.64	57.14	5.88
2001 to 2002	38.18	16.36	35.59	12.31

Annually, the percentages of positive change patches that intersect hot spot patches range from 28 to 100 percent; whereas, the percentage of negative change patches that intersect hot spot patches range from 0 to 32 percent. In the time period with the fewest positive patches (1997 to 1998), one hundred percent of positive patches intersect hot spots. As well, the lowest percentages of intersections are associated with the two time periods having the largest number of positive change patches (1995 to 1996 and 1996 to 1997). Overall, there is a significant inverse relationship between the number of positive change patches and the percentage of positive patches intersecting hot spot patches (Kendall's Tau = -0.715, p=0.024). No trend is apparent between the number of negative patches and the percentage of negative patches with hot spot intersections (Kendall's Tau = 0.215, p=0.559).

For patches with intersections, the amount of areal overlap was explored. Hot spot patches that intersect positive change had areal overlaps ranging from near 0 to 100 percent (Figure 7.8). However, in all years, the majority of patches have areal overlaps of greater than 50 percent. While hot spots that intersect with negative patches tend to have smaller areal overlaps, and the majority are less than 50 percent, in some years maximum overlaps are as high as 100 percent (Figure 7.9).

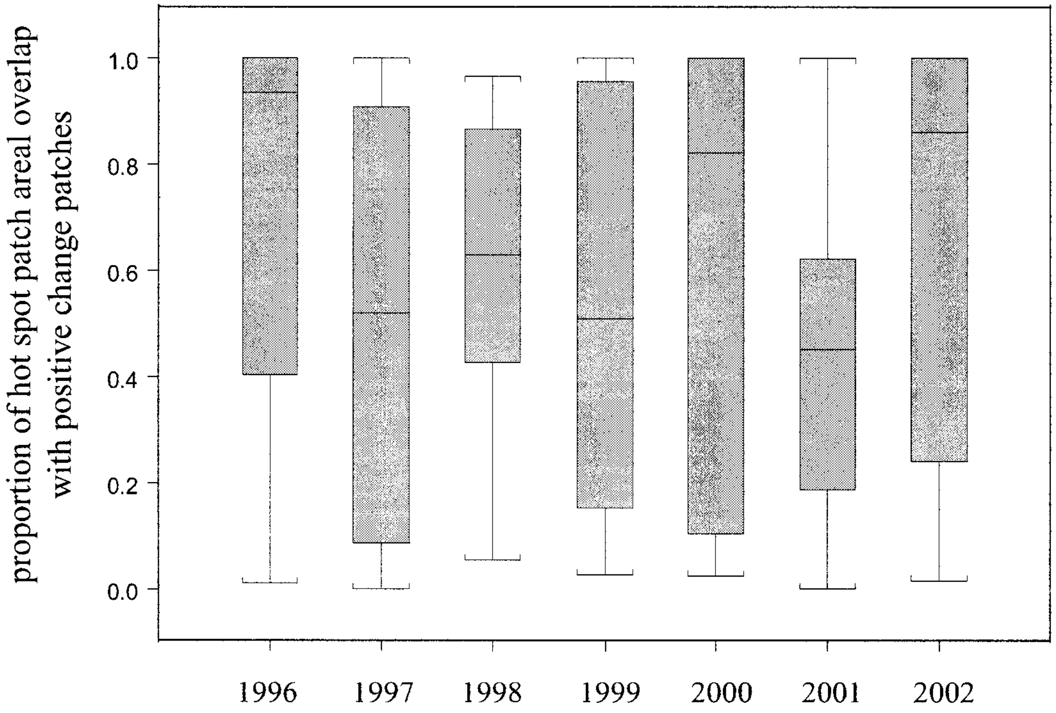


Figure. 7.8. Distributions of hot spot patch (t_{i+1}) areal overlap with positive change patches (t_i to t_{i+1}) in the Morice TSA. Data are partitioned by hot spot year.

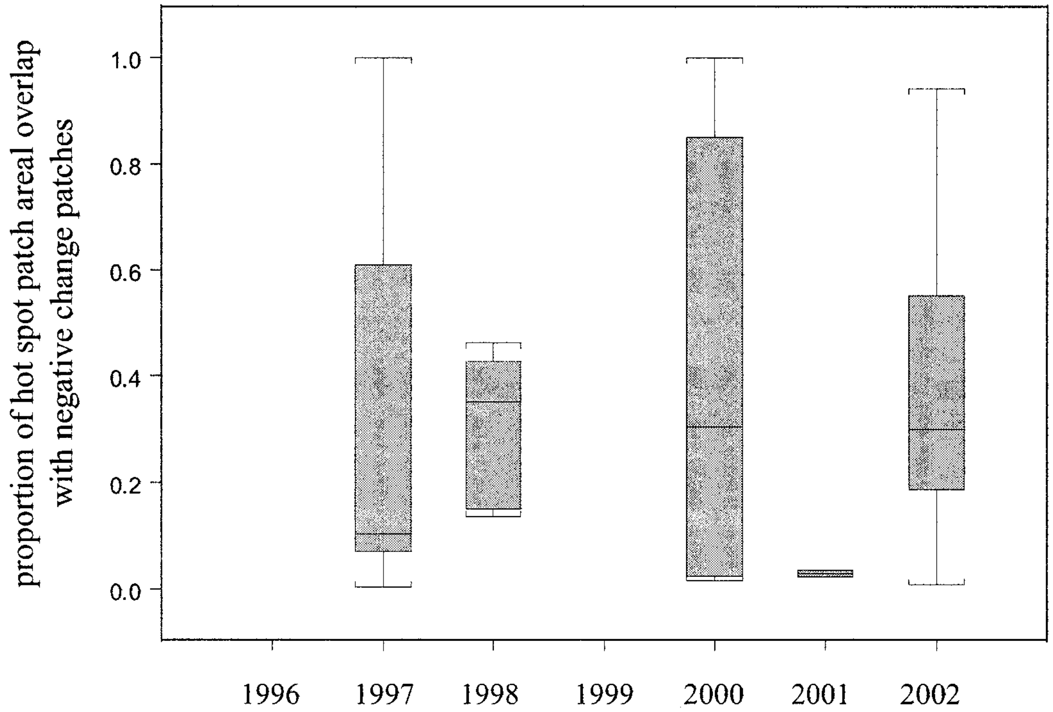


Figure. 7.9. Distributions of hot spot patch (t_{i+1}) areal overlap with negative change patches (t_i to t_{i+1}) in the Morice TSA. Data are partitioned by hot spot year, and there is no data in 1996.

When change patches intersect hot spots, the percentage of change patch areal overlap was also computed. When a large portion of positive change patches intersect with hot spot patches, the percentages of areal overlap were high, with the majority of individual patches having areal overlaps of greater than 90 percent (Figure 7.10). In years with low percentages of intersections, areal overlaps range from zero to 100 percent. Except from 1995 to 1996, the period with the highest number of positive patches, the majority of individual patches have areal overlaps greater than 50 percent.

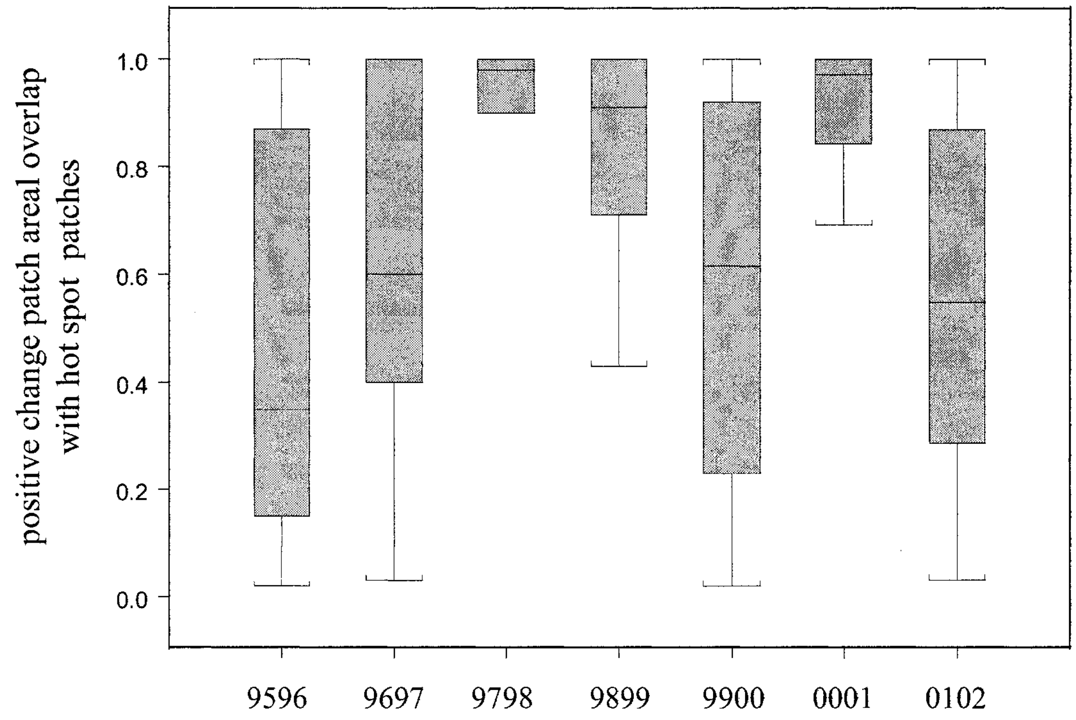


Figure. 7.10. Distributions of positive change patch (t_i to t_{i+1}) areal overlap with hot spot patches (t_{i+1}) in the Morice TSA. Data are partitioned by years of change.

When negative patches intersect with hot spot patches, the amount of areal overlap ranges from near zero to 100 percent, except in years with two or fewer intersecting patches (Figure 7.11). In all years, the majority of individual patches have areal overlaps of less than 50 percent.

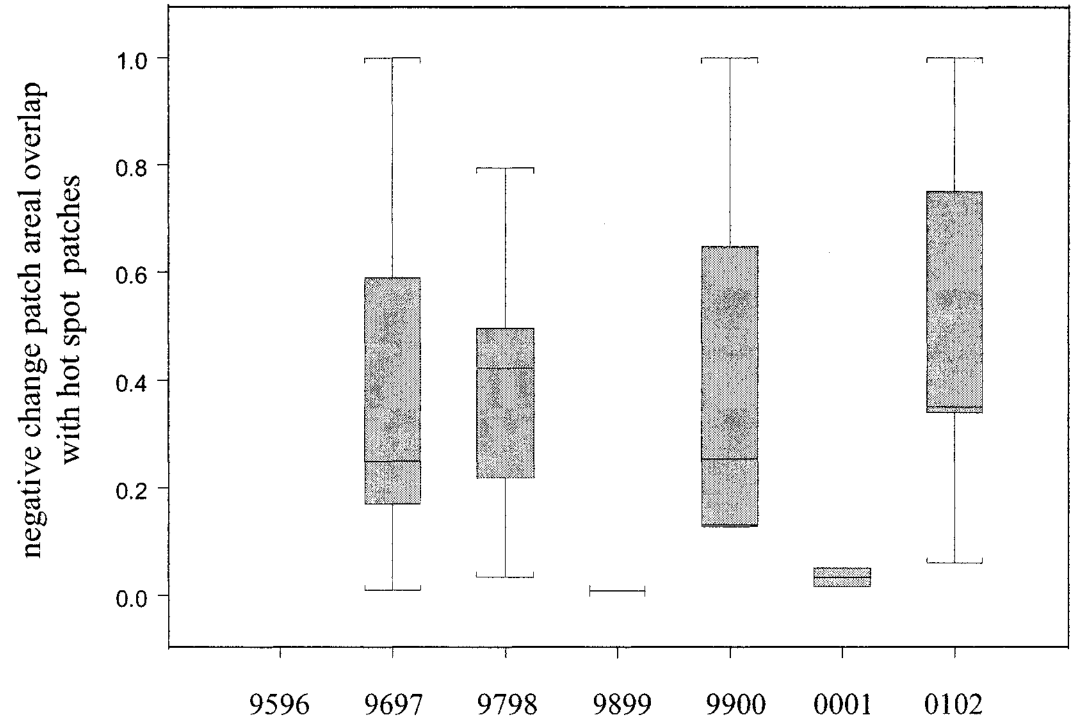


Figure. 7.11. Distributions of negative change patch (t_i to t_{i+1}) areal overlap with hot spot patches (t_{i+1}) in Morice TSA.). Data are partitioned by years of change

For change and hot spot patches having no intersections, the minimum distances between patches were explored. In Figure 7.12 relative frequency distributions of the minimum distances between hot spot patches and positive change patches, and hot spot patches and negative change patches are shown. Relative frequency distributions are generated from minimum distances between hot spot patches and change patches as well as change patches and hot spot patches. Only minimum distances of 10 kilometres or less are included in the histograms.

The modal minimum distance between hot spots and positive change patches is 3.2 kilometres, beyond which the number of observations decreases with distance. The relative frequency of observations increases slightly near six and nine kilometres. The modal minimum distance between non-intersecting hot spot and negative change patches is two kilometres. The relative frequency of minimum distances declines with distance to four kilometres and then is near uniform.

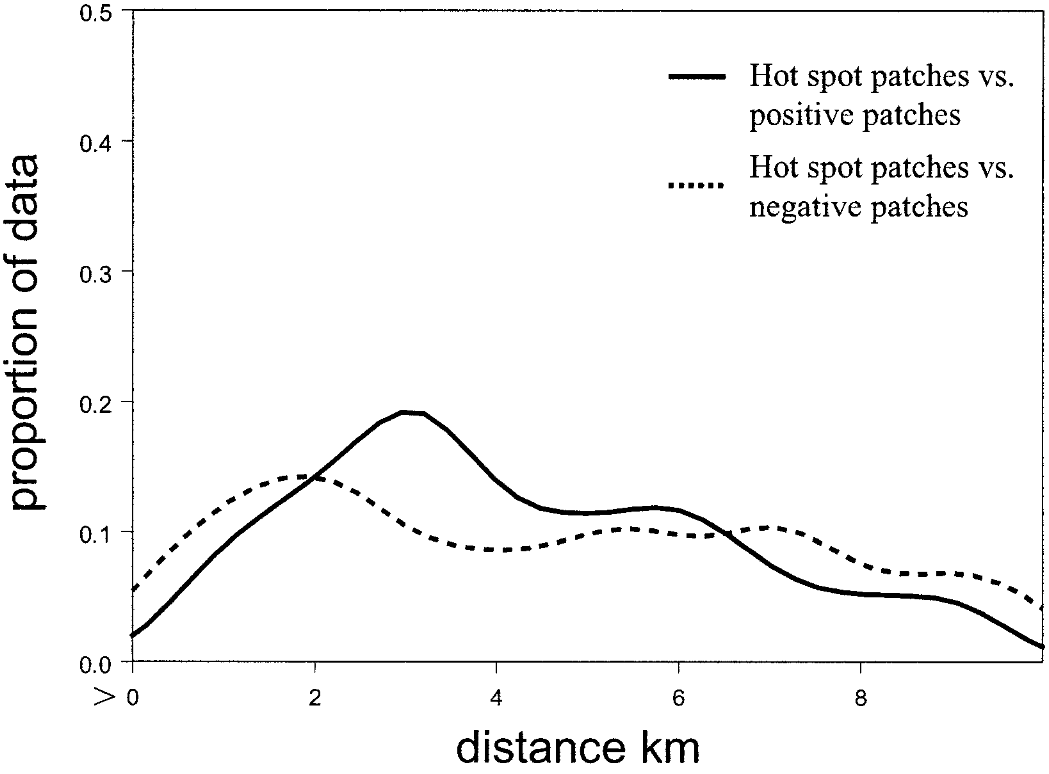


Figure 7.12. Minimum distances between hot spot patches (t_{i+1}) and change patches (t_i to t_{i+1}) in the Morice TSA from 1995 to 2002.

Minimum distances associated with positive patches and hot spots are typically longer than minimum distances associated with negative change and hot spot patches. It is interesting that non-intersecting positive change and hot patches are typically not located nearby. The shorter modal minimum distances between negative change and hot patches may indicate that associations between hot spots and negative change patches are more localized.

The directions between patches that do not have intersections are shown in Table 7.5. Regardless of the comparison, directions between patches are near uniform. This suggests little directionality in the spatial relationships between change and hot spot patches that do not intersect.

Table 7.5. Directions between hot spot patches (t_{i+1}) and change patches (t_i to t_{i+1}) that do not intersect in the Morice TSA from 1995 to 2002.

	positive change to hot spots	**negative change to hot spots**	**hot spots to positive change**	**hot spots to negative change**
NE	25.37%	30.05%	23.57%	23.04%
SE	26.87%	22.40%	21.02%	24.51%
SW	21.64%	19.13%	27.39%	31.37%
NW	26.12%	28.42%	28.03%	21.08%

7.4 SUMMARY

There is better correspondence between hot spots and positive change than between hot spots and negative change. A larger number of corresponding pixels are observed in time periods with the most positive change or hot spot pixels. The largest percentage of positive change pixels that are also hot is observed when the number of positive change pixels is lowest. Yet, the highest percentage of hot pixels having positive change is found when the number of hot pixels is largest. Associations between negative change and hot spot pixels seem regulated, at least in part, by the number of negative change pixels.

Larger numbers of hot spot and positive change patches have intersections than hot spots and negative change patches. Temporal variations are difficult to interpret;

however, the largest percentage of positive patches intersecting hot spot patches is observed when patches are few. The two time periods having the most positive patches also have the lowest percentages of positive patches with intersections.

The majority of hot spot patches that intersect positive patches have areal overlaps of greater than 50 percent, whereas hot spot patches that intersect negative patches have lower areal overlaps and most are less than 40 percent. Similarly, positive patches that intersect with hot spots have larger areal overlaps than do negative patches. Overall, hot spots and positive changes have more correspondence than hot spots and negative changes. Minimum distance trends between non-intersecting patches may provide evidence of long-range dispersal between locations of mountain pine beetle abundance and are supported by stand scale observations of beetle dispersal within three kilometres.

