A GIS-based Risk Rating of Forest Insect Outbreaks Using Aerial Overview Surveys and the Local Moran's I Statistic

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Abstract

The objective of this study is to provide an approach for assessing the short-term risk of mountain pine beetle *Dendroctonus ponderosae* Hopkins (Coleoptera: Scolytidae) attack over large forested areas based on the spatial-temporal behavior of beetle spread. This is accomplished by integrating GIS, aerial overview surveys, and local indicators of spatial association (LISA) in order to measure the spatial relationships of mountain pine beetle impacts from one year to the next. Specifically, we implement a LISA method called the bivariate local Moran's I_i to estimate the risk of mountain pine beetle attack across the pine distribution of British Columbia, Canada. The bivariate local Moran's I_i provides a means for classifying locations into separate qualitative risk categories that describe insect population dynamics from one year to the next, revealing where mountain pine beetle populations are most likely to increase, stay constant, or decline. The accuracy of the model's prediction of qualitative risk was higher in initial years and lower in later years of the study, ranging from 91% in 2002 to 72% in 2006. The risk rating can be continually updated by utilizing annual overview surveys, thus ensuring that risk prediction remains relatively high in the short-term. Such information can equip forest managers with the ability to allocate mitigation resources for responding to insect epidemics over very large areas.

Keywords: local indicators of spatial association, Moran's I_i, aerial overview surveys, mountain pine beetle, insect outbreaks.

1. Introduction

The mountain pine beetle, *Dendroctonus ponderosae* Hopkins (Coleoptera: Scolytidae) is the most destructive insect pest of pine forests in western North America (Safranyik 1988). Since 1999, the insect has affected more than 16 million ha of pine forests in western Canada (Westfall and Ebata 2010). The current epidemic, largely located in British Columbia, has resulted in substantial commercial timber loss (Pederson 2004), increase risk to fire and habitat loss (Jenkins et al. 2008, Coops et al. 2009), and alterations to carbon cycling processes (Coops and Wulder 2010; Kurz et al. 2008; Pfeifer et al. 2011). In addition, there is concern that the beetle will infest further beyond its historical range (Sambaraju et al., 2011) as warmer seasonal temperatures exacerbate the outbreak and permit it to move to higher latitudes and elevations than previously recorded (Logan et al. 2003), and across the geoclimate divide as defined by the Rocky Mountain range of North America (Safranyik et al. 2010). Such concerns indicate a need for risk analyses that can inform forest management decision making over vast areas in a timely manner.

In British Columbia, the mountain pine beetle mostly attacks lodgepole pine (*pinus contorta*) (Flint et al. 2009). The process begins in the summer as beetles emerge from their host and spend time in flight searching for a new tree to attack. Once located, the beetle attempts to bore through the bark and release pheromone chemicals to attract additional beetles to the suitable host (Powell et al. 2000). After boring through the phloem of the tree, beetles copulate and proceed to dig galleries that are used to oviposit (Raffa et al. 2008). As beetles bore through the bark, they inoculate the tree with two types of blue stain fungi that rapidly penetrate living tree cells, thereby impacting the capacity for translocation of moisture and nutrients through the tree, consequentially limiting the ability of the tree ward off attack (Paine et al. 1997; Six and Paine 1998). The combination of pheromone release and fungi inoculation facilitates a mass attack of beetles on an individual tree that are needed to overcome a tree's defensive mechanisms (Safranyik 2004). Reproduction ensues in the weeks following tree mortality, and young beetles then overwinter under the bark and then emerge in the following summer to repeat the same process.

Individual trees vary in their susceptibility to attack as beetles have preference for trees that provide ample resources for reproduction and growth while also providing minimal resistance to attack (Berryman 1978). Trees with larger diameters, for example, receive relatively higher densities of attack because the rougher bark associated with larger trees is preferred for initiating galleries (Safranyik 1971), and the thicker phloem provides protection from predators and extreme temperatures (Reid 1963), thus increasing the likelihood of progeny survival. Beetles also prefer older trees, generally over 80 years of age, because their vigor diminishes as age increases (Safranyik 2004). In addition, dense stands of older trees are preferred as increased competition for resources comprise their ability to resist attack (Mitchell et al. 1983).

Identifying forest stands at risk to mountain pine beetle attack aids in the mitigation and prevention of outbreaks. The term risk in the bark beetle literature has come to refer to "the short-term expectancy of tree mortality in a stand as a result of mountain pine beetle infestation" (Shore et al., 2000, p.44), with risk being a function of both stand susceptibility (i.e., the ability of a stand to support a beetle population) and the magnitude of surrounding mountain pine beetle populations – often referred to as population pressure (Bentz et al. 1993).