The lack of correspondence between hot spots and negative change indicates that once mountain pine beetle populations are large, a decline in numbers of beetles is most likely to take more than one year. Infestation rates associated with hot spots do not typically decline significantly between two years. In contrast, the development of intense infestations or hot spots is often associated with significant increases in infestation rates over two years. In general, the temporal scale of population growth is finer than population decline.

While associations between positive change and hot spots were anticipated, any relationship between negative change patches and hot spots was somewhat unexpected.

One explanation for the correspondence may be that negative change locations indicate the presence of an active and dynamic mountain pine beetle population. In some cases, negative change locations may be the source of beetles for hot spots. If negative change is occurring as the result of treatment or host depletion, populations may move to nearby locations. This may explain why the areal overlap between negative patches and hot spot patches tends to be smaller, and minimum distance between non-intersecting patches shorter, than between positive change and hot spot patches.

Further investigations into the link between hot spots that correspond with negative change and treatment would provide useful information on the efficacy of management approaches. As well, in future research it would be helpful to explore how definitions of positive change, negative change, and hot spots impact the results found in this chapter. Finally, in this investigation we have only explored the change between t_i and t_{i+1} and hot spots in t_{i+1}. Approximately 35 percent of hot spot patches in t_{i+1} are associated with change patches (t_i to t_{i+1}). It would be interesting to determine if other hot spot patches are associated with positive changes that occur in an earlier time period. Such an investigation would provide further evidence on the temporal development of hot spot patches.

8 MODELLING FOREST RISK OVER LARGE AREAS

8.1 INTRODUCTION

A common strategy for exploratory analysis of spatial patterns is to evaluate characteristics of an empirical pattern relative to those expected from the realization of a null/hypothesized model (Getis and Boots, 1978; O'Sullivan and Unwin, 2003). As the properties of the model are known, this procedure may be used diagnostically to explore the empirical pattern. More formally, one or more test statistics may be computed from the empirical pattern and the probability of these occurring under the null model evaluated.

One means of evaluating a test statistic is to use a permutation test in which the test statistic is computed for the original data and then the observed data are permuted and the test statistic computed for each permutation (Conner and Simberloff, 1986; Edgington, 1995). Collectively, the empirical test statistic and those generated from the permutations provide a reference distribution for evaluating the empirical test statistic. The probability (or significance) of the empirical test statistic is equal to the proportion of permutations that have test statistic values greater than or equal to the empirical test statistic. When the data are permuted randomly, we refer to this as a randomization test (Fortin and Jacquez, 2000).

For spatial data, complete randomization is equivalent to assigning the data values at random to locations within the study region, that is, the data values are located uniformly and independently over the entire study region. However, there are situations where complete randomization is inappropriate, as either or both of the assumptions of uniformity and independence are impossible (*e.g.*, Legendre and Fortin, 1989; Stine and Hunsaker, 2001). For example, environmental heterogeneity may lead to clustering of events or interaction between events may lead to spatial dependence. In these circumstances, using complete randomization would typically reduce the significance of the test statistic (Legendre and Fortin, 1989; Legendre *et al.*, 2002). For example, mountain pine beetle infestations do not occur uniformly across a landscape, rather they cluster in locations with mature pine (Safranyik *et al.*, 1974). In such cases, complete randomization may be conditioned using *a priori* knowledge of the study region or phenomena under investigation.

There are several ways to condition a randomization. Of interest for this research are randomizations conditioned on *a priori* knowledge of where events are likely to have higher occurrences. This approach has been used most extensively in epidemiology where randomizations are conditioned on the population at risk (Besag and Newell, 1991; Kulldorf *et al.*, 2003). Similar examples are found in ecology where the statistical significance of the spatial pattern of an animal is tested using randomizations restricted by habitat (Davis *et al.*, 2000).

For spatial patterns, the test statistic may be one which summarizes the entire data set (global) or one which is computed for every data site (local) (Fotheringham and Brunsdon, 1999). Local statistics are particularly useful for identifying differences, rather than similarities, in spatial data via mappable measures (Fotheringham, 1997;

Boots, 2002). Using local methods, we can undertake exploratory, diagnostic investigations of spatial variation in probabilities of the empirical test statistic.

The goal for this chapter is to assess the utility of applying a stand scale mountain pine beetle model of forest risk (defined below) to large areas. We do this by evaluating local statistics calculated for the observed data on infestations, using a randomization conditioned on forest risk. As described below, our investigations are undertaken using a raster format, making it possible to generate a local test statistic and to evaluate its likelihood for each pixel. Those pixels where the test statistics have low probabilities indicate locations where the test value is unlikely under the null model. Pixels with unlikely values are investigated diagnostically, enabling exploratory analysis of the observed data.

By investigating characteristics of the landscape at locations where the observed data differs substantially from a random expectation conditioned on the forest risk model, we are able to suggest modifications to stand scale models when applied to a landscape during an epidemic. To meet this goal, objectives include: modifying the forest risk model to aid operationalization in Morice; detecting and visualizing pixels with expected and unexpected values in each year; visualizing expected and unexpected infestation magnitudes in multiple time periods; and exploring landscape characteristics underlying locations with expected and unexpected values.

8.2 FOREST RISK MODEL

Forest risk is typically a description of the likelihood of a mountain pine beetle outbreak, tree mortality, or stand loss during a specific time period (Bentz *et al.*, 1993; Shore *et al.*, 2000). Here we assess the effectiveness of the Shore and Safranyik risk model, as in Western Canada it is the primary model used for forest management. This model also has the benefit of incorporating most of the current knowledge on the biological behaviour of the mountain pine beetle.

The Shore and Safranyik risk model, which from here on will be referred to simply as the risk model, is defined as the short-term expectation, or probability, of tree mortality in a stand as a result of infestations (Shore and Safranyik, 1992). In this definition, mortality is quantified by loss in stand volume (rather than individual trees). The probabilistic representation of stand loss provides an effective approach to comparing output to observed data via conditional randomizations.

Another benefit of the risk model, when making comparisons with observed data, is the time scale. Many models related to mountain pine beetle infestation behaviour are designed to assess multi-temporal impacts of various management strategies (Fall *et al.*, 2002), underlying landscapes (Hughes, 2002), or beetle populations (Logan *et al.*, 1998). For instance, given a landscape, beetle conditions, and several different management scenarios, variations in the impact of forest management over 10 years can be estimated (Fall *et al.*, 2002). The risk model is designed for a different purpose and is a short-term expectation of the likelihood of infestation based on landscape and beetle conditions in a single year. While "short-term" is not explicitly defined, in our experience risk appears most related to mountain pine beetle infestations occurring in the following year. Risk is the probability that locations will be infested at a known point in time. When data are available for multiple consecutive years, risk generated using data in time t_i can be used to conditionally randomize data in t_{i+1}. For conditioning a randomization, risk provides a more direct representation of the likelihood of attack than models that are developed for longer time series.

All models of mountain pine beetle behaviour have uncertainty related to parameters and attribution. However, when models are designed to assess mountain pine beetle behaviour over several time periods, more process-based inputs are typically required. For example, variables related to the complex pheromone ecology of the mountain pine beetle are used in several models (Powell *et al.*, 1998; Fall *et al.*, 2002, Hughes, 2002). Although process studies and models are helpful for investigating mountain pine beetle behaviour, many processes are still poorly understood (Hughes, 2002). Relative to pheromone ecology models, variables associated with the risk model are fairly well documented. While recognizing that the forest risk model has limitations, the relatively straightforward input variables are a benefit when interpreting the relationship between stand and landscape level mountain pine beetle behaviour.

8.2.1 Stand Susceptibility

Forest risk is considered a function of two components, stand susceptibility and beetle pressure. Stand susceptibly reflects the inherent characteristics of a stand that affect the probability of volume loss if attacked by mountain pine beetle (Shore and Safranyik, 1992). In this context, a stand is defined as a homogenous aggregate of trees. Stand susceptibility (S) ranges from zero to 100 and is calculated as

$$S = PADL \tag{8.1}$$

where: P is the percentage of susceptible pine basal area, A is a pine age factor, D is stand density, and L is a location factor. Each variable used in the calculation of stand susceptibility incorporates a factor important for mountain pine beetle host selection.

The percentage of susceptible pine basal area (P) is designed to consider tree dbh and stand composition. P is calculated as

$$P = \frac{(\text{average basal area/ha of pine} \geq 15\text{ cm dbh})}{(\text{average basal area/ha of all species} \geq 7.5\text{ cm dbh})} 100 \tag{8.2}$$

In equation 8.2, the 15 centimetre dbh threshold reflects mountain pine beetle preferences for mature trees (Hopping and Beal, 1948). Under epidemic conditions smaller trees may be attacked, but fewer beetles will emerge than were required to attack the tree and volume loss will be low (Safranyik *et al.*, 1974). The lower threshold of 7.5 centimetres is a practical limitation, as smaller trees are not typically included in forest inventories.

Forest age relates directly to a pine tree's ability to resist a mountain pine beetle attack. Older trees, which are less able to resist attack, are more susceptible to the mountain pine beetle. In Shore and Safranyik's initial publication on the forest risk model (1992), the age factor (ranging from zero to one) was determined using a lookup table with three values (Table 8.1). The age factor and therefore, susceptibility values, were limited to discrete categories. In reality, forest age and susceptibility will vary continuously over a landscape. Therefore, equations were developed based on these tables to provide a continuous forest age factor and representation of susceptibility (Wulder *et al.*, 2004; Riel, pers com) (Table 8.2).

Table 8.1. Discrete age factor look up table for the forest susceptibility model.

Average pine age (years)	**Age factor**
$\leq$ 60	0.1
61 to 80	0.6
$\geq$ 81	1.0

Table 8.2. Continuous age factor equations for the forest susceptibility model.

Average pine age (years)	**Age factor calculation**
$\leq$ 40	0
> 40 - $\leq$ 80	$0.1 + (0.1((\text{age} - 40) / 10)^{1.585})$
> 80 - $\leq$ 120	1
> 120 - 400	$1 - (0.05(\text{age} - 120) / 20)$

The relationship between tree mortality and stand density reflects factors such as tree vigour and the microclimate (wind, light, and temperature). The highest pine mortality occurs when stand density is between 250 and 2500 stems per hectare. In the original discrete version of forest susceptibility, stand density is converted to a density factor ranging from zero to one using Table 8.3. A more continuous density factor can also be generated using equations found in Table 8.4 (Wulder *et al.*, 2004; Riel, pers com).

Table 8.3. Discrete stand density factor look up table for the forest susceptibility model.

Stand density (stems per ha of trees $\geq$ 7.5 cm dbh)	**Density factor**
$\leq$ 250	0.1
251 to 750	0.5
751 to 1,500	1
1,501 to 2,000	0.5
2,001 to 2,500	0.5
$\geq$ 2501	0.1

Table 8.4. Continuous stand density equations for the forest susceptibility model.

Stand density (stems per ha of trees $\geq$ 7.5 cm dbh)	**Stand density calculation**
< 650	$0.0824(\text{density} / 250)^2$
$\geq 650 - < 750$	$1 - (0.7(3 - (\text{density} / 250))^5$
$\geq 750 - < 1500$	1
> 1500	$1 / (0.9 + (0.1 \exp (0.4796((\text{density} / 250) - 6))))$

The location factor is an indicator of climate and is based on latitude, longitude, and elevation in British Columbia. In locations where the latitude, longitude, and elevation suggest that the temperatures are colder, the value of *L* is lower. Warmer climates are associated with higher values of *L*. To determine *L*, first calculate a parameter (*Y*) as,

$$Y = (24.4\,\text{Longitude}) - (121.9\,\text{Latitude}) - (\text{Elevation (m)}) + (4545.11)\,. \qquad 8.3$$

Using *Y*, the discrete location factor can be acquired from Table 8.5 or a continuous factor generated using equations from Table 8.6.

Table 8.5. Discrete location factor look up table for the forest susceptibility model.

Y	**Location factor**
≥ 0	1.0
0 to -500	0.7
≤ -501	0.3

Table 8.6. Continuous location factor equations for the forest susceptibility model.

Y	**Location factor calculation**
> 0	1
≤ 0	$1 / (0.9 + (0.1\exp(-0.8(Y / 250))))$

8.2.2 Beetle Pressure

The second component of forest risk is beetle pressure (*B*), which is defined as the magnitude of a beetle population that might affect a stand. Beetle pressure is related to both the number and proximity of infested trees. In the initial forest risk model, beetle pressure was determined using two lookup tables. The first table is used to determine the size of the infestation based on the number of attacked trees within a stand and the number of trees within three kilometres (Table 8.7). The second table uses the infestation size (determined in Table 8.7) and the proximity of the nearest infestation to determine beetle pressure from a look up table with values ranging from zero to one (Table 8.8). More recently, a semi-continuous version of beetle pressure can be calculated using equations in Table 8.9.

Table 8.7. Mountain pine beetle infestation size used for generating beetle pressure.

Number of infested trees outside stand within 3 km	Number of infested trees inside the stand		
	< 10	10-100	> 100
< 900	Small	Medium	Large
900 to 9,000	Medium	Medium	Large
> 9,000	Large	Large	Large

Table 8.8. Discrete beetle pressure look up table for the forest risk model.

Relative size of infestation	**Distance to nearest infestation (km)**					
	in stand	0-1	1-2	2-3	3-4	> 4
Small	0.5	0.5	0.4	0.3	0.1	0.06
Medium	0.8	0.7	0.6	0.4	0.2	0.08
Large	1.0	0.9	0.7	0.5	0.2	0.10

Table 8.9. Continuous beetle pressure equations for the forest risk model.

BP category	**Beetle Pressure Calculation**
None	0
Small	0.582 - (0.123(nnd/1000))
Intermediate	0.803 - (0.163(nnd/1000))
Large	1.003 - (0.209(nnd/1000))

nnd = nearest neighbour distance; bp = beetle pressure

8.2.3 Forest Risk

While susceptibility is a probabilistic measure of forest loss, without information on the beetle population, it provides only a long-term representation of infestation likelihood. Beetle pressure, which represents the state of the current mountain pine beetle population, is necessary for characterizing short-term conditions. Forest risk ranges from zero to one and is calculated as,

$$Risk = 2.74\left(S^{1.77}\,2.718^{-0.0177*S}\right)\left(B^{2.78}\,2.718^{-278*B}\right). \tag{8.4}$$

8.3 CALCULATING FOREST RISK

Model adjustments were required to make the forest risk model operational in Morice. While some modifications were helpful for adapting the model to our purposes, others were required due to limited data availability. Modifications to the forest risk model include: converting spatial units from irregular polygons to grid cells, modifying input variables for calculating susceptibility, assigning susceptibility to locations with missing data, varying susceptibility through time, and smoothing susceptibility. Each modification will be discussed below.

8.3.1 Spatial Units

The forest risk model was developed for use with forest stands or inventory polygons, which are the most common management and data collection unit. When input data are collected for stands, this spatial unit works well and there is no utility in using a finer grained unit. While the input data for forest susceptibility in Morice are represented as stands, the mountain pine beetle data allow beetle pressure to be represented at finer than stand scale. Forest inventory polygons in Morice have an average size of 168,000 square metres (standard deviation = 291,460), but points representing an infestation cluster represent a maximum area of 31,400 square metres (circle with a 100 metre radius).

From a spatial analysis perspective, beetle pressure generated for forest stands produces avoidable uncertainty. Polygons are variable in size and shape and the rate of infestation varies depending on the size of forest inventory polygons. As well, additional uncertainty is associated with the number of infested trees within three kilometres when irregular polygons are used. To avoid compounding uncertainty and to retain spatial detail, forest risk was computed using 200 metre grid cells, which approximate the maximum grain of mountain pine beetle GPS point data.

To compute forest susceptibility for a raster surface, polygons with input variables were converted to grids prior to calculating forest susceptibility. Representing beetle pressure using grid cells was more complex. Infestation size (Table 8.7), used for determining beetle pressure, is generated using stand specific thresholds. On average, stands are four times the size of the grid cells; therefore, the lookup table for infestation size was modified as seen in Table 8.10 (Shore, pers com). Beetle pressure was then calculated using the semi-continuous equations provided in Table 8.9. It may be worth mentioning that prior to computing beetle pressure variables, points representing mountain pine beetle infestations were converted to grids. This was done by overlaying the points with a 200 metre grid and assigning cells that contained points the sum of the point attribute values. Each pixel in the grid was also assigned the number of infested trees within three kilometres and the distance to the nearest infestation.

Table 8.10. Grid-based mountain pine beetle infestation size used for generating beetle pressure.

Number of infested trees outside pixels & within 3 km	**Number of infested trees inside the pixel**		
	< 2.5 (< 0.625/ha)	2.5-25 (0.625-6.250/ha)	> 25 (> 6.250/ha)
< 900	Small	Medium	Large
900 to 9,000	Medium	Medium	Large
> 9,000	Large	Large	Large

8.3.2 Input Variables for Susceptibility

As with many locations in British Columbia, the primary data source available for Morice is the provincial forest inventory data. The forest inventory does not have basal area or density information, requiring a modification to the input parameters used for modelling forest susceptibility. The Cariboo Forest Region suggested a modified version of the forest risk model, where dbh is used as a surrogate for density and percentage of pine in a stand replaces basal area (Howes, 1995; Wulder *et al.*, 2004). While we recognize that these modifications may weaken the model, stand density and basal area information are rarely available and adjustments to the input parameters are typically required to make the risk model operational at a broad scale

To operationalize the susceptibility portion of the risk model for Morice, the total proportion of pine in each polygon was calculated using the sum of all species fields and values ranging from zero to one. Diameter at breast height was converted to a dbh factor based on thresholds used in the Cariboo Forest Region report (Table 8.11). Out of 38,383 pine stands, 36,280 have dbh recorded, and 2,103 did not. When dbh was not present, as in the Cariboo Forest Region report, age was used as a surrogate for dbh (Table 8.12). The age and location factors were calculated using the continuous equations.

Table 8.11. Diameter at breast height factor used as a surrogate variable for density when calculating forest susceptibility.

dbh (cm)	dbh factor
≤ 20	0.1
> 20 and ≤ 22.5	0.6
> 22.5 and ≤ 25	0.8
> 25	1

Table 8.12. Age-based diameter at breast height factor.

age (years)	dbh factor
< 60	0.1
≥ 60 and < 80	0.8
≥ 80	1

8.3.3 Susceptibility and No Data

In Morice, 6.7 percent of the area is considered "not sufficiently restocked" and no species information or other characteristics are provided. Not sufficiently restocked polygons are typically those that are not being managed for commercial use at the time of the inventory. In many cases such locations have been left to regenerate naturally; although species and age details are not recorded, trees are often present at these locations. According to the mountain pine beetle GPS data, infestations, and therefore mature pine, exist in 872 of the 2,675 polygons labelled not sufficiently restocked. This represents an area of 994 kilometres squared, approximately three percent of the study area. Although the mountain pine beetle data are not error free, the presence of mountain pine beetle in not sufficiently restocked polygons provides supplementary information useful for locating pine.

If a not sufficiently restocked forest inventory polygon had one or more mountain pine beetle infestation clusters, all cells associated with that polygon were assigned a susceptibility value. Forest inventory polygons are homogenous units; therefore, if pine was found at a location within a polygon, the entire area likely had some pine. With limited information we are only able to develop a crude adjustment to not sufficiently restocked locations, although a relatively small portion of the study area (approximately three percent) is impacted. While infestation magnitude and susceptibility levels were found to be non-proportional, the mean susceptibility for the entire study area is 40 and the majority of susceptibility values range from 20 to 60. As such, pixels associated with not sufficiently restocked polygons that contain one or more mountain pine beetle points were assigned a susceptibility of 40.

8.3.4 Varying Susceptibility Through Time

In this study, forest risk is generated for eight years (1995 to 2002). Yet forest inventory data, which are the primary data source for susceptibility modelling, are only updated periodically (Leckie and Gillis, 1995). In Morice, the inventory data were last updated in the mid 1990s and as a result the forest inventory data best reflect 1995 conditions. An effort was made to consider temporal variations in forest conditions. Local experts suggested that from 1995 to 2002, the key forest activities impacting susceptibility were mountain pine beetle infestations and harvesting.

The only available data with a temporal component were the mountain pine beetle data. Although these data were not helpful for identifying subtle changes to susceptibility, they were useful for locating abrupt changes. Change in untreated mountain pine beetle infestations will likely be continuous over time. In contrast, harvesting results in abrupt change. If the mountain pine beetle infestation level increases over time to a maximum and the following year declines dramatically, it likely indicates that the area has been harvested (Carroll, pers com). By determining an appropriate adjustment to susceptibility at these locations, we can account for some of the temporal variation in forest conditions. While recognizing that this approach has limitations, we find it useful for addressing changes in susceptibility at locations that have a high likelihood of harvesting.

To identify grid cells needing adjustments to forest susceptibility values, we first determined the year of maximum infestation (maxyr) based on the corrected kernel density surfaces. Then we apply the following rule,

$$\mathrm{if}(\hat{\lambda}_{\mathrm{maxyr}} 0.1 \geq \hat{\lambda}_{\mathrm{maxyr}_{+1}})\,\mathrm{then\ reduce\ susceptibility\ in\ maxyr}_{+1}\,. \tag{8.5}$$

For example, if the infestation magnitude of a pixel is the highest in 1995 and in 1996 the infestation level declines by at least 90 percent, the 1996 susceptibility value is reduced. Initially, we investigated the correlation between the percentage decline in infestation levels from yrmax to yrmax$_{+1}$, and the mean infestation magnitude in yrmax$_{+2}$, however relationships were found to be non-proportional. To determine the validity of the 90 percent cut off, mean infestation levels in yrmax$_{+2}$ were calculated for pixels where infestation magnitudes declined by at least 90 percent and less than 90 percent between yrmax and yrmax$_{+1}$ (Table 8.13). Using a Kolmogorov-Smirnov test, in every year the null hypothesis of distribution similarity was rejected (α=0.05). In other words, areas that experience a large decline in attack magnitude, following the year of maximum infestation, are less intensely attacked in the following year.

Table 8.13. The relationship between maxyr and maxyr$_{+1}$ decline and the maxyr$_{+2}$ infestation magnitude by year for the Morice TSA.

decline between maxyr and maxyr$_{+1}$	maxyr 1995	maxyr 1996	maxyr 1997	maxyr 1998	maxyr 1999	maxyr 2000	maxyr all
	1997 mean	1998 mean	1999 mean	2000 mean	2001 mean	2002 mean	all mean
≥ 90%	0.24	0.24	0.62	0.13	0.24	0.15	0.37
< 90%	3.35	1.69	2.65	2.73	3.04	3.85	2.95

When mean values for all years were combined, the maxyr$_{+2}$ average infestation magnitude for cells declining by at least 90 percent was 0.37 trees per 200 metres squared. For all other locations the infestation size was 2.95 trees per 200 metres squared. These calculations indicate that the average magnitude in maxyr is 87.5 percent lower when the infestation magnitude declines by at least 90 percent between maxyr and maxyr$_{+1}$. As such, the susceptibility of pixels identified using the rule in equation 7.5 was reduced by 87.5 percent.

8.3.5 Smoothing Susceptibility

Even after all the above corrections were made, only 81 percent of the mountain pine beetle points (for all years) were located in cells where susceptibility values were greater than zero. By smoothing the susceptibility with a three by three averaging filter, 97 percent of the mountain pine beetle points were associated with susceptibility values greater than zero. Understanding that all the analysis is impacted by data uncertainty, and that we are interested in relative rather than absolute values for conditioning randomization, smoothed susceptibility surfaces were used for calculating risk.

8.3.6 Assessing Modifications to Susceptibility

To assess the appropriateness of modifications to susceptibility, randomizations for 2002 (described below) were conditioned on risk surfaces with modified and unmodified susceptibility. This allowed investigation of which susceptibility surface best represented observed conditions when combined with beetle pressure. While randomizations were undertaken for all years, only 2002 data were used to investigate modifications made to the susceptibility model, as 2002 is the year most impacted by the alterations.

8.4 CONDITIONAL RANDOMIZATION

An overview of the randomization procedure is provided below (Figure 8.1). To implement the randomization, observed data and forest risk surfaces were used as input and an appropriate randomization algorithm chosen. The randomization algorithm and test statistics were selected based on the data, an understating of mountain pine beetle behaviour, and the null model. Here a kernel density estimate, used to determine the intensity of mountain pine beetle infestations at a particular location (for details see Chapter 4), was selected as the test statistic. Ninety-nine random realizations of the observed data were produced and kernel density surfaces created. For each cell, a reference distribution was generated from the kernel density estimated values, computed from the random realizations of the observed data. Statistical significance of the observed kernel density estimated values was determined through comparisons with the reference distribution.

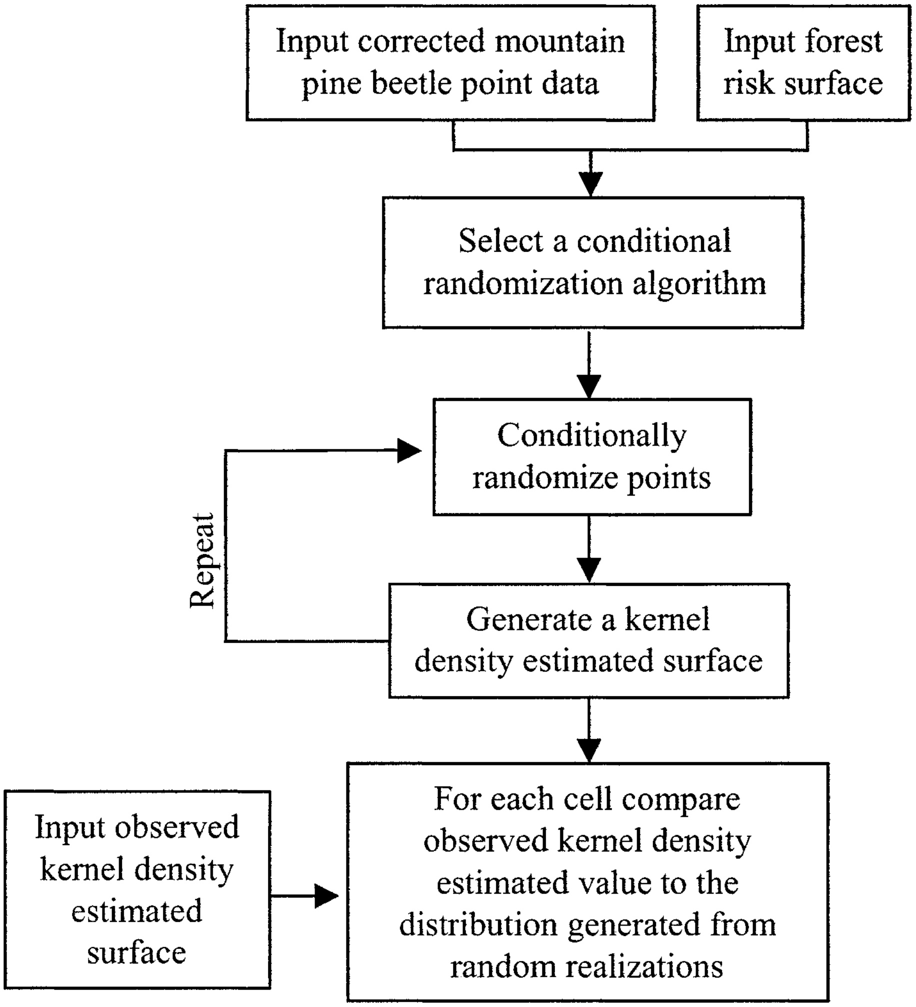


Figure 8.1. An overview of the conditional randomization method.

8.4.1 Randomization Inputs

Annual forest risk and mountain pine beetle data were used as input for conditional randomization. The mountain pine beetle data were points with attributes equal to the number of infested trees. Attribute uncertainty was incorporated into point data prior to conditional randomization. For each point, 99 realizations of the attribute value were generated by drawing values from a distribution that modelled the attribute uncertainty. The 99 values were then averaged together to generate point attributes that incorporated uncertainty.

8.4.2 Algorithm Selection

During the development of an ecologically appropriate randomization approach, four randomization algorithms were explored (Table 8.14). Algorithms can be categorized into theoretical approaches based on whether the randomizations involve individually infested trees or infestation clusters. Each algorithm reflects a different way of conceptualizing the data and mountain pine beetle processes, and allows testing of a different null model.

All algorithms are described below, as they inform the development of the algorithm ultimately used for this work (the fourth algorithm). With the generation of each algorithm we add more conditions, moving away from traditional randomization and towards an ecologically appropriate model. The algorithm development process is important, as the understating of mountain pine beetle behaviour over a landscape is in its infancy and large area research often requires an exploratory approach. By investigating several algorithms we are able to comment on the connection between stand level mountain pine beetle behaviour and landscape level patterns of infestation.

Table 8.14. An overview of four algorithms explored for conditional randomization.

Algorithm	Approach	Allocation Characteristics	Advantages	Disadvantages
1	Individual Tree	Inhomogeneous planar Poisson process in which the intensity of infested trees is proportional to risk	Considers infestation clusters as individual trees	Unrealistic in terms of MPB processes; attribute distributions of observed data are not reproduced
2	Individual Tree & Cluster	Inhomogeneous planar Poisson process in which the presence of infestation clusters is proportional to risk and infestation size grows proportional to risk	Considers infestation occurrence and size proportional to risk	Attribute distributions of observed data are not reproduced; does not adequately reflect MPB processes
3	Cluster	Inhomogeneous planar Poisson process in which the presence of infestation clusters is proportional to risk	Retains attribute distributions of observed data	Infestation size is not considered
4	Cluster	Inhomogeneous planar Poisson process in which the presence and size of infestation clusters is proportional to risk	Retains attribute distributions of observed data; realistic in terms of MPB behaviour	

Using an individual tree approach to randomization, we conceptualize the infestation data as single trees on the landscape; whereas using the cluster approach we consider points to represent groups of infested trees. In the first algorithm, which uses the individual tree approach, we determine the total number of infested trees from the observed data and randomly assign individual trees to the landscape using the condition of forest risk. It is possible for more than one tree to be allocated to each pixel and the allocation of each tree is independent of other tree locations. In other words, infested trees are allocated by an inhomogeneous planar Poisson process in which the intensity of infested trees is proportional to risk. The most likely source of difficulty with this algorithm is that it ignores the stand-level aggregative processes associated with mountain pine beetles. Mountain pine beetles do not independently select trees to infest;

processes of aggregation and dispersion are required to allow successful infestation, and trees near current infestations have a greater likelihood of attack. Results from exploring randomization algorithms may indicate that aggregative mountain pine beetle behaviour, which has been observed within stands, is expressed at a landscape scale.

A second algorithm combines the individual tree and cluster approaches by first assigning the observed number of clusters, where each cluster has a minimum size of one infested tree, and then assigning the remaining observed trees (total numbers of trees – number of clusters) to the cluster sites. For both clusters and trees, the assignment is random conditioned by forest risk. This algorithm assumes that mountain pine beetles first select locations according to an inhomogeneous planar Poisson process, in which the occurrence of an infestation cluster is proportional to risk, and then grow the infestation to a size that is also proportional to risk. If this algorithm accurately modelled mountain pine beetle processes, the distribution of cluster sizes produced by the allocation should be similar to that of the observed data. Several variations of this algorithm were unsuccessfully tested in an effort to replicate the observed cluster size distribution. It appears that more process information is required before an individual tree approach to randomization will be meaningful. Since the goal of this paper is not to model mountain pine beetle behaviour, but rather to evaluate the performance of a stand level model for representing forest conditions over larger areas, we leave exploration of the process(es) that generate the empirical cluster distribution for another time.

The third and fourth algorithms are based on clusters and retain the observed distribution of cluster sizes. The third algorithm randomly assigns clusters to locations conditioned on forest risk, without considering the size of the cluster. This is equivalent to an inhomogeneous planar Poisson process in which the cluster occurrence is proportional to risk, but the cluster size is independent of risk. Such a scenario is improbable as risk reflects the likelihood of loss in stand volume, emphasizing both the presence and magnitude of mountain pine beetle infestations.

The fourth algorithm assigns clusters to locations based on the inhomogeneous planar Poisson process where both cluster occurrence and size are proportional to risk. To achieve this, the clusters are divided into n ordered groups ($g_1, \ldots, g_i, \ldots, g_n$) on the basis of size. Similarly, the locations are divided into n ordered groups ($r_1, \ldots, r_i, \ldots, r_n$) on the basis of magnitude of risk. Then the clusters in group g_i are randomly assigned to locations in the corresponding group r_i. While this algorithm has a stochastic component, it generally forces the largest clusters to be in the highest risk locations. Any number of groups could be used and class breaks can be determined in several different ways. The more partitions, the less stochastic the algorithm becomes. In this study, n was set equal to three. Algorithm four reflects stand-scale biological theory on the mountain pine beetle, which suggests that higher risk areas are likely to have more and larger clusters than areas with less risk (Shore and Safranyik, 1992). Additionally, it has the benefit of retaining the empirical distribution of cluster sizes. Therefore, algorithm four was selected for operationalizing the conditional randomizations.

8.4.3 Generating a Test Distribution and Assessing Significance

Data for each year were randomized, conditional to the risk model generated for the previous year. For example, the risk surface generated using 1995 data were used to condition randomizations in 1996, as such, the 1995 data could not be randomized. Each realization of the conditionally randomized points was converted to a kernel density estimated surface. Examples of kernel surfaces, generated by randomizing 2002 data conditionally on the 2001 risk surface are shown in Figure 8.2. Ninety-nine randomizations and associated kernel density estimated surfaces were generated to compute a reference distribution for each cell. Using 99 randomizations, the smallest critical value that could be used for statistical testing was 0.01. Observed values were obtained from the corrected kernel density surfaces (described in Chapter 4), and statistical significance of observed data from 1996 to 2002 determined. If the observed value was greater or less than the 99 random values from the randomization, the observed value was considered significant.

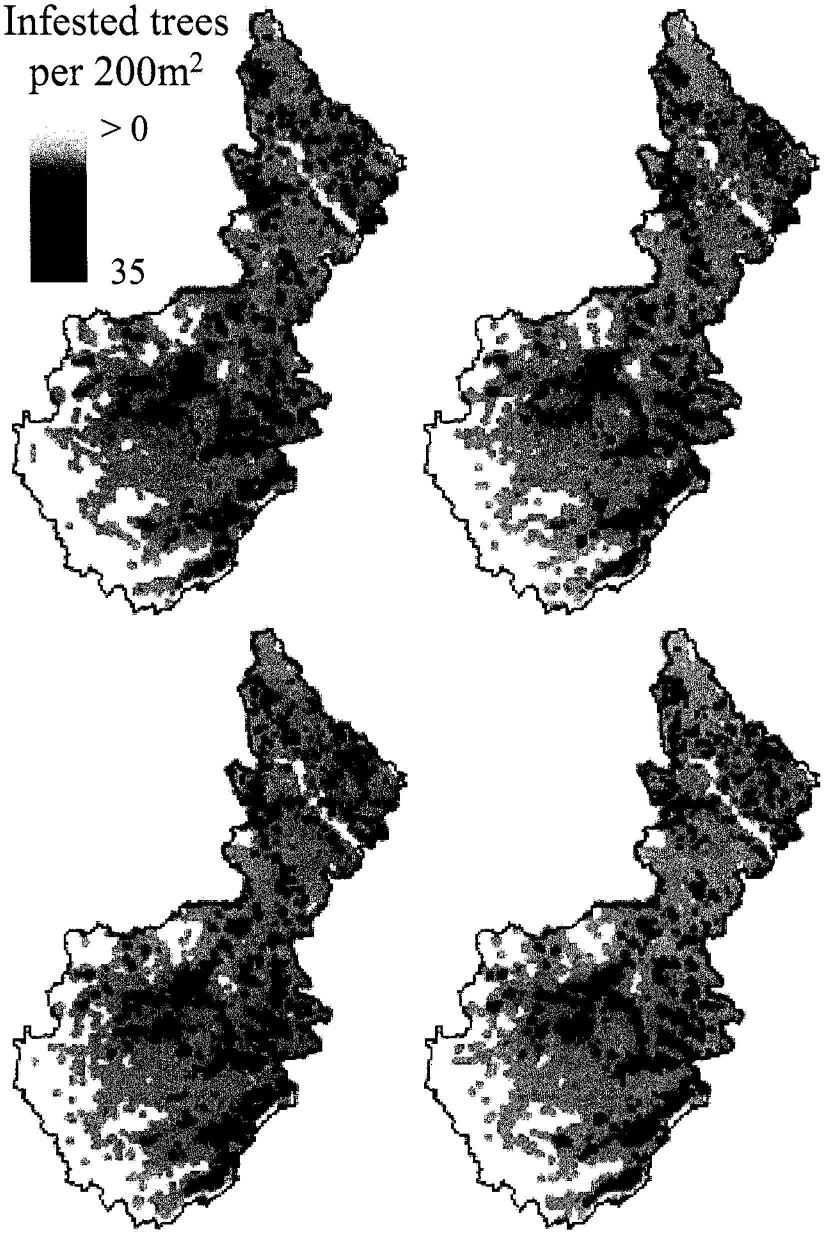


Figure 8.2. Four realizations of the kernel density estimated surfaces generated from randomizations of the 2002 data, conditional to 2001 forest risk in the Morice TSA.