When beetle infestations expand over large areas as has occurred with the current outbreak, estimating risk becomes a complicated task because of the data required for calculating susceptibility. Risk models with a susceptibility component (Amman et al. 1978; Berryman 1978; Mahoney 1978; Schenk et al. 1980, Shore and Safranyik 1992) rely upon data that provide details concerning, for example, average tree age, tree diameter, phloem thickness, basal area, crown competition and stand growth. Such data can be collected and analyzed in a timely manner when infestations remain relatively small. However, large outbreaks require that risk models be applied over large areas, which means that models must then rely upon regional inventory records to provide the necessary data (Robertson et al. 2008). For example the British Columbia Ministry of Forests, Lands and Natural Resource Operations provides the Vegetation Resources Inventory (VRI), which is a photo-based, two-phased vegetation inventory with attributes estimates through a combination of aerial photo interpretation and ground sampling (BCMSRM 2002). The utility of such inventories becomes increasingly limited when bark beetle outbreaks cause changes to forest composition (via beetle-induced tree mortality or harvesting-based mitigation efforts) occur far more swiftly than inventory updates. This is especially true in British Columbia where the current mountain pine beetle outbreak has grown swiftly since 2000 (see Figure 1).

Insert Figure 1 here

In contrast to the data needs associated with estimating susceptibility under large-area mountain pine beetle outbreak scenarios, estimating population pressure under similar scenarios can be accomplished through the use of a single dataset: forest health aerial overview survey (AOS) data. In British Columbia, AOS are annual, systematic surveys of a broad range of forest health issues. Designed to cover the largest possible area, the AOS are conducted by trained practitioners in fixed-wing aircraft, who provide estimates of beetle-induced tree mortality (and other forest health information) (Wulder et al., 2006). The AOS is a strategic-level data source that is rapidly disseminated to the public (i.e., within 3 months of survey completion) (Wulder et al., 2009), and that can serve as a surrogate for beetle population pressure. Furthermore, because the AOS are conducted annually, changes in population pressure can be estimated across a region, which is important for determining if populations are increasing or decreasing in specific areas in order to prioritize mitigation efforts.

While focusing risk estimates solely on population pressure is only part of the risk equation, we posit that data on regional population dynamics collected from AOS can aid in identifying and prioritizing areas of imminent risk to mountain pine beetle infestations over large areas. As such, this study proposes a GIS-based risk rating system of mountain pine beetle infestations by integrating multi-year AOS data and local indicators of spatial association (LISA) (Anselin 1995) for estimating infestation risk at a regional scale. We extend previous applications of LISA for estimating mountain pine beetle infestations (Nelson and Boots 2008) by applying the bivariate local Moran's I_i to determine local spatial relationships in beetle infestations in subsequent years. The objective of developing a regional risk rating system based on surrogate measures of population pressure across multiple years is to inform management of where lies increasing, constant or declining risk. As mountain pine beetle population dynamics are controlled by numerous local and regional processes that interact with each other over time, it is difficult to project where populations will arrive, increase or diminish from one year to the next over a region without examining the spatial and temporal distributions of populations. We anticipate that this regional risk rating system will be able to be used in unison with more localized data on susceptibility characteristics in order to provide a more effective means of mitigating outbreaks.

2. Methods

2.1 Study Site and Data

The study site (see Figure 2) is defined by the distribution of lodgepole pine in British Columbia, which is an area covering approximately 30 million hectares of the provinces' 95 million hectare land mass (BC Ministry of Forests 2004). The pine distribution data exists as a 1km resolution raster grid in which each cell is represented by the estimated percentage of pine at that location. The dataset was developed by Robertson et al. (2009) to support estimates of the compositional change of pine forests in British Columbia due to mountain beetle attack.

Insert Figure 2 here

The severity of mountain pine beetle attack, which refers to the percentage of trees successfully attacked within a given area (Wulder et al., 2006), was used as a proxy for beetle population levels. Severity information was acquired from annual forest health aerial overview surveys (AOS) (http://www.for.gov.bc.ca/hfp/health/overview/overview.htm), which are conducted province-wide by trained observers in fixed-wing aircraft. These AOS are completed quickly and efficiently, making them ideally suited for mapping the general location, gross area, and general trend (i.e., increasing, decreasing, or stable) in damage caused by mountain pine beetle over large areas. Damage is observed and recorded on basemaps with scales of either 1:100,000 or 1:125,000, and a severity class (i.e., trace, light, moderate, severe, or very severe) is assigned according to the proportion of pine trees that are killed by the beetle (Table 1). The limitations of these survey data include large errors of omission when damage is very light and a lack of rigorous positional accuracy. The surveys were analyzed by Wulder et al. (2009) in order to develop spatial datasets representing severity values across the province at the 1 ha scale. For this study, the data were aggregated to a 1 km scale in order to agree with the resolution of the pine distribution data.