A distinction was made between locations where the spatial pattern of infestation was statistically unexpected due to high observed values (high-unexpected) and those where the spatial pattern was statistically unexpected due to low observed values (low-unexpected). Identifying low-unexpected values was problematic in locations where there were no observed data. Cells with no data were always significantly low, yet at such locations it is possible that the random kernel values generated were always very small (*i.e.,* 0.0001). When no data are observed, many low-unexpected locations are likely meaningless, therefore only cells with observed values greater than zero were considered significantly low and meaningful. The drawback of this approach is that some meaningful low-unexpected areas may be lost; however, the benefit is the increased confidence that areas identified are of consequence.

The local nature of the test statistics allows the spatial variation in high- and low-unexpected locations to be mapped and visualized. Visualization was carried out for both single and multiple years. Due to the lack of low-unexpected areas, resulting from the exclusion of locations with no observed data, the multi-temporal analysis focused on high-unexpected locations. Spatial-temporal representations of randomization results are provided for each cell using the number of years with high-unexpected observed values and the percentage of active years that have high-unexpected values.

8.5 EXPLORING EXPECTED AND UNEXPECTED LOCATIONS WITH THE UNDERLYING LANDSCAPE

The landscape characteristics underlying locations of statistically expected and unexpected observed patterns were investigated as in the previous chapters (see Chapter 5 for details of methods). For each subarea, the relative frequency distributions for pine age, percent pine, elevation, and aspect underlying expected and unexpected locations were investigated and compared to the relative frequency distributions for all pine cells.

Comparisons were made for expected and unexpected locations identified in single and multiple time periods. This procedure allows investigation of landscape conditions associated with locations that are adequately and inadequately represented by the forest risk model when applied to a large area, and provides a mechanism for identifying adjustments that may improve landscape level modelling.

Owing to the large number of relative frequency distributions used to assess relationships between randomization results and the landscape, only a sample of distributions, representative of general trends, is presented. Due to the limited number of pixels having low-unexpected infestation magnitudes in multiple years, investigation of landscape characteristics associated with low-unexpected locations are presented for single years. Only results for percent pine and elevation are shown, as all relative frequency distributions associated with forest age and aspect, for low-unexpected locations, were similar to the distributions for all pine. For high-unexpected locations, results are shown for all landscape characteristics. Multi-temporal trends associated with the landscape characteristics of high-unexpected locations were similar regardless of the representation used (*i.e.,* the number of high-unexpected years versus the percentage of active years that are high-unexpected). As such, multi-temporal relationships between landscape characteristics and high-unexpected locations are demonstrated for a single multi-temporal representation. Relative frequency distributions of aspects associated with high-unexpected locations in multiple time periods did not deviate from aspect frequency distributions for all pine are not presented.

8.6 RESULTS AND DISCUSSION

8.6.1 Forest Risk

Using the modifications outlined above, susceptibility surfaces were generated for each year. However, only the susceptibility surface for 1995 is shown (Figure 8.3), as differences between years are minor and difficult to visualize. Susceptibility values range from zero to 100, with zero only occurring in locations without pine or where pine is less than 40 years old. Forest risk surfaces calculated for 1995 through 2001 are shown in Figure 8.4. The probability of forest risk ranges from zero to 100. For risk to equal zero, susceptibility must also be zero. As temporal changes to susceptibility are subtle, annual variations in risk are primarily the result of changes in beetle location. This can be demonstrated by comparing Figure 8.4 with Figure 4.9, where kernel density estimators are used to visualize infestation intensity.

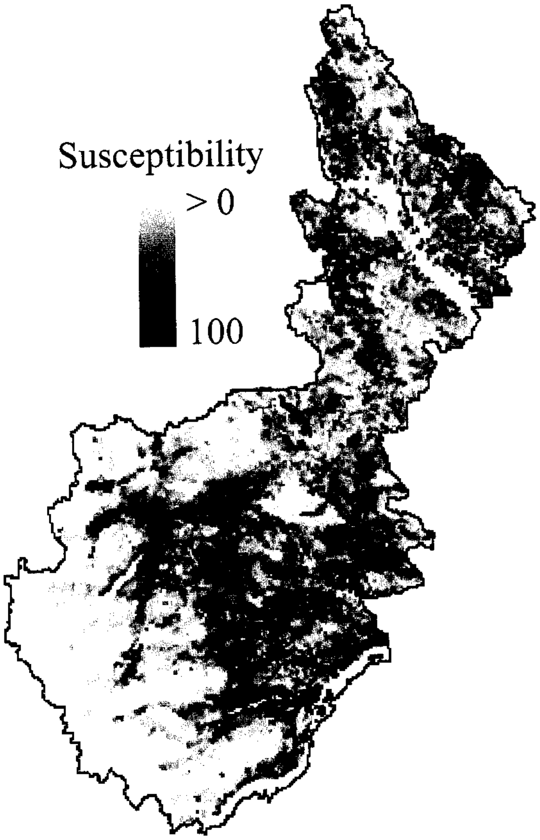


Figure 8.3. 1995 forest susceptibility to mountain pine beetle infestations in the Morice TSA.

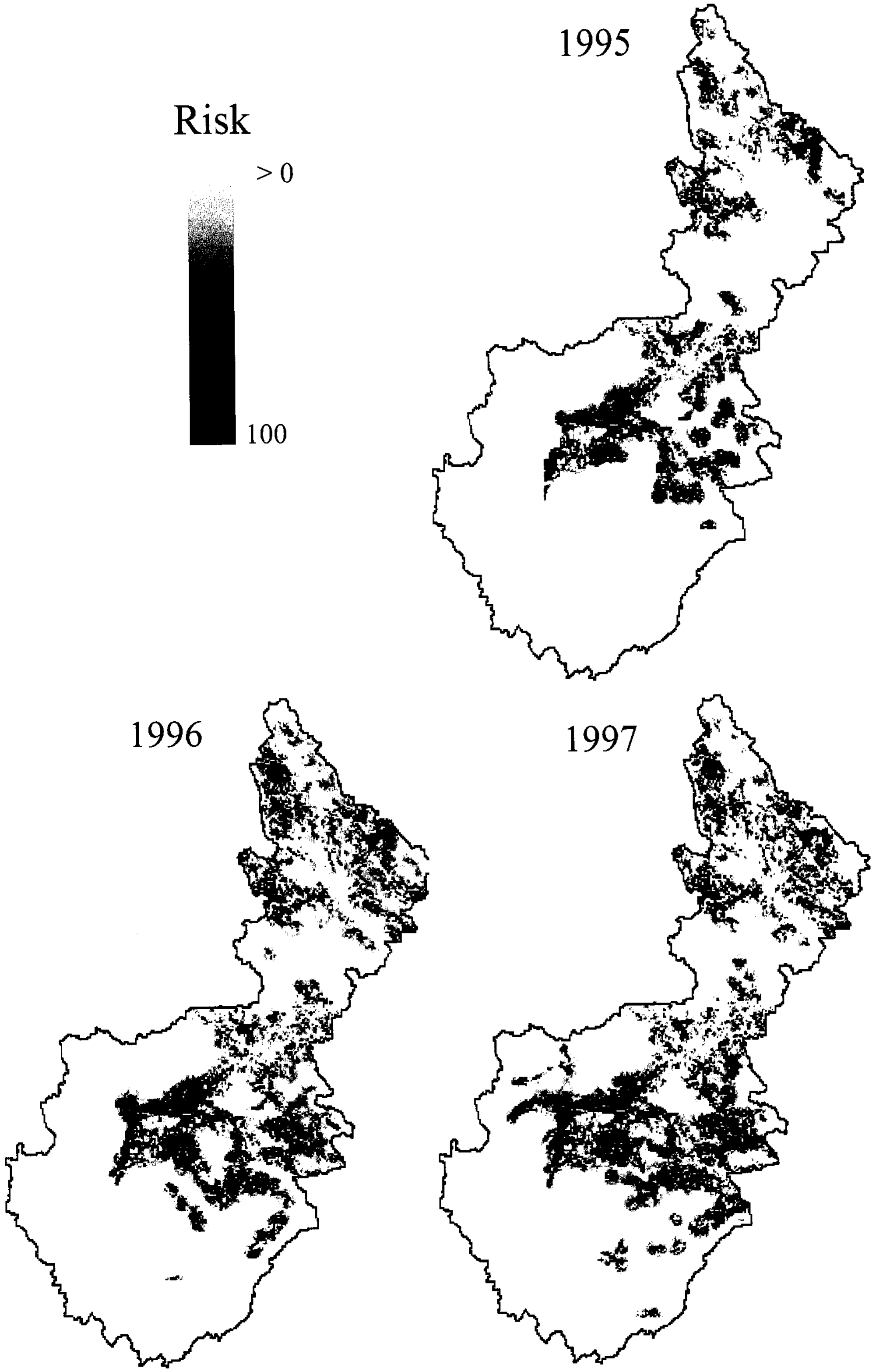


Figure 8.4. The probability of forest risk calculated for 1995 to 2001 in the Morice TSA.

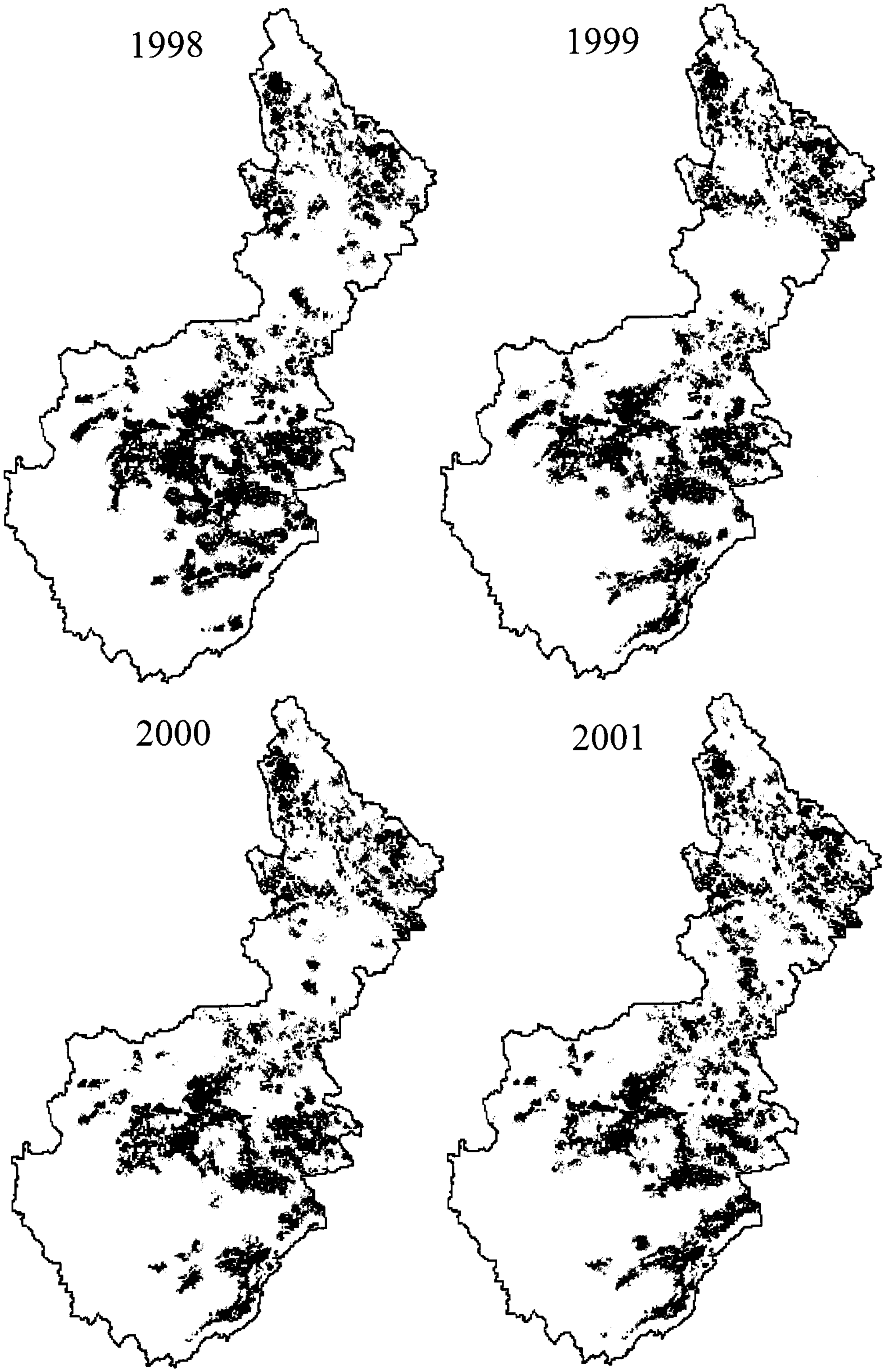


Figure 8.4. (continued) The probability of forest risk calculated for 1995 to 2001 in the Morice TSA.

Prior to reporting results of the conditional randomization, we demonstrate the impacts of modifying susceptibility when calculating risk. Unexpected locations in 2002, detected using randomizations conditioned on forest risk with and without modifications to susceptibility, can be seen in Figure 8.5. When susceptibility was not modified, 38,296 pixels had values that were statistically high-unexpected and 43,319 locations were low-unexpected (Table 8.15). The same comparison made using forest risk generated from modified susceptibility, resulted in fewer unexpected locations; 33,636 pixels were high-unexpected and 41,328 were low-unexpected. Most unexpected locations were the same in both methods (31,327 high-unexpected and 33,955 low-unexpected). However, the increased number of unexpected locations, associated with unmodified susceptibility, suggests that the alterations allow risk to more realistically represent forest conditions.

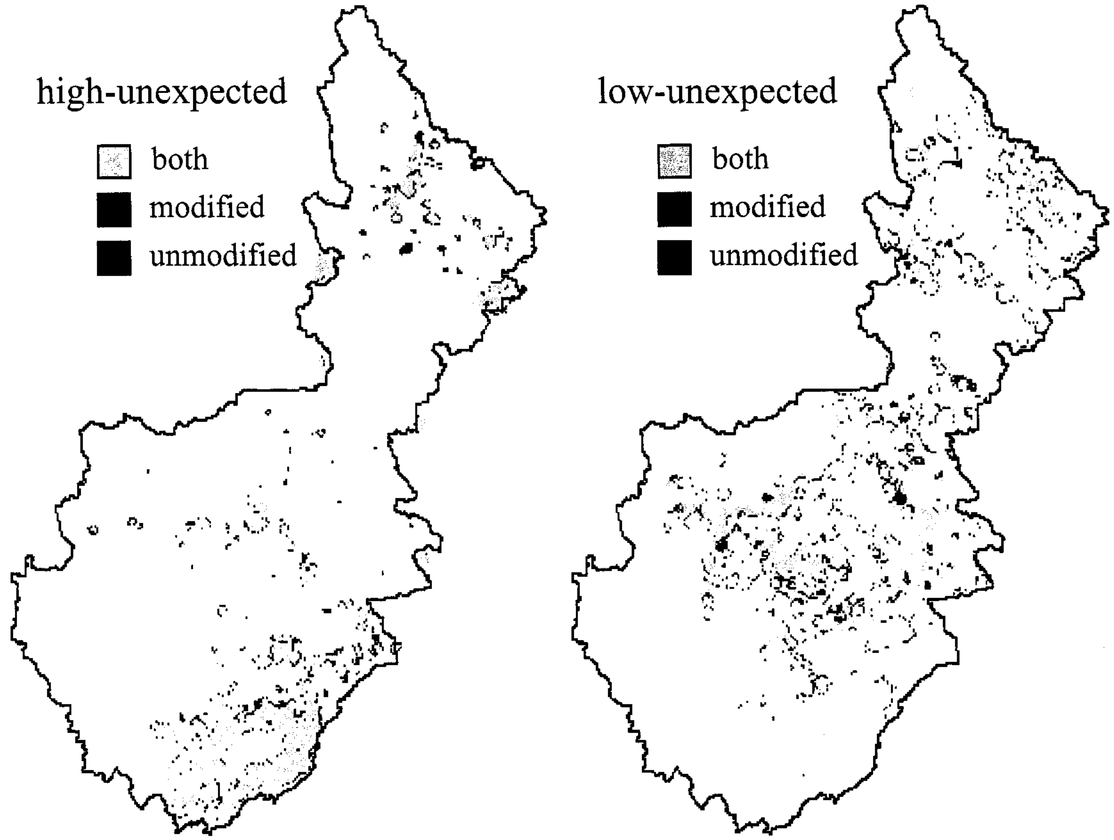


Figure 8.5. Comparison of 2002 randomizations conditioned on forest risk with modified and unmodified susceptibility in the Morice TSA.

Table 8.15. The number of unexpected pixels in 2002 when susceptibility is modified versus when susceptibly is not modified in the Morice TSA.