2.2 Predicting Risk Classes

LISA represents a set of localized statistical approaches that typically measure the relationship between individual locations and their surrounding neighbors to uncover patterns of spatial clustering. For this study, we employ the local Moran's I_i, a decomposition of the global Moran's I_i, for quantifying spatial autocorrelation. While the global statistic provides an overall measure of spatial autocorrelation, the local Moran's I_i relates each observation to its neighbors and assigns them to classes with a value indicating the degree of spatial autocorrelation. The local Moran's I_i estimates the similarity in x between observation i and observations j in the neighborhood of i defined by a matrix of weights w_{ij}. The strength of the relationship between the neighbors is accordingly captured. The statistic, provided by Anselin (1995), is calculated as:

$$I_i = \left[\frac{z_i}{\left(\frac{\sum_i z_i^2}{n} \right)} \right] \sum_j w_{ij} z_j \qquad (1)$$

where $z_i = x_i - \bar{x}$.

In essence, equation 1 standardizes value x for observation i to determine if it is high or low relative to the mean, and standardizes values of x for j to determine if the neighborhood is high or low relative to the mean. The standardization operates in a similar manner as a statistical z-score that compares observations to the mean in order to determine the observations' relative position within a distribution. In the absence of such standardization, the resulting Moran's I_i values would be disproportionately influenced by extreme values of severity. Multiplying the standardized value x for observation i and the neighborhood j produces a scalar Moran's I_i value; these values can conceptually be placed into one of four categories representing the relationship between each point and its neighbors: (1) Low-Low, (2) High-Low, (3) Low-High, and (4) High-High. The results from the local Moran's I_i operation can be visualized in a Moran's scatterplot that displays the location of each observation within the solution space of its assigned class. Within the scatterplot, the local Moran's I_i value describes the relative location of observation *i* within the two-dimensional solution space of each category. Note that not all Moran's I_i values are significant: a test of significance is computed for each point to determine if the spatial relationship is significant given a specified level of confidence. Thus, just because a Moran's I_i value provides a means for classifying a data point's spatial relationship with its neighbors, it does not guarantee that this relationship is significant. For further reading on the parameterization and utility of both the global and local Moran's I_i, please see Tiefelsdorf and Boots (1995), Waldhor (1996), and Zhang et al (2008).

An extension of this method is the bivariate local Moran's I_i in which variable *x* of observation *i* is compared to variable *y* of the neighborhood *j*. The modified equation from for bivariate local Moran's I_i takes the form:

$$I_i = \left[\frac{z_i}{\left(\frac{\sum_i z_i^2}{n} \right)} \right] \sum_j w_{ij} (y_j - \overline{y}) \qquad (2)$$

The bivariate Moran's I_i facilitates the examination of multi-temporal data relating to mountain pine beetle severity. The severity at a location from two years prior to the present (year *t-2*) can be compared to the severity in its neighborhood at year *t -1* to determine the spatial and temporal patterns of beetle spread at time *t*. Examining the relationship between tree mortality at a location in a specific year versus tree mortality in the neighborhood in a subsequent year results in a severity rating that incorporates change; in the absence of the temporal component of our analysis we would be ignoring the potential that mountain pine beetle populations are increasing or decreasing in an area. For example, severity in 2000 at a specific location is compared to severity in its neighborhood in 2001. The resulting estimated bivariate local Moran's I_i class, (referred to hereafter as risk class) is then used to represent risk for that location in 2002. This is repeated for each year in order to retrieve the risk classes for the period between 2002 and 2006. Equation 2 thus becomes

$$I_{i,t} = \left[\frac{z_{i,t-2}}{\left(\frac{\sum_i z_{i,t-2}^2}{n} \right)} \right] \sum_j w_{ij} z_{j,t-1} \qquad (3)$$

where $I_{i,t}$ is the Moran's I_i for location *i* at time *t*, $z_{j,t-1} = x_{j,t-1} - \overline{x}_{j,t-1}$, and $z_{i,t-2} = x_{i,t-2} - \overline{x}_{i,t-2}$.

The Moran's I_i identifies spatial autocorrelation in values extreme relative to mean values and subsequently facilitates the classification of locations into risk classes. A Moran's I_i scatterplot provides a depiction of how each observation can be categorized based on its relationship with its neighbors. The scatterplot's x-axis defines the value of observation *i* relative to the mean of all observations, while the y-axis defines the value of observations in the neighborhood of *i* relative to the mean of all observations. The scatterplot consists of four quadrats, each defining the relationship between an observation and its neighbors. Figure 3 depicts a Moran's I_i scatterplot in the context of this study. Class 1 (Low-Low) represents an observation *i* that experiences zero to minimal severity at time *t-2* and whose neighborhood experiences zero to minimal severity at time *t-1*. Therefore, we expect that observations in class 1 will not experience a significant increase in severity and hence have zero to minimal severity at time *t*. We term this the Null class as we do not expect large magnitude infestations in the immediate future. Locations in the Null class exhibit positive Moran's I_i values (the larger value the greater the difference in severity between the location and the mean neighborhood severity) in concert with low severity.

Insert Figure 3 here

Observations in class 2 (High-Low) experienced greater than average severity at time *t-2* and below average severity in the neighborhood at time *t-1*. These locations exhibit negative Moran's I_i values as the relationship between a location and its neighborhood are governed by negative spatial autocorrelation. Thus, we expect that the severity at *t* should be declining towards low to moderate severity because there exists a diminished attack severity in the neighborhood of *i* in the subsequent year. This class is referred to as the Decline class as it represents areas where infestations are expected to diminish.

Observations in class 3 (Low-High) are also defined by a negative spatial autocorrelation relationship as the locations experienced low severity at *t-2* but above average severity in the neighborhood at *t-1*. Therefore, severity should be increasing highest amongst all classes towards moderate to high severity because there exists greater insect population pressure in the neighborhood in the subsequent year. We refer to this class as the Increase class because such locations are experiencing a growth in the infestation.

Observations in class 4 (High-High) experienced higher than average severity at *t-2* and higher than average severity in the neighborhood at *t-1*; this class, which exhibits positive Moran's I_i values, is thus defined as the Constant class. Our expectation for severity in class 4 depends on length of time a location has been in the class. For locations that enter class 4, we expect that severity will increase as heightened population levels attack stands of varying susceptibility. For locations in class 4 for multiple years, we expect severity to decline due to the diminishing availability of susceptible hosts.

The neighborhood in the local Moran's I_i should be representative of the distance over which a location exhibits a relationship with its surrounding area. With regards to mountain pine beetle dispersal, this task entails defining a neighborhood based on the distance that the insect typically fly during their summer dispersal period. We estimated a measure of insect dispersal by examining the nearest neighbor distance between cells that exhibited attack in a specific year and cells that exhibited attack for the first time in the subsequent year. This measure represents our best estimate at determining the least distance that mountain pine beetle disperses from one year to the next. The bivariate local Moran's I_i was computed using the software program GeoDa (Anselin et al. 2006) – a GIS-based application focused on estimating local and global spatial relationships in attributes represented in GIS data.

2.3 Risk Rating Evaluation

The use of the bivariate local Moran's I_i to assign a risk class was first assessed by performing a cell-by-cell comparison between our estimated risk classes against observed severity classes in ArcGIS 10 (Esri 2011). The severity classes were defined using the Government of British Columbia's severity rating system shown in Table 1, which also include the total area in the province within each class in 2006. The Moran's I_i is considered to be correct if:

1. *A cell assigned to the Null risk class at time t represents a location that belongs to the None severity class at time t.*
2. *A cell assigned to the Increase risk class represents a location that experienced an increase from one severity class to another (e.g. from light to moderate).*
3. *A cell assigned to the Constant risk class represents a location that (a) did not experience a change in severity classes and (b) is not in the None severity class.*
4. *A cell assigned to the Decline risk class represents a location that experienced a decline from one severity class to another (e.g. from moderate to light).*

The relationship between estimated and observed severity was also examined in a graphical context to determine if and how the Moran's I_i either over- or underestimated severity.

Next, we examined the distribution of risk classes with regards to our expectations (described in section 2.2) of how the classes should represent spread. During early years of the infestation, the Constant class should constitute the nucleus of the infestation, the Increase class will exist in the frontier of the infestation, and the Null class will compose the remainder of the landscape where beetle-induced tree mortality is absent. As the infestation increases over time, the cluster pattern remains the same with the exception of the Decline class emerging in the center of the infestation. The Decline class represents locations where host trees become exhausted and mountain pine beetle populations move onto alternative locations.

3. Results

3.1 Estimating Neighborhood Size

The appropriate neighborhood size for the local Moran's I_i statistic was estimated from the nearest neighbor calculations performed in ArcGIS 10 (Esri 2011) between the datasets representing successive years of attack. The results from the nearest neighbor analysis are presented in Figure 4. The frequency distributions represent the minimal distance over which mountain pine beetle dispersed in order to attack trees located in a cell that had yet to experience attack. The majority of dispersal occurs within a distance of 3 km, while longer-range dispersal is observed at varying distances from one year to the next. We thus selected 3 km as our neighborhood size for the local Moran's I_i statistic, which is supported by previous research (Safranyik 1989, Shore and Safranyik 1992).