Method	**number of high-unexpected pixels**	**number of low-unexpected pixels**
susceptibility modified	33,636	41,328
susceptibility not modified	38,296	43,319
susceptibility modified only	2,309	7,373
susceptibility not modified only	6,969	9,364
both	31,327	33,955

8.6.2 Visualizing Expected and Unexpected Locations

For 1996 to 2002, locations identified as high-unexpected or low-unexpected can be seen in Figures 8.6 to 8.12. Generally, more locations are found to be significantly high than low. There are two possible explanations for this. The first is that under epidemic mountain pine beetle conditions the risk model is more likely to under estimate, rather than over estimate, risk. Alternately, these results may suggest that restricting the identification of significantly low areas to locations with observed data is too conservative.

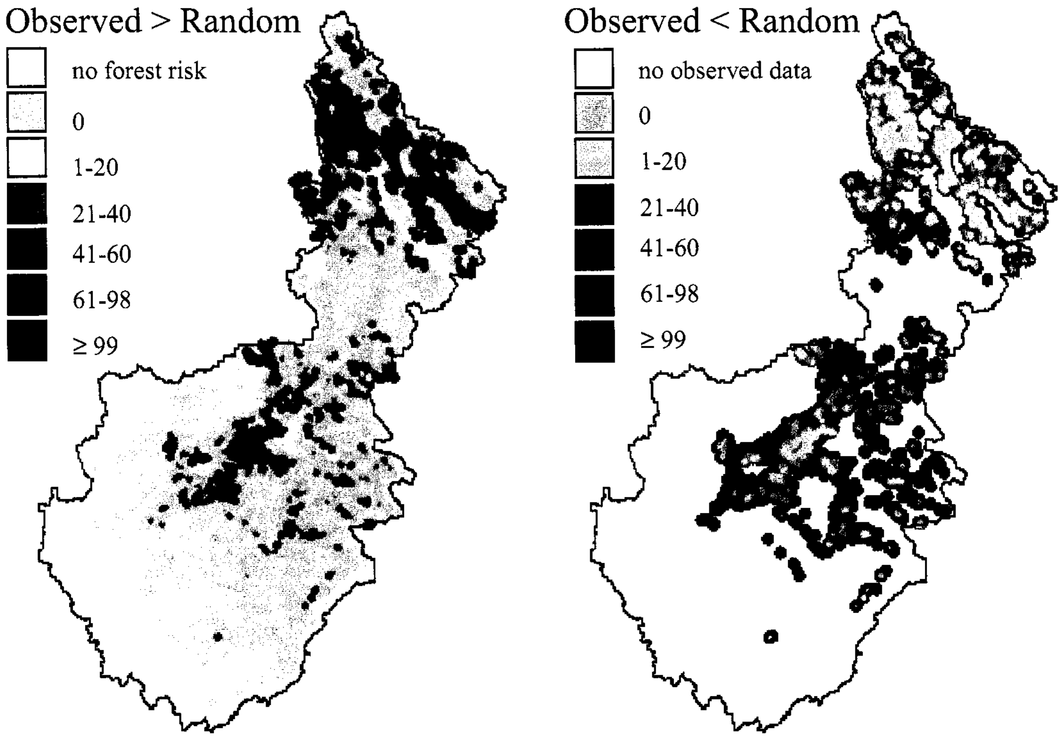


Figure 8.6. Conditional randomization results for 1996 in the Morice TSA. Black represents statistically significant locations.

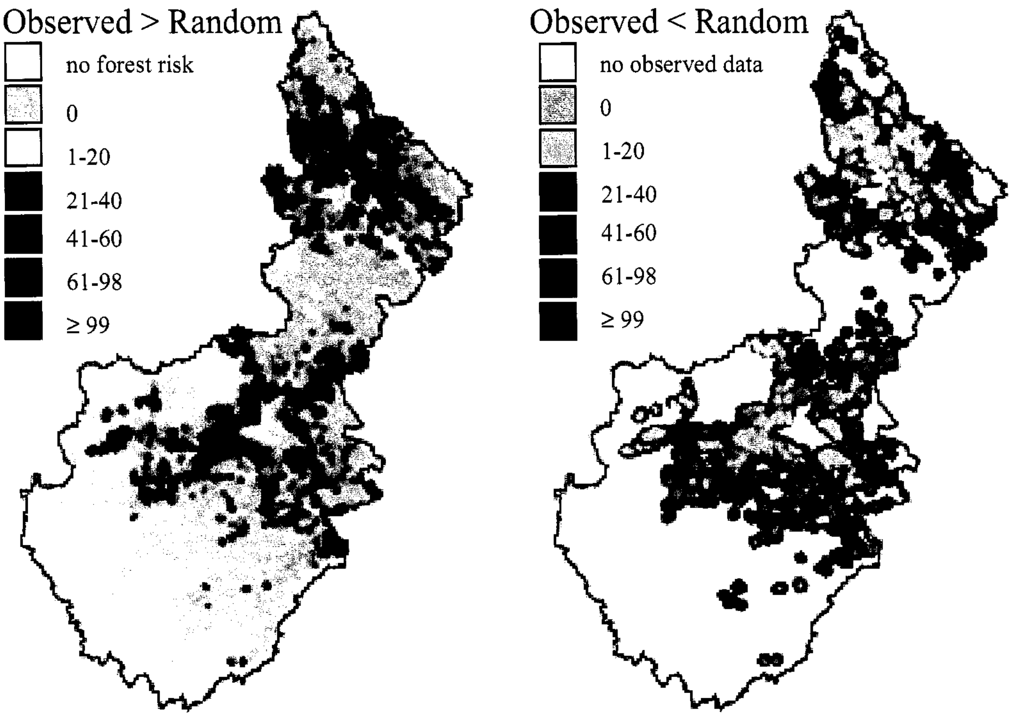


Figure 8.7. Conditional randomization results for 1997 in the Morice TSA. Black represents statistically significant locations.

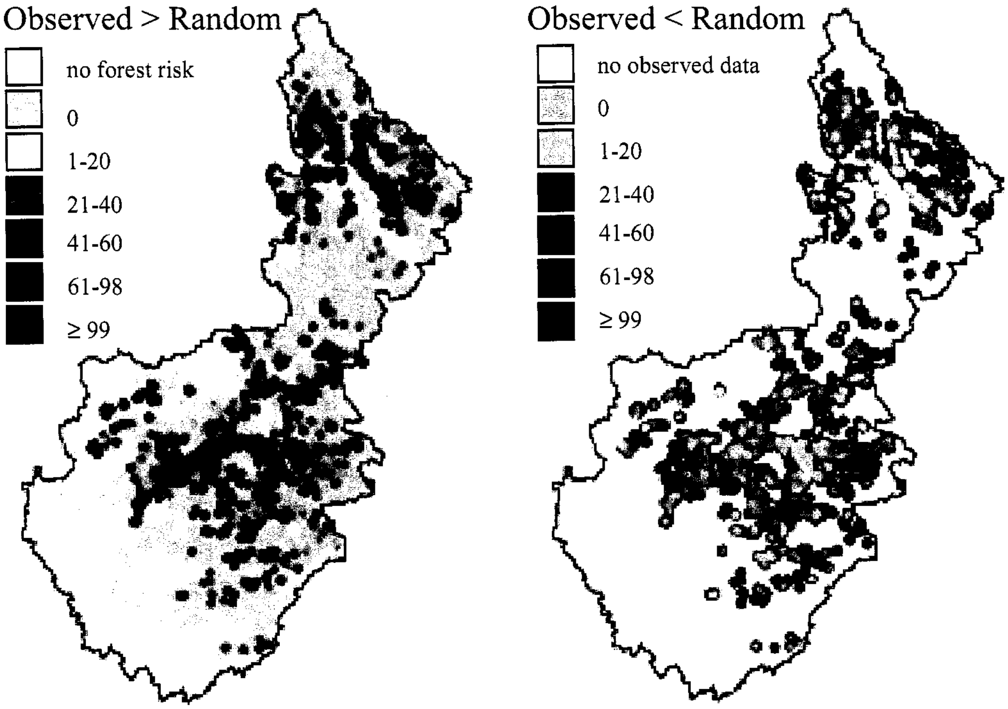


Figure 8.8. Conditional randomization results for 1998 in the Morice TSA. Black represents statistically significant locations.

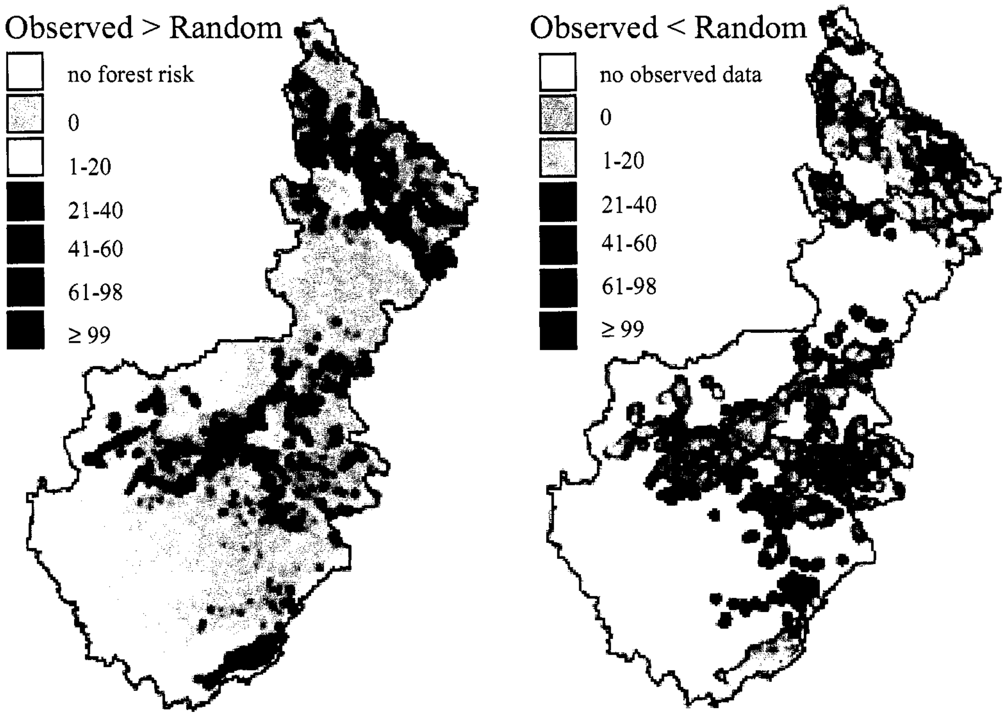


Figure 8.9. Conditional randomization results for 1999 in the Morice TSA. Black represents statistically significant locations.

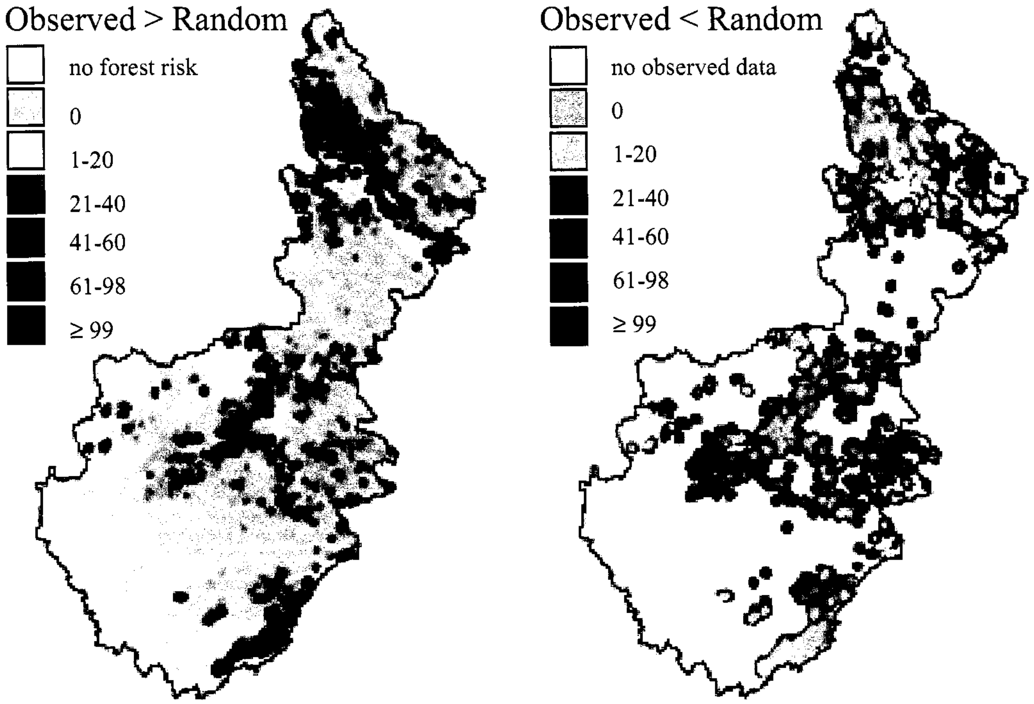


Figure 8.10. Conditional randomization results for 2000 in the Morice TSA. Black represents statistically significant locations.

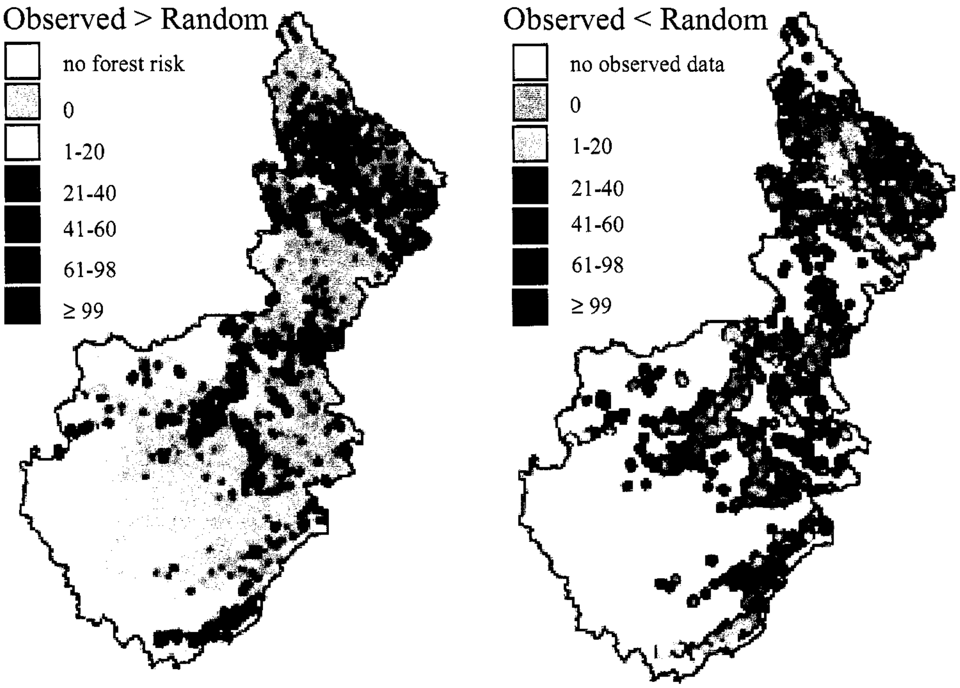


Figure 8.11. Conditional randomization results for 2001 in the Morice TSA. Black represents statistically significant locations.

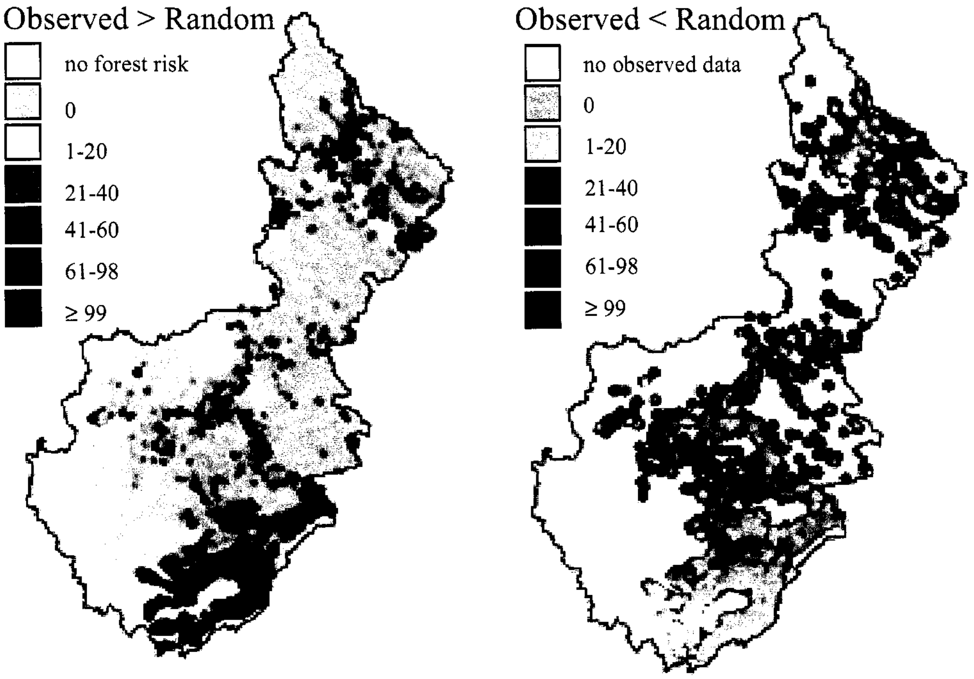
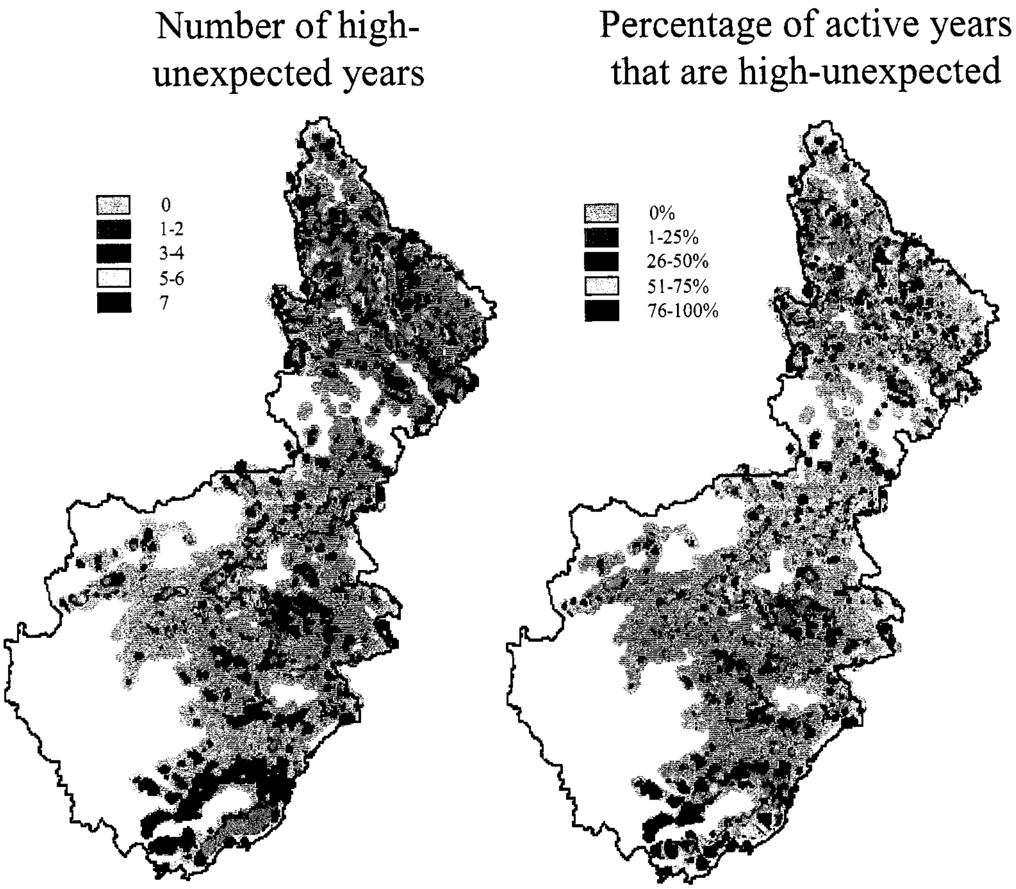


Figure 8.12. Conditional randomization results for 2002 in the Morice TSA. Black represents statistically significant locations.