Insert Figure 4 here

3.2 Assessment of Risk Classes

The results from the accuracy test from each year of the study are presented in Figure 5. The local Moran's I_i demonstrated a measure of accuracy in its description of mountain pine beetle spread between 72% and 91%. Accuracy was highest in the initial years of the study when the mountain pine beetle infestation was relatively minimal, which is important as it is during this period that mitigation strategies could prove most effective at minimizing spread. Lower accuracy in later years of the study is likely a result of the limits of adequately predicting the transition from the Constant to Null classes.

The graphical comparison between the risk and severity classes is presented in Figure 6. The bars represent the severity classes for each year at time *t*, and the sections within the bars indicate the proportion of each risk class that corresponds with the specific severity class. One observation from the graphs is that the majority of locations that fall within the None severity class were also in the Null risk class. In addition, the Null risk class diminishes as severity increases. A proportion of the Light severity class was assigned to the Null risk class suggesting that the local Moran's I_i underestimates light infestations. Furthermore, there exists a small proportion of the None class that is composed of the Increase and Constant risk classes. This indicates that the local Moran's I_i does not overestimate the severity of attack when no risk is present.

Insert Figure 5 here
Insert Figure 6 here

The Decline risk class only constitutes a very small proportion (i.e., 0% – 10%) of severity classes. However, the percentages increase in later years of the infestation indicating that certain locations experience declining populations over time. Furthermore, the highest percentage of the Decline class occurs in the Light severity class for 2005 and 2006, which likely represents that these locations have been under attack for multiple years, but resources are now limited forcing populations to move to other areas.

The Increase and Constant risk classes both increase substantially as severity increases. Minimal proportions of these classes in the None severity class gradually increases in the Light severity class, and constitute the majority of the Moderate to Very Severe severity classes. Furthermore, during the earlier years of the infestation the Increase risk class is more prominent than the Constant class, the latter of which increases as the infestation grows. This indicates that, in general, there are more locations during the earlier part of the infestation that are being colonized by longer range dispersal (i.e., from outside a 1km x 1km cell) than short range. As the infestation grows, it is likely that population levels increase to the point where forest stands with low susceptibility now become at risk to being attacked.

3.3 Spatial Distribution of Risk Values

The spatial distribution of risk classes for each year between 2002 and 2006 are presented in Figure 7. The maps illustrate the location over which beetle-induced pine mortality occurred over time and how the spatial distribution of risk classes changes from year to year. The result for 2002 depicts the Constant class in west-central British Columbia as well in dispersed satellite locations, all of which confer with observations of the current epidemic (Aukema et al. 2006). The Increase class generally surrounds the Constant class and is also located at distances from the core of the main infestation. Each year the Constant class grows outward from the initial nucleus, and the Increase class remains on the frontier of the infestation and in areas where mountain pine beetle likely engaged in longer-range dispersal. In general, most locations in the Increase class made the transition in later years to the Constant class as expected.

Insert Figure 7 here

The Decline class emerged in locations where the Constant class resided for several years. This is evident in the transition from the initial core of the infestation shown in red in 2002 that gradually makes the transition to the Decline class by 2006. In addition, there are several locations across the province – mainly in the locations distant from the core infestation – where class transition occurred from Increase to Decline. This is evident north of the main infestation from 2002 to 2003, the south-eastern edge of the main infestation between 2004 and 2005, and the scattered infestations along the southern border between 2005 and 2006. Many of these locations, especially in the south-eastern edge of the main infestation, eventually made the transition from the Decline to Constant class.

4. Discussion

In this study we aimed to investigate the utility of local indicators of spatial association, namely the bivariate local Moran's I_i, as a method for estimating risk of mountain pine beetle attack over very large areas with GIS and coarse-scale multi-temporal AOS data. Specifically, we were interested to determine if the bivariate local Moran's I_i could be used to define individual classes of risk that could overcome the limitations of using existing methods for the extent of the current epidemic. Rather than using a quantitative linear rating scale as per Bone et al. (2005), the local Moran's I_i enables a definition of risk based on changes to beetle population levels. The qualitative risk indicators are useful for determining locations that are on the frontier of the infestations (i.e. the Increase class) versus locations where infestations are entrenched (i.e. the Constant class) versus those areas where populations are in decline. This information is used by forest managers to target different areas with specific mitigation strategies that account for local population dynamics.

While it is challenging to compare the accuracy of the presented approach with that of other risk rating systems, Zhu et al. (2008) developed regression models with similar explanatory power in a single year over a smaller spatial extent. However, the method presented in our study uses a strategic-level dataset and provides a level of accuracy that would allow management to prioritize mitigation activities across large areas. Furthermore, not all Moran's I_i values were found to be significant, which means that efforts to utilize the bivariate local Moran's I_i for rating risk will have need to exercise caution in areas where spatial relationships are not entirely meaningful. However, it should be noted that in this study, the number of Moran's I_i values that were found to be significant coincided with the area impacted by mountain pine beetle (Figure 8). Thus, as the mountain pine beetle infested new areas, the bivariate local Moran's I_i captured the relationship between these locations and their surroundings.