Unexpected locations, whether high or low, cluster spatially. As with other spatial patterns (hot spots and change) groups of spatially continuous high- or low-unexpected locations clump together as patches. Consistency in the spatial configuration of unexpected locations from year to year provides assurance that unexpected spatial patterns are identified consistently over all time periods.

High-unexpected areas usually occur where the infestation is most active. For example, high-unexpected areas occur in the North and Middle subareas in the mid 1990s, but by 2002 the majority of high-unexpected pixels are found in the South subarea. This reflects trends in the intensity of mountain pine beetle activity in Morice. High magnitude infestations initially occur in the North and Middle subareas, but by 2002 the mountain pine beetle population was largest in the South. The spatial patterns of low-unexpected locations are less clear and typically occur at the periphery of the active areas.

The two multi-temporal representations of high-unexpected mountain pine beetle infestations are shown in Figure 8.13. Differences in these representations are clearest in the South subarea. Here, the number of high-unexpected years are typically few, yet a large percentage of active years are high-unexpected. In the Middle and North subareas, several locations that are high-unexpected for many years are also high-unexpected in a large percentage of active years. At pixels having many years with high-unexpected observed values, risk may be underemphasized, regardless of the annual variability in mountain pine beetle populations and forest conditions.



Number of high-unexpected years

Percentage of active years that are high-unexpected

Figure 8.13. Multi-temporal representation of high-unexpected locations in the Morice TSA from 1995 to 2002. Non-pine areas are white.

8.6.3 Expected and Unexpected Locations and Age

The relative frequency distribution of forest age associated with high-unexpected mountain pine beetle populations becomes more similar to the distributions for all pine, as infestations age (Figure 8.14). Most commonly, the forest age of pixels with high-unexpected infestation magnitude is 180 years in the North subarea, 140 years in the Middle subarea, and older than 180 years in the South subarea. The reason for the unique trend in the Middle subarea is unclear, but may be related to the lower proportion of trees that are 180 years old in this area.

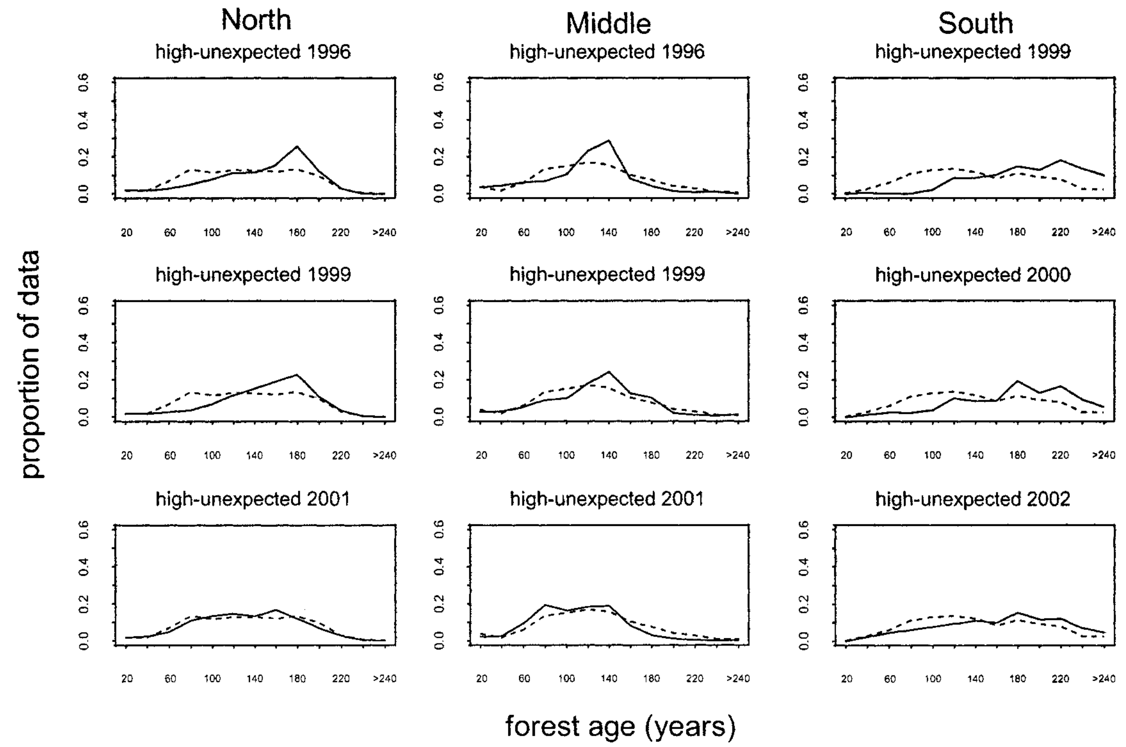


Figure 8.14. Partitioned by Morice TSA subareas, relative frequency distributions of forest age for high-unexpected pixels (solid line) and all pine pixels (dotted line).

Comparisons between the percentage of high-unexpected years that were active and forest age, show that relative frequency distributions become more different from the distributions associated with all pine as the number of high-unexpected years increase up to 75 percent (Figure 8.15). For high-unexpected pixels, identified in both single and multiple years, age relative frequency distributions are always similar to distributions for all pine pixels. Relationships vary spatially for cells with high-unexpected intensity in greater than 75 percent of active years. In the North subarea, the relative frequency distribution is similar to the age distribution for all pine. In the Middle subarea, there was a sharp increase in the number of locations associated with forests 80 years old, while in the South subarea the distribution became similar to the relative frequency distribution for all pine pixels except more pixels were found in age classes greater than 220 years.

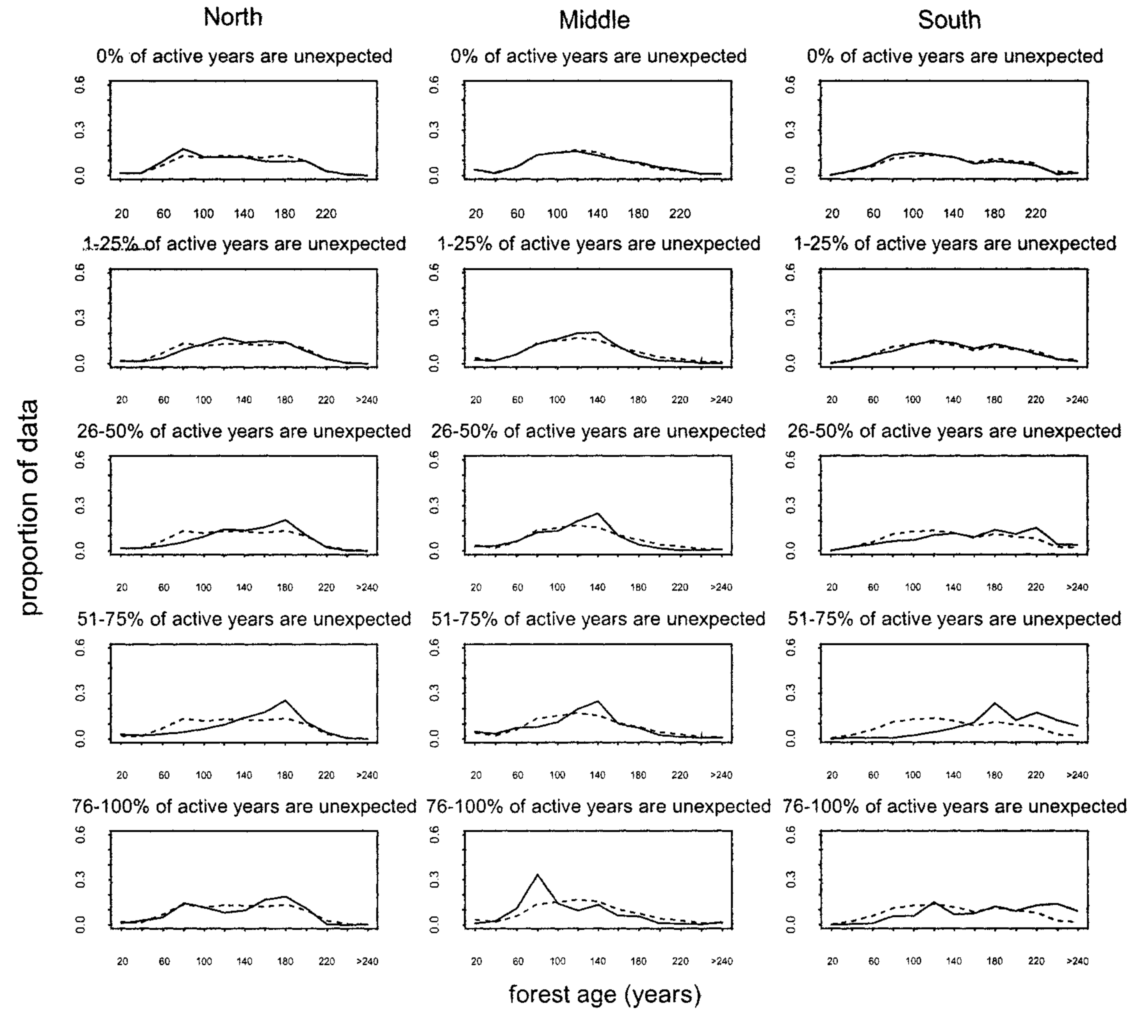


Figure 8.15. Partitioned by Morice TSA subareas and the percentage of active years that are high-unexpected, the relative frequency distributions of forest age for high-unexpected pixels (solid line). For comparison, the forest age relative frequency distributions for all pine pixels are also provided (dotted line).

Under epidemic conditions these results may suggest that the forest risk model under predicts risk for some forest age classes relative to others. It appears, that at a landscape scale, relationships between forest age and risk vary over the infestation lifecycle. The difference in the trends found for pixels that have high-unexpected infestation intensity for greater than 75 percent of active years, versus those high-unexpected for fewer years, may also indicate that the duration of risk and the occurrence of risk in a single year are related to separate factors. For example, in the Middle subarea during the 1990s, forest risk may be higher than calculated for forests 140 years old (see Figure 8.14). Yet, higher than expected infestations repeatedly occur in younger stands approximately 80 year old (see Figure 8.15).

8.6.4 Expected and Unexpected Locations and Percent Pine

The percentage of pine associated with high-unexpected locations varies markedly for each subarea (Figure 8.16). In the North subarea, locations with high-unexpected values tend to be associated with low percent pine pixels (30%), in the Middle subarea they are more associated with high percent pine pixels (60 to 70%), and in the South subarea moderate percent pine pixels (30 to 50%) dominant. In the Middle and South subareas, as the infestation ages the relative frequency distributions of high-unexpected areas become more similar to the relative frequency distributions of percent pine for all pine pixels.

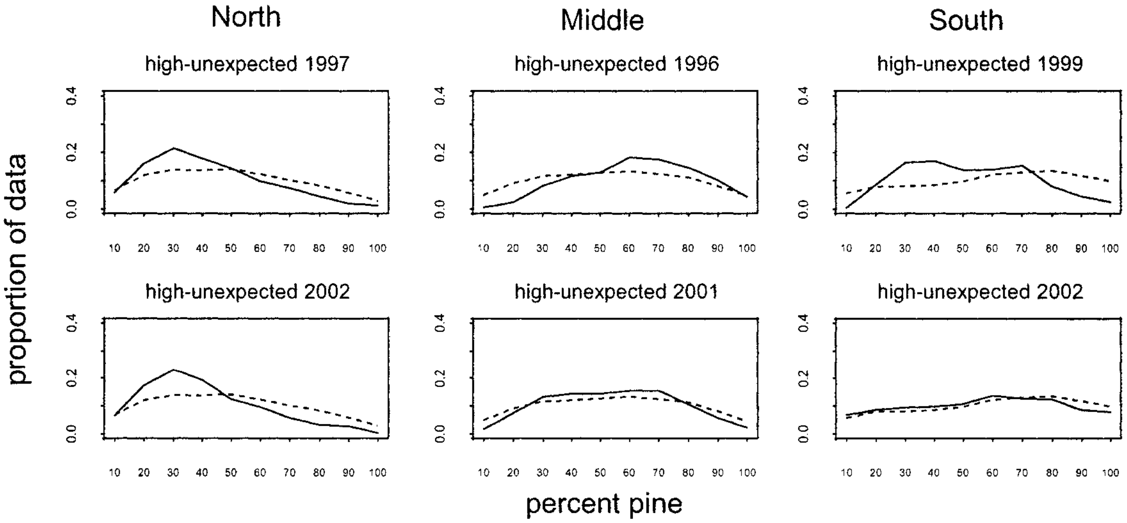


Figure 8.16. Partitioned by Morice TSA subareas, relative frequency distributions of percent pine for high-unexpected pixels (solid line) and all pine pixels (dotted line).

The relationship between the percentage of active years that are high-unexpected and pine has comparable trends to those seen for age (Figure 8.17). Relative frequency distributions associated with pixels having a greater percentage of high-unexpected years are more different from the relative frequency distributions for all pine pixels. In the Middle and South subareas, unexpected trends exist when greater than 75 percent of active years are high-unexpected. In the Middle subarea, cells with 60 percent pine dominate the distribution, and in the South subarea there is a sharp increase in the number of pixels associated with 10 percent pine. While variability in subarea trends makes commenting on the relationship between high-unexpected locations and pine difficult, it seems that risk is over emphasized for locations of high percent pine.

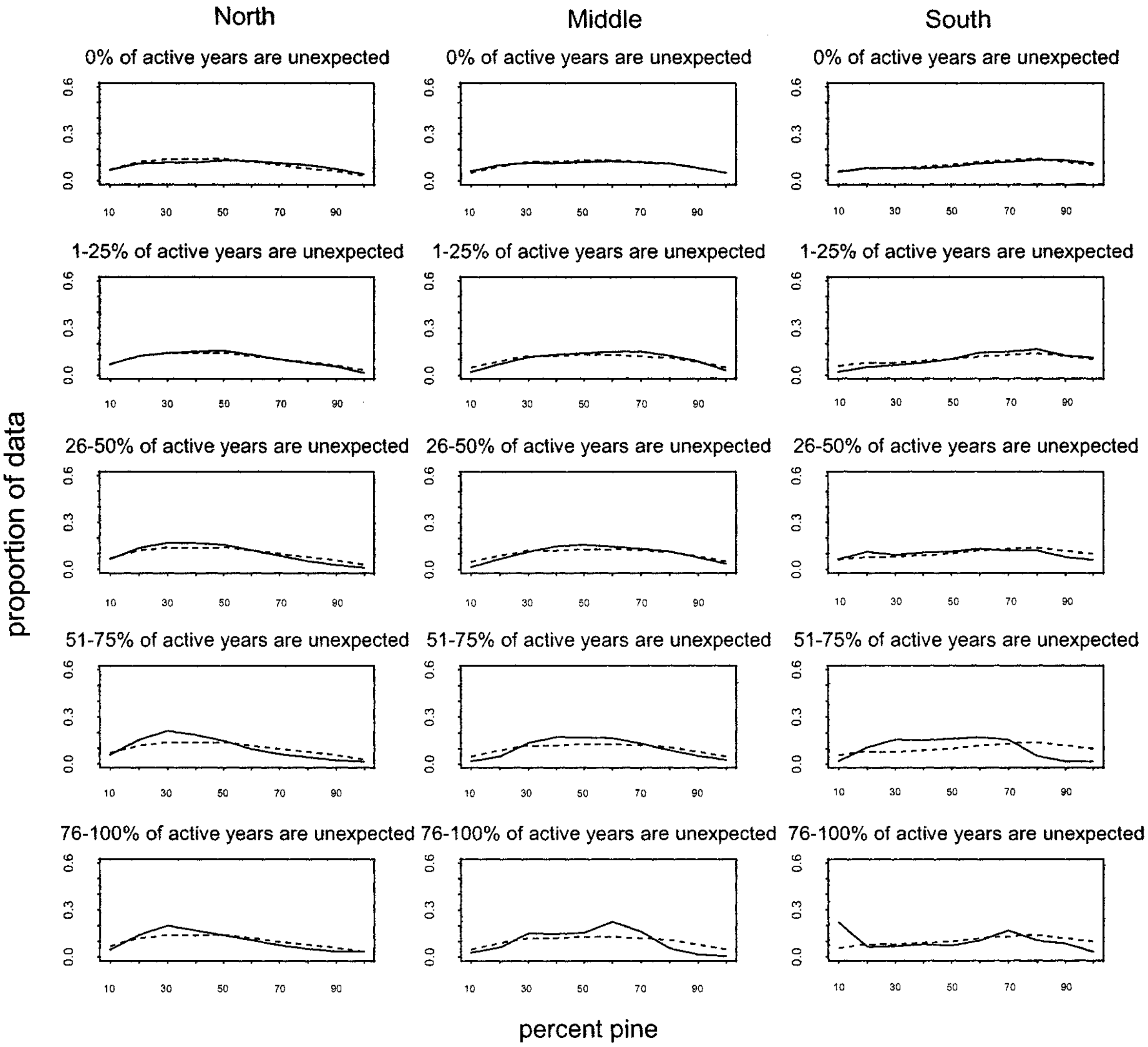


Figure 8.17. Partitioned by Morice TSA subareas and the percentage of active years that are high-unexpected, the relative frequency distributions of percent pine for high-unexpected -pixels (solid line). For comparison, the percent pine relative frequency distributions for all pine pixels are also provided (dotted line).