Insert Figure 8 here

The nature in which locations change from one risk class to another did not always strictly adhere to the expectations outlined above, but nonetheless are indicative of previous observations of mountain pine beetle dynamics. For example, there exists several locations, most notably on the frontier of the infestations in early years, that make the transition straight from the Increase class to the Decline class without the population stabilizing for any period of time. This process, previously observed in some forest districts in British Columbia (Wulder et al. 2009), can be a result of either high insect mortality or an exhaustion of susceptible hosts. High mortality can be induced from extreme cold temperatures during the winter months (Safranyik 1989, Régnière and Bentz 2007), which will cause a sharp decline in populations that are on the rise. Alternatively, areas in the Decline class that had relatively high severity one year and a significant drop the next are likely a result of mountain pine beetle consuming available hosts and thus migrating to a new area in search of susceptible trees. Another observation regarding population dynamics is that numerous locations on the frontier of infestations made the transition from the Increase class to the Decline or Constant class and then back to the Increase class, indicating that populations can become dormant in localized frontier locations until enough insects from the core of the infestation reach these areas (et al. 2006).

The risk rating classes derived from the bivariate local Moran's I_i are a sufficient step towards directing decision-makers on how to prioritize different areas given spread behavior. This is not to suggest that the Moran's I_i is a replacement for other risk rating approaches such as regression models (Robertson et al. 2008; Zhu et al. 2008) Instead there is a need to examine the integration of qualitative and quantitative rankings at appropriate scales. Over large geographic areas – such as the scale of the current outbreak – the bivariate local Moran's I_i provides a means to determine where more precise analyses can be carried out. In areas defined by the Increase Class, for example, regression models can be applied at finer scales to determine where to precisely focus mitigation efforts.

5. Conclusion

The potential for the mountain pine beetle to move further eastward into naïve forest environments and species (e.g., jack pine, *Pinus banksiana*) across the boreal forest of Canada (Safranyik et al. 2010) emphasizes the importance of developing methods to integrate broad scale datasets in a timely manner for efficiently devising mitigation strategies and assigning resources to areas of high priority. This is a common theme in insect disturbance ecology as warming climates are leading to range expansions for a variety of insects, especially bark beetles in North America (Waring et al. 2009).

The GIS-based statistical method presented in this study builds on the previous research regarding risk ratings (Shore and Safranyik 1992), the use of local statistics for examining mountain pine beetle infestations (Long et al. 2010; Nelson and Boots 2008), and the use of multi-temporal spatial data for detecting changes in mountain pine beetle populations (Wulder et al. 2008). Moving forward, in order to make the local Moran's I_i -derived risk rating system operational, broad-scale susceptibility measures such as climatic variables and physiological stresses should be incorporated to help refine areas potentially subject to attack. This could involve future climate scenarios that can estimate the change in susceptible areas over time due to changes in temperature, precipitation, and other variables that have been found to influence beetle spread (Sambaraju et al. 2011).

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Figures

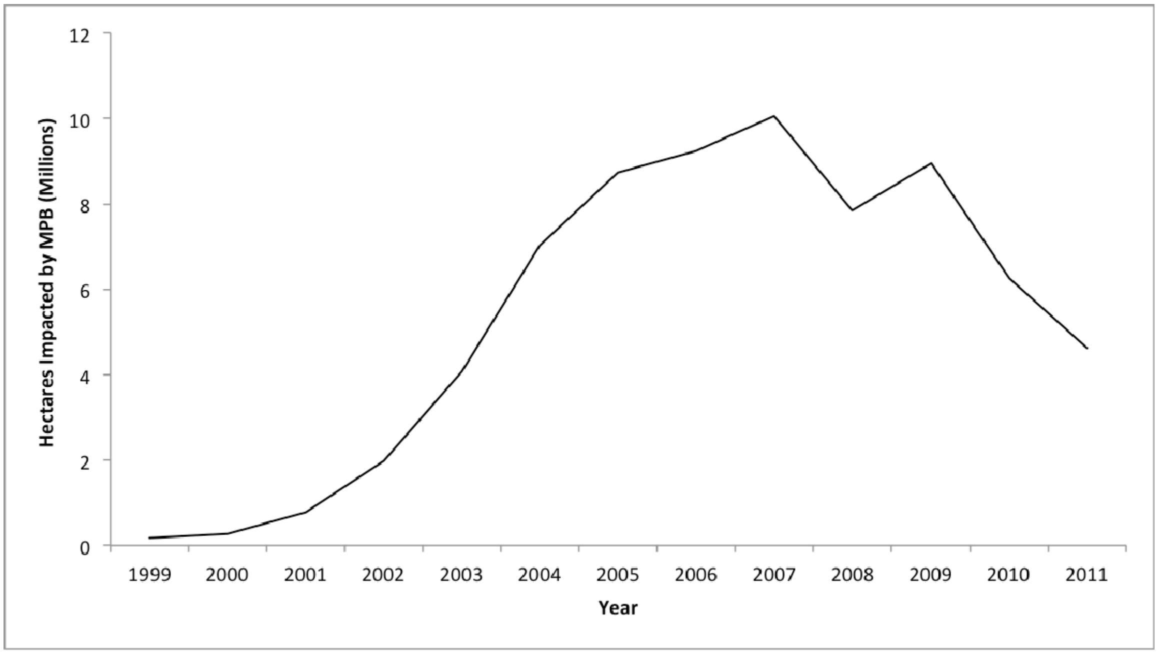

Figure 1. Number of hectares impacted by mountain pine beetle from 1999 to 2011.

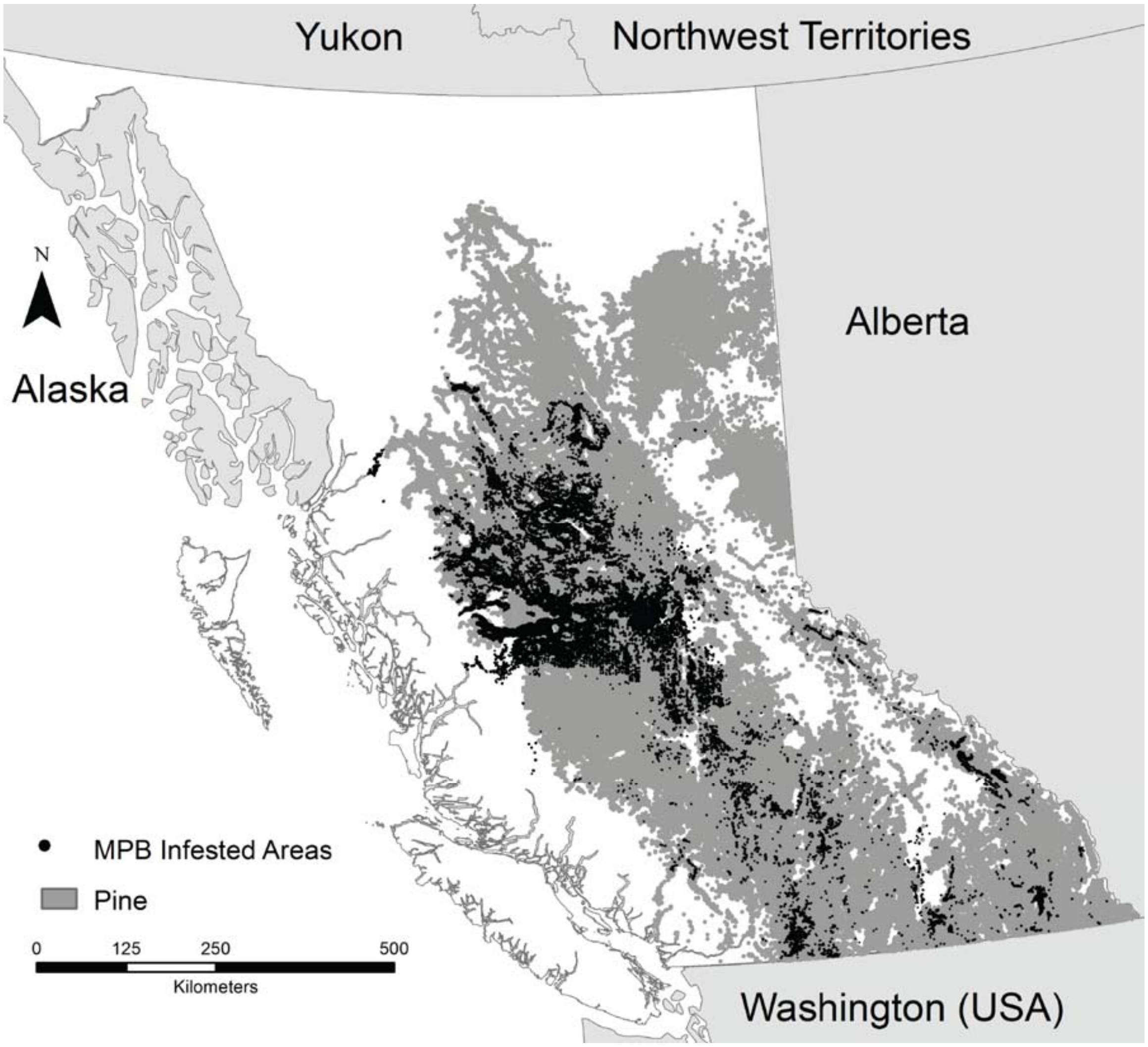

Figure 2. Study site (pine distribution) and the extent of the mountain pine beetle infestation as of 2006.