Low-unexpected pixels have a more consistent relationship with percent pine than high-unexpected pixels (Figure 8.18). Typically low-unexpected locations are associated with pixels having the highest percentages of pine (greater than 60 percent). It is interesting that in the North and Middle subareas, forest age distributions associated with pixels having low-unexpected values are most similar to the distributions for all pine in the early years of the infestation.

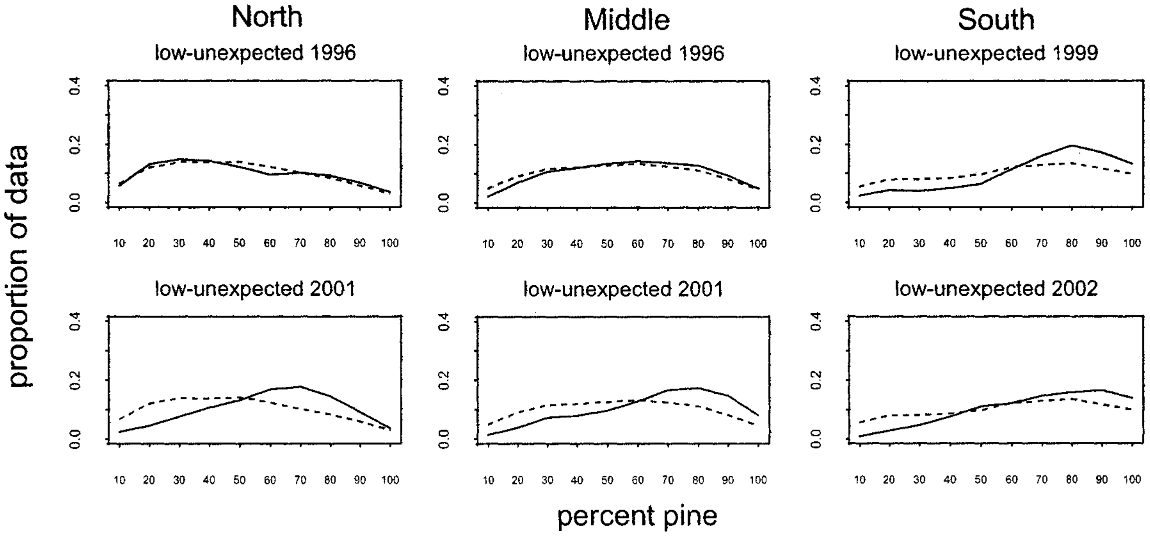


Figure 8.18. Partitioned by Morice TSA subareas, relative frequency distributions of percent pine for low-unexpected pixels (solid line) and all pine pixels (dotted line).

8.6.5 Expected and Unexpected Locations and Elevation

When high-unexpected locations are compared to elevation, a larger percentage of cells is associated with lower elevations than are distributions for all pine locations (Figure 8.19). In the North subarea, there is no dominant elevation consistently related to high-unexpected locations. However, in 2002, there is an abundance of high-unexpected pixels associated with 700 metres. In the Middle subarea, elevations of 800 metres consistently have a strong association with high-unexpected locations, while in the South subarea elevations of 800 to 900 metres prevail.

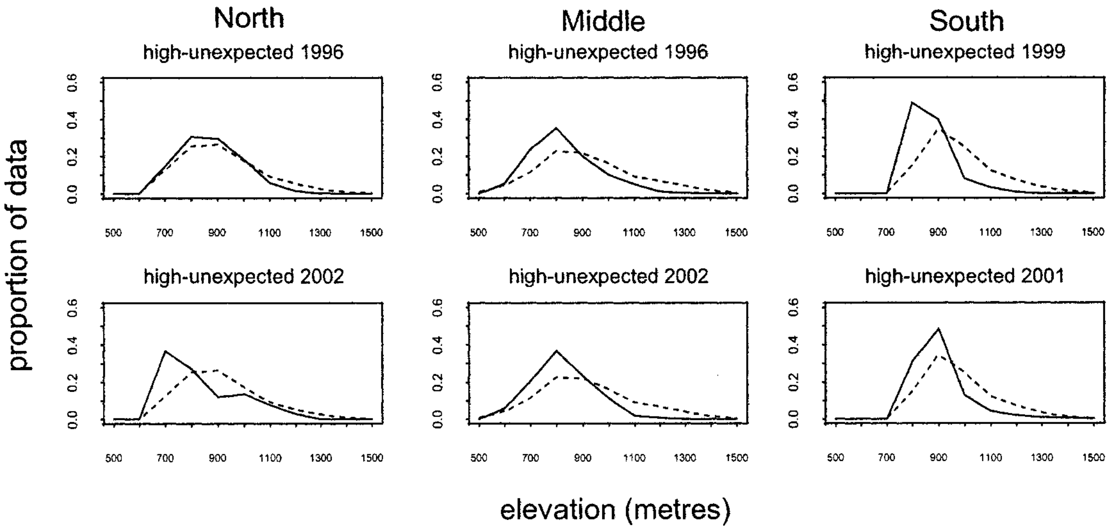


Figure 8.19. Partitioned by Morice TSA subareas, relative frequency distributions of elevation for high-unexpected pixels (solid line) and all pine pixels (dotted line).

The relative frequency distributions for elevations associated with the percentage of active years that are high-unexpected are seen in Figure 8.20. Locations with mountain pine beetle magnitudes that are never unexpected are less frequently found at 800 and 900 metres than anticipated based on the distributions for all pine locations. The South subarea also shows that elevations of 800 metres are the most likely to have unexpected patterns in all years. As the percentage of active years having high-unexpected spatial patterns increase, more pixels are associated with elevations of 700 to 800 metres in the North, 800 metres is the Middle, and 900 metres in the South subareas. In all subareas, trends change for pixels where greater than 75 percent of active years are high-unexpected; in the North pixels at 700 and 1000 metres are prevalent, in the Middle elevations of 900 and 1000 metres dominant, and in the South elevations greater than 1100 metres are the most common. Generally, this suggests that when pixels are often high-unexpected, elevations are high. There also seems to be a trend whereby pixels with high-unexpected values are associated with lower elevations as latitudes become more northerly. While additional data on climate is necessary to further investigate elevation trends, it appears a relationship exists between elevation and climate over different latitudes. As latitudes increase, temperatures warm enough to support large mountain pine beetle populations are limited to lower elevations.

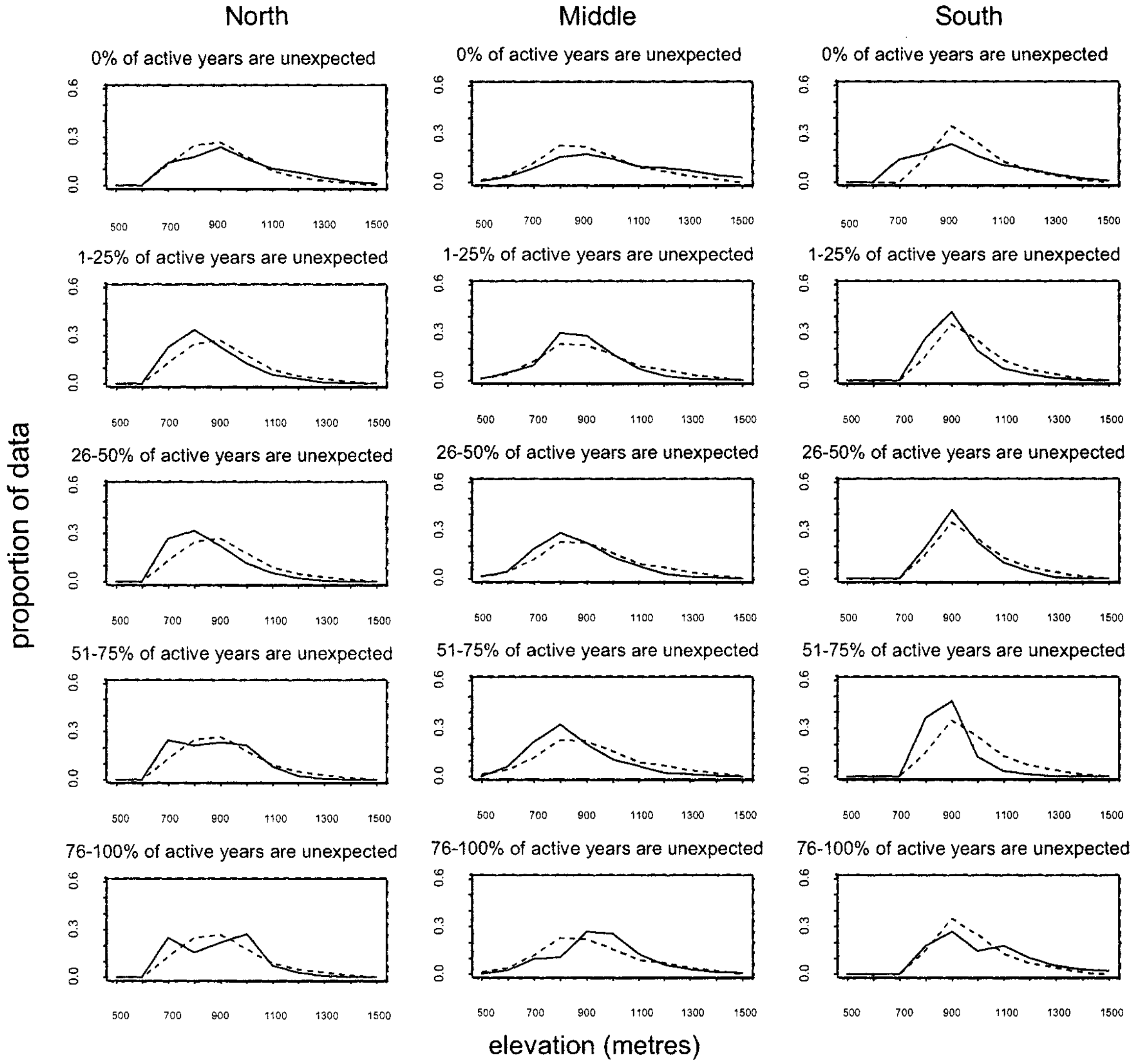


Figure 8.20. Partitioned by Morice TSA subareas and the percentage of active years that are high-unexpected, the relative frequency distributions of elevation for high-unexpected pixels (solid line). For comparison, the elevation relative frequency distributions for all pine pixels are also provided (dotted line).

The relative frequency distribution of elevation associated with low-unexpected pixels have interesting trends in the South, where they are dominated by elevations ranging from 800 to 900 metres (Figure 8.21). Both high- and low-unexpected locations in the South subarea are associated with similar elevations. Throughout this thesis, analyses of elevation trends have been difficult to interpret and this is no exception. However, it seems that generally risk is under predicted for lower, likely warmer, elevations.

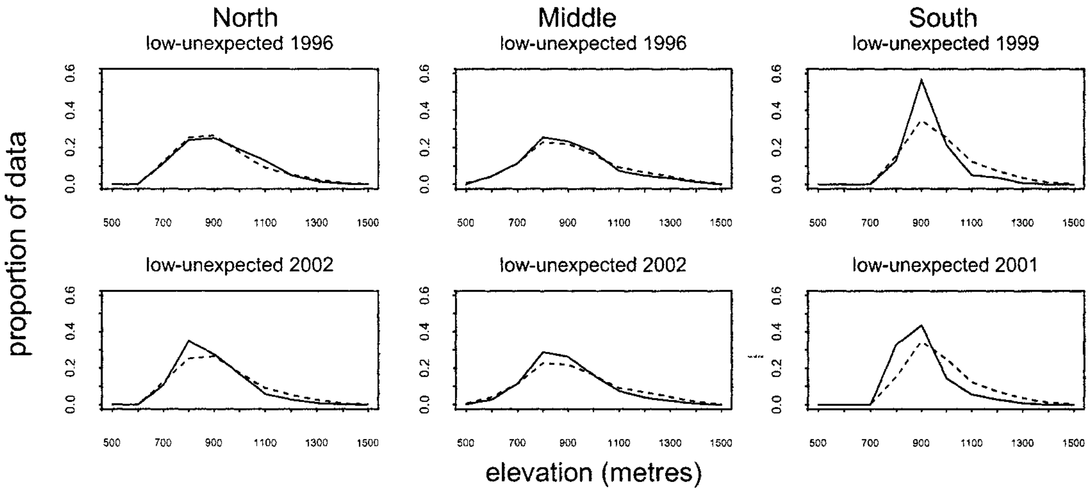


Figure 8.21. Partitioned by Morice TSA subareas, relative frequency distributions of elevation for low-unexpected pixels (solid line) and all pine pixels (dotted line).

8.6.6 Expected and Unexpected Locations and Aspect

Only the South subarea shows meaningful relationships with aspect (Figure 8.22). In general, south facing slopes are more related to high-unexpected cells and through time, the relative frequency distribution associated with high-unexpected areas becomes more similar to the relative frequency distribution for all pine pixels. Results may indicate that aspect, which is currently not a risk model parameter, is an important consideration during the initial stages of a mountain pine beetle epidemic.

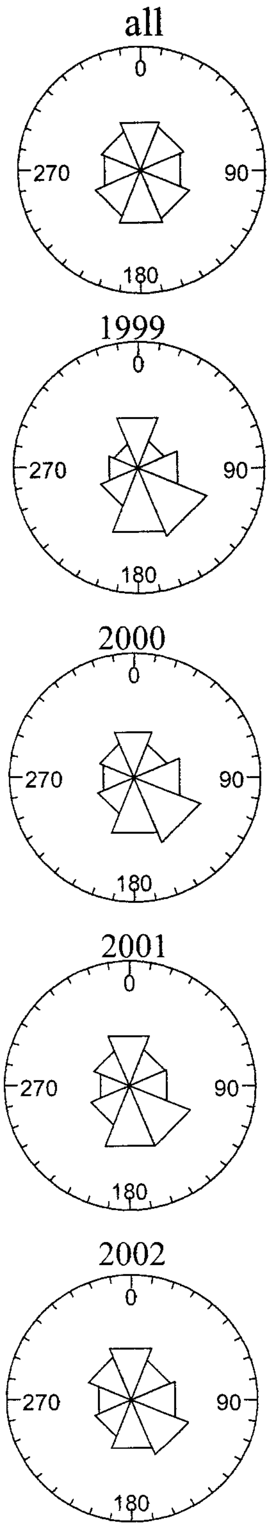


Figure 8.22. For the South subarea of the Morice TSA, relative frequency distributions of aspect (degrees) for pixels with high-unexpected values and all pine pixels.

8.7 SUMMARY

The forest risk model used in this study incorporates much of the current knowledge regarding mountain pine beetle behaviour. While developed at a stand level, forest risk has potential for application to large areas. Forest risk is the probability of loss in stand volume due to infestation, and is not meant to predict the exact location of mountain pine beetle infestations. Therefore, direct comparisons between the level of risk and the observed infestation magnitude is insufficient for investigating the utility of applying forest risk models to large areas.

Taking advantage of the probabilistic output and time scale associated with forest risk, we conditioned randomizations of observed data on forest risk to investigate variations in the suitability of the model over large areas. Generating the forest risk model for our purposes required a number of modifications, some of which may be useful in other contexts. For instance, converting the spatial unit of the risk model from forest inventory polygons to raster grid cells, allows increased precision to the beetle pressure component of the model. Although temporal modifications to susceptibility are coarse, they appear useful for identifying key locations of reduced susceptibility and improve the fit between model output and observed data.

Four randomization algorithms were investigated. A cluster-based algorithm that allocated data using an inhomogeneous planar Poisson process, in which the presence and size of infestation clusters are randomly assigned in proportion to risk, is the most appropriate of those examined. This algorithm has the benefit of retaining the attribute distribution of the empirical data whilst providing a realistic representation of mountain pine beetle processes. Exploring additional algorithms indicates that infestation of individual trees is not independent; rather, the aggregative processes associated with stand scale mountain pine beetle behaviour are expressed at a landscape level.

Spatial dependence is inherently incorporated through the conditioning of randomization on the risk model. However, a limitation of all the randomization approaches is that they do not explicitly consider spatial dependence of the empirical data. Explicit consideration of spatial dependence may have additional benefits and characterizing the spatial dependence of infestations will provide further insights into mountain pine beetle spatial processes. Generally, an adequate method for considering the spatial structure of observed data during randomization is lacking and further research in this area would benefit a wide range of spatial randomization investigations.

Conditional randomizations allow identification of cells where observed infestation magnitudes were both high-unexpected and low-unexpected. High-unexpected locations were found more often than low-unexpected locations. The abundance of high-unexpected locations may suggest that risk tends to be under predicted where mountain pine beetle populations are at epidemic levels. The presence of few low-unexpected locations may alternately be an artifact of restricting such findings to pixels with data.

Visualizing high-unexpected pixels in many time periods provides evidence of space-time variability in the effectiveness of risk modelling over large areas. In some cells the observed infestation is always higher than values generated from randomizations conditioned on forest risk and in other cells this is never the case. This may suggest that the primary difficulty in applying stand level models to landscapes is the variability associated with large areas. The abundance of high-unexpected locations may also relate to the atypical nature of the current mountain pine beetle population in British Columbia. The forest susceptibility, beetle pressure, and forest risk models were all developed for incipient and epidemic mountain pine beetle populations. While conditions in the early and mid 1990s could be considered epidemic, by 1999 the infestation had become a pandemic. Therefore, we need to be cautious when interpreting results, particularly those that are derived from observations made after 1999.

Visualization demonstrates that, rather than being dispersed over the landscape, unexpected pixels cluster spatially. Since this characteristic is consistent over space and time, it may indicate that there is a systematic component to landscape level mountain pine beetle processes that is not accounted for by the forest risk model.

Exploring the relationship between unexpected pixels and landscape characteristics reinforces the view that there is spatial and temporal variability in the forest risk model's ability to represent forest conditions. Trends between unexpected locations and landscape characteristics are inconsistent between subareas and change with the duration of infestations. At a stand level, forest age is considered a well-understood component of mountain pine beetle behaviour. At a landscape scale, the relationship between forest age and risk of attack by epidemic mountain pine beetle populations seems to be regulated by local factors and shows substantial variability.

While the percentage of pine is not the preferred attribute for implementing forest risk, the nature of available data necessitates in its use. Although the percentages of pine most commonly associated with unexpected observed patterns are variable between subareas, it appears that risk may be overemphasized for pixels with a high percentage of pine. High-unexpected cells are most often associated with low percentages of pine and low-unexpected pixels occur where percentages of pine are greater.

For each subarea, the observed infestations are typically higher than expected at low elevations and lower than expected at high elevations. Warmer temperatures at low elevations result in greater susceptibility to mountain pine beetle populations.

While the susceptibility and risk models are developed using a stand level understanding of beetle behaviour, the location factor, which considers the impact of temperature, is generalized for the province of British Columbia. The location factor is perhaps best suited for coarse grained analysis of large areas, and would also likely perform well for fine grained analysis of small areas, when the impacts of climate are fairly homogenous. Model results are best interpreted relative to one another and the impact of climate over small areas will be small. Performance of the climate factor will likely be inadequate when analysis is fine grained and the spatial extent of the study area large. In such cases, the heterogeneity within the study area will be substantial and the detail of the location factor insufficient.

Aspect, which is not included in the model, may be an important factor in some mountain pine beetle infestation scenarios. Particularly during the initial phase of infestation, southern slopes appear to be at higher risk than other locations. Associations with aspect, draw attention to the importance of climate conditions on mountain pine beetle populations. Although investigations of wind and temperature are typically limited by the lack of available data, it is likely that such factors are influential.

Exploratory investigation of the associations between unexpected spatial patterns and the landscape are an important fist step to optimizing the representation of landscape scale risk. These initial analyses have indicated that associations between mountain pine beetle and landscape characteristics change through time, and formal quantification of this relationship would have utility. Such analysis should consider if the driver behind temporal variability in how mountain pine beetle utilize the landscape is related to host depletion. As landscape characteristics are dependent, multivariate analysis may also be useful. Finally, future work on the impact of spatial grain and extent on the expression of mountain pine beetle spatial processes will a better understanding of the impact of applying stand level processes to large areas.

9 CONCLUSIONS

British Columbia is currently experiencing the largest mountain pine beetle epidemic on recorded. With over seven million hectares of forest affected (Westfall, 2004) the impact has already been substantial. The spatial extent of the current epidemic has highlighted the importance of understanding large area mountain pine beetle behaviour. As well, over the last decade, there has been a growing awareness of the need to consider spatial aspects of ecological phenomena and the physical environment. Recognizing the benefit of an improved understanding of both spatial and large-area mountain pine beetle behaviour, the goal of this research is to explore landscape scale spatial and spatial-temporal patterns of lodgepole pine mortality caused by epidemic mountain pine beetle populations.

Monitoring programs, combined with technological advancements in data collection and storage, have generated unique large area and multi-temporal data sets. The Morice TSA has collected point data on mountain pine beetle infestations, via GPS helicopter surveys from 1995 to 2002, for a 1.5 million hectare area. Such data provide an unprecedented opportunity to explore the spatial and spatial-temporal patterns of mountain pine beetle infestations over large areas.

A spatial understanding of phenomena often begins with exploratory analysis. As knowledge of large area spatial mountain pine beetle dynamics is in its infancy, much of the research in this thesis takes on an exploratory nature. By characterizing spatial and spatial-temporal patterns observed in large area mountain pine beetle infestations many of the results presented become the starting point for hypothesis-based investigations. Research results also provide new information to decision makers and will benefit efforts to model mountain pine beetle spatial processes through time.

In this section we summarize results from seven key research areas including:

1. Aerial survey accuracy,
2. Kernel density estimation,
3. Landscape characteristics associated with hot spots,
4. Dispersal,
5. Spatial-temporal patterns of change in infestation rates,
6. Conditional randomization, and
7. Forest risk modelling.

For each research area, we outline key findings, implications for mountain pine beetle management and research, and suggest directions and topics of future research. This material is summarized in Table 9.1.

Table 9.1. Summary of the key research areas, findings, implications, and future research directions.

Research Area	Key Findings	Implications	Future Research
Aerial survey accuracy	Most survey points have small attribute errors (87% of errors ± 10 trees).	Aerial survey data quality is suitable for management, but errors should be considered when undertaking spatial analysis.	Randomly selecting the locations of some field sites will enable assessment of infested areas missed during areal surveys.
	Aerial data best represent infestations that occurred one to two years previously.	As found in other studies, aerial surveys are inappropriate for detecting green attack.	
	The main source of error is related to the timing of crown foliage discolouration.	Modifications to aerial surveying procedures are unlikely to improve monitoring. Field programs are important for ensuring quality data collection.	
Kernel density estimation	Using kernel density estimators to visualize point data on mountain pine beetle infestations improves data representation.	Visualization using kernel density estimators improves communication of large area point data.	
	It is possible to incorporate uncertainty when visualizing large uncertain point data sets.	Methods for dealing with uncertainty will enable spatial analysis of existing large area and multi-temporal data sets.	Using kernel density estimators and Monte Carlo simulations the impact of incorporating uncertainty into other data sets should be investigated.
	Kernel density estimators can be a beneficial pre-processing step when analysing point data through space and time.		In future work the impact of kernel density estimator cell size (spatial resolution) on spatial analysis should be explored.
Landscape characteristics and hot spots	Hot spots, defined using a threshold of the 90th percentile of infestation intensity, have unique underlying landscape characteristics when compared to all pine locations.		Alternate definitions of hot spots should be explored.
	Relationships between landscape characteristics and hot spots change through time.	Strategies for mountain pine beetle management and model attribution should vary over the infestation cycle.	It would be helpful to know if the temporal variability of associations between hot pots and landscape characteristics are related to host depletion.

	Associations between hot spots and landscape characteristics show that conditions leading to infestation development are not the same as conditions that support infestations with a long duration.		Multivariate analysis may be beneficial for dealing with relationships between landscape characteristics.
Dispersal	Three types of dispersal are observed at a landscape scale: coalescence, short-range dispersal, and long-range dispersal.	Models of spread should include both short- and long-range dispersal.	Are the spatial and spatial-temporal patterns observed for hot spots and hot spot patches different than those expected under a random scenario? Investigate spatial-temporal relationships in hot spot patches through multiple time periods.
	Hot spots patches that result from short-range dispersal persist longer than those resulting from long-range dispersal.	Focus treatment efforts on patches that intersect with patches in the previous year, as populations in patches without intersections are more likely to decline naturally.	Are the spatial and spatial-temporal patterns observed for hot spots and hot spot patches influenced by the underlying landscape characteristics?
Spatial-temporal patterns of change in infestation rates	Change is not persistent through time and spatial-temporal relationships of change are often random.		Investigate alternate definitions of change. Are the spatial and spatial-temporal patterns observed for change different than what would be expected under a random scenario?
	When compared to mountain pine beetle population growth, population decline seems to be slower and more localized.	The typical size of negative change patches ($3km^2$), likely represents the size of effective treatment.	Are the spatial and spatial-temporal patterns observed for change influenced by the underlying landscape characteristics?
Conditional randomization	Randomization algorithms based on mountain pine beetle stand behaviour are currently the most suitable approach to landscape scale randomizations.	It is important to consider the characteristics of the phenomenon being studied when undertaking randomization.	Characterize the nature of spatial dependence in mountain pine beetle infestation clusters and develop a randomization approach that considers spatial dependence.
	Aggregative behaviour observed at a stand scale is expressed at landscape levels.	When detailed information on large area mountain pine beetle behaviour is unavailable, stand-level trends are an appropriate starting point.	Investigate the relationship between spatial dependence in risk model output and spatial dependence in mountain pine beetle data.
Forest risk modelling	Adjustments are appropriate when applying a stand-scale model of forest risk to large areas.	Generate a more detailed location factor and consider incorporating parameters such as aspect.	Undertake similar investigations in areas with other physical and beetle population conditions

Associations between the level of risk and landscape characteristics change over the duration of the infestation cycle.	Temporally vary relationships between risk, and forest age or percentage of pine.	. Quantify relationships that will enable temporal adjustment of model attributes.

9.1 AERIAL SURVEY ACCURACY

Point-based GPS aerial surveys are used to monitor mountain pine beetle infestations in the Morice TSA. The Morice data collection program is unique as aerial surveys are complemented with a field data collection program. This combination of data enables exploration of the information content and uncertainty associated with aerial surveys. As commonly found with aerial survey data, these data best represent infestations that occurred one to two years previously. The data have sufficient spatial detail for tactical planning of insect mitigation and harvesting, as eighty-seven percent of points have attribute errors of less than or equal to ± 10 trees. The main source of error in the aerial survey data is related to the timing of crown foliage discolouration, and as such it is unlikely that modifications to the survey techniques will lead to improvements in data accuracy. This research corroborates other investigations, which indicate that aerial surveying us not a suitable approach for monitoring current attack, and demonstrates that field surveying, such as the program in Morice, is essential to ensure accurate data collection. While the quality and richness of this data collection program is unique, one recommendation would be to randomly select some field locations in order to allow a more thorough assessment of errors of omission.

9.2 KERNEL DENSITY ESTIMATAION

Kernel density estimation provides a flexible approach for modelling point data on the number of trees infested by mountain pine beetles. The application of kernel density estimators to data on mountain pine beetle infestations is novel and has both practical and conceptual benefits. Using kernel density estimation, we are able to incorporate data uncertainty, improve visualization, and represent infestation patterns using a continuous data model. As well, kernel density estimation can be a valuable pre-processing tool for smoothing data and generating consistent spatial indexing for multi-temporal investigations.

The method demonstrated here, for incorporating data uncertainty when visualizing spatial pattern, is applicable to other large area point data sets. Techniques for considering data uncertainty are important as small errors can have a significant cumulative impact on spatial analysis of large areas and multiple time periods. As technology for data collection and storage improves, the availability of large area and multi-temporal data sets will increase. Although these data are typically collected as part of monitoring programs, they offer new potential for spatial analysis. However, optimal use of such data requires the development of techniques for dealing with uncertainty.

All spatial analyses of raster surfaces are affected by cell size. As implementation of kernel density estimators requires output values be stored in pixels, issues related to impact of resolution should be investigated. For instance, it would be valuable to explore how the composition and spatial configuration of hot spot and change locations is impacted when the resolution of kernel density estimated surfaces is modified.

9.3 LANDSCAPE CHARACTERISTICS ASSOCIATED WITH HOT SPOTS

Landscape characteristics associated with hot spots and hot patches vary through space and over time. Initially, intense infestations occur in locations having forest conditions considered favourable, at a stand scale, for the mountain pine beetle. Over time, locations having less favourable characteristics become associated with abundant mountain pine beetle populations. As well, characteristics associated with locations having intense infestations initially are different from those associated with temporally persistent high attack levels. For instance, locations with mature trees are infested first, but locations with younger forests are infested intensely for longer periods of time.

Relationships between hot locations and landscape characteristics demonstrate the importance of mountain pine beetle management strategies that fluctuate through time. Similarly, spatial-temporal modelling of mountain pine beetle behaviour needs to incorporate variability that occurs over the course of an infestation. The landscape characteristics favourable to the mountain pine beetle at the beginning and end of an epidemic differ.

Defining hot spots using a threshold of the 90th percentile of infestation intensity, identifies pixels associated with landscape characteristics that are different from general characteristics found for all pine locations. This definition has utility as it focuses investigations on a practical amount of area for mountain pine beetle management within a district or TSA. However, all spatial analysis of hot spots is influenced by the hot spot definition. As there are many possible definitions of hot spots, future work should consider how other hot spot definitions impact the spatial location of hot spots and the associations between hot spots and the landscape.

In this analysis, due to limitations of the data, the distribution of pine characteristics was constant, even though pine was depleted by mountain pine beetle infestations. Temporal trends are likely associated, at least in part, by the depletion of host. It would be helpful to quantify the impact of host depletion on temporal trends. As well, interpretation of relationships between hot spots and landscape characteristics may be complicated by dependence in environmental factors. Future analysis of landscape characteristics may profit from a multivariate approach.

9.4 DISPERSAL

Three types of mountain pine beetle dispersal seem to occur at a landscape scale. When infestation hot spot patches are very large, evidence suggests they result from hot spot coalescence, or the merging of intense infestations. While an important process, coalescence is relatively uncommon, and more frequent forms of dispersal include short-range and long-range transport. Short-range dispersal is observed in hot spot patches that overlap in neighbouring years, suggesting that the mountain pine beetle move from one susceptible host to the next. Long-range dispersal accounts for hot spot patches occurring where none were previously.

The observed processes of dispersal indicate why mountain pine beetle spread can be difficult to model. Approximately 52 percent of spread occurs from short-range dispersal or coalescence, and 48 percent results from long-range dispersals. Intense infestations may occur both near to and far from hot spot patches in the previous time period. Temporal models of mountain pine beetle spread need to include both short- and long-range dispersal. Evidence of long-range dispersal reinforces the importance of characterizing the susceptibility of regions based on forest conditions. During epidemic conditions, susceptible forests are at risk even if mountain pine beetles are not observed nearby.

Hot spot patches developing from short-range dispersal persist longer than those that develop from long-range dispersal. In other words, hot spot patches intersecting hot patches in the previous time period are more likely to be hot in the future than patches with no intersections. Therefore, when tactical planning for mountain pine beetle mitigation, efforts should focus on hot spot patches that have intersections with patches in the previous years as populations at these locations are unlikely to decline quickly without treatment.

There are several extensions of this work that would be useful to further our understanding of dispersal. Firstly, while trends in the spatial and spatial-temporal relationship of hot spot patches provide evidence of various dispersal processes, it is unclear if the patterns identified are different than would be expected under a random scenario. Secondly, the impact of the underlying environmental and forest conditions is unknown. It is possible that the distances between patches are influenced by heterogeneity in landscape conditions. Finally, in this analysis temporal investigations were limited to two years. Studying interactions between hot spot over more time periods could have additional benefits.

9.5 SPATIAL-TEMPORAL PATTERNS OF CHANGE IN INFESTATION RATES

Temporal patterns in locations with statistically significant positive and negative change in infestation levels are related to the definition of change. At a given location, positive change is rarely followed by further positive change, and two consecutive years of negative change are also uncommon. Typically, significant change is followed by insignificant change, or positive change is followed by negative change. In other words, temporally significant change is not persistent.

Positive change between two time periods is more common than negative change. As well, negative change patches tend to be smaller than positive change patches. This indicates that during an epidemic, population growth occurs more quickly than population decline, as between two years population growth is more commonly detected. As well, the smaller patches of negative change suggest that population decline results from more localized processes than population growth. When significant negative change is detected between two years it is likely the result of treatment, and the typical size of negative change patches, three square kilometres, may be indicative of the effective scale of treatment.

Future work on change could focus on alternate definitions of change. As with hot spot patch analysis, it would also be interesting to examine how patterns in change patches differ from a random expectation. Also, the impact of the spatial structure of the underlying landscape should be examined.

9.6 CONDITIONAL RANDOIMZATION

Randomization methods are powerful tools for exploratory and confirmatory spatial investigations. Often pure randomizations are inappropriate for ecological investigations and conditional approaches should be applied. For mountain pine beetle investigations, conditional randomization algorithms based on a stand-scale understanding of beetle behaviour are currently the most suitable approach to landscape scale randomizations. Many of the findings from this thesis indicate that there are similarities between stand and landscape scale mountain pine beetle behaviours. While we should not assume that all processes are alike, it appears that the current understanding of stand scale processes is a reasonable starting point for investigations at a landscape level.

Using randomization algorithms that considered pine trees to be infested independently, conditional to forest risk, we were unable to reproduce attribute distributions of the empirical data. This suggests that aggregative processes observed at a stand scale are expressed a landscape-level. Further investigation of the nature of spatial dependence in empirical mountain pine beetle data would be helpful to further understand the landscape level expression of aggregative behaviour and other spatial processes. As well, a method that incorporates spatial dependence of observed data when performing randomizations would be beneficial for numerous spatial randomizations studies.

9.7 FOREST RISK MODELLING

The probabilistic nature of the forest risk model enables conditional randomization to be used for the exploration of mountain pine beetle infestation intensity. Diagnostic investigation of locations that are unexpected based on a random model conditioned on forest risk, suggest modifications to the forest risk model when applied to a landscape with an epidemic mountain pine beetle population. Overall, conditions found favourable by the mountain pine beetle vary over space and through time. Therefore, the forest risk model may be improved by varying the weight of parameters over space and throughout the infestation cycle. As well, additional variables, particularly factors associated with climate, may allow better model performance under some conditions. For instance, it may be appropriate to consider aspect during the early stages of infestation.

Guidance for future work is provided by exploratory investigations into the application of the forest risk model to a landscape. Similar investigations should be undertaken in other landscapes and for different mountain pine beetle conditions. More research will be required to determine precisely how to best modify the model. For instance, while we have demonstrated that relationships between forest age and risk will vary over time, supplementary examinations are required to determine how to modify the model.

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