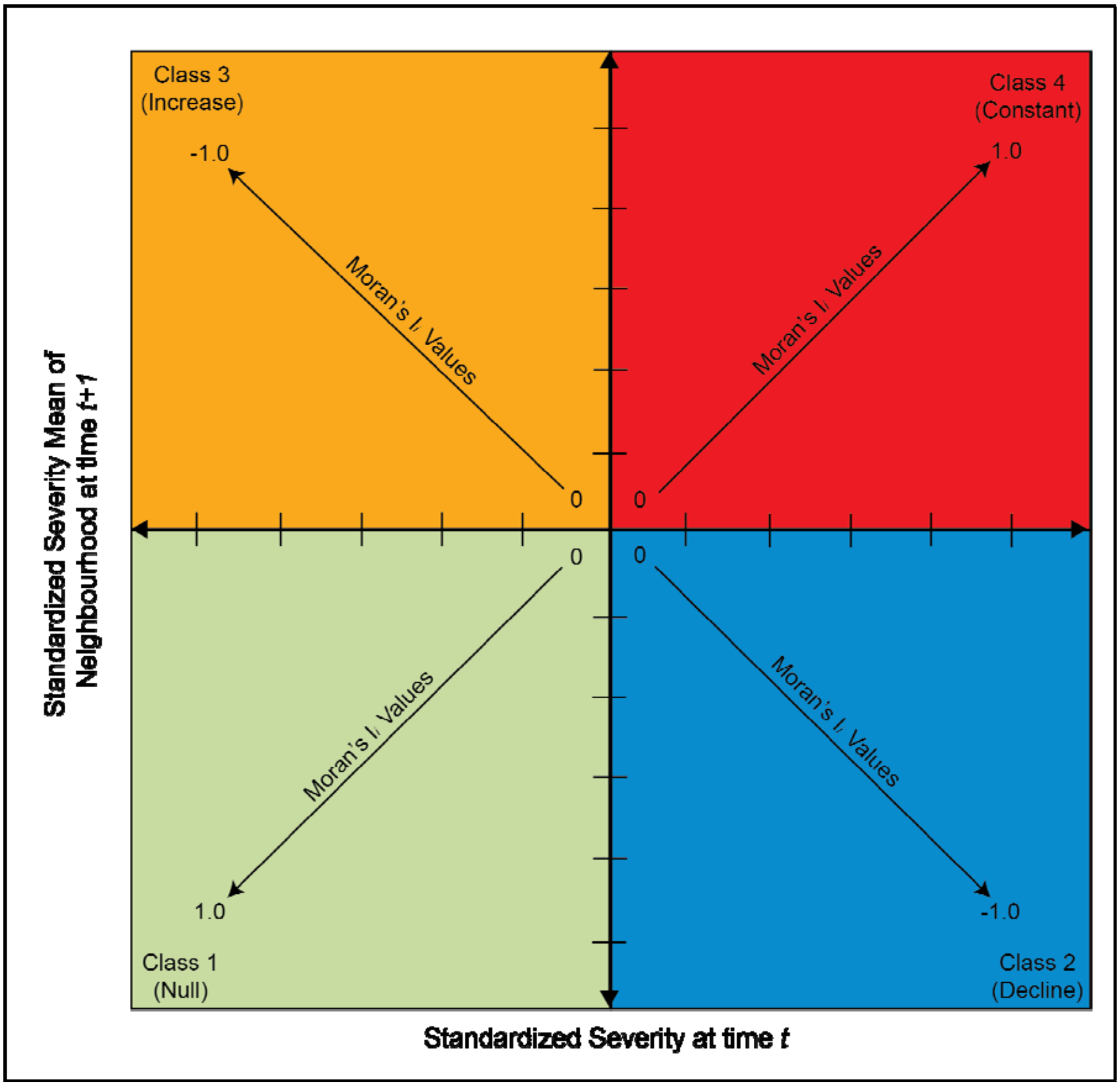

Figure 3. A conceptual schematic of the Moran's I_i scatterplot. Arrows within each class represents the direction of LISA values from 0 to 1. Each quadrat represents the relationship between observation *i* and its neighborhood. In addition, each quadrat represents a different class of mountain pine beetle risk.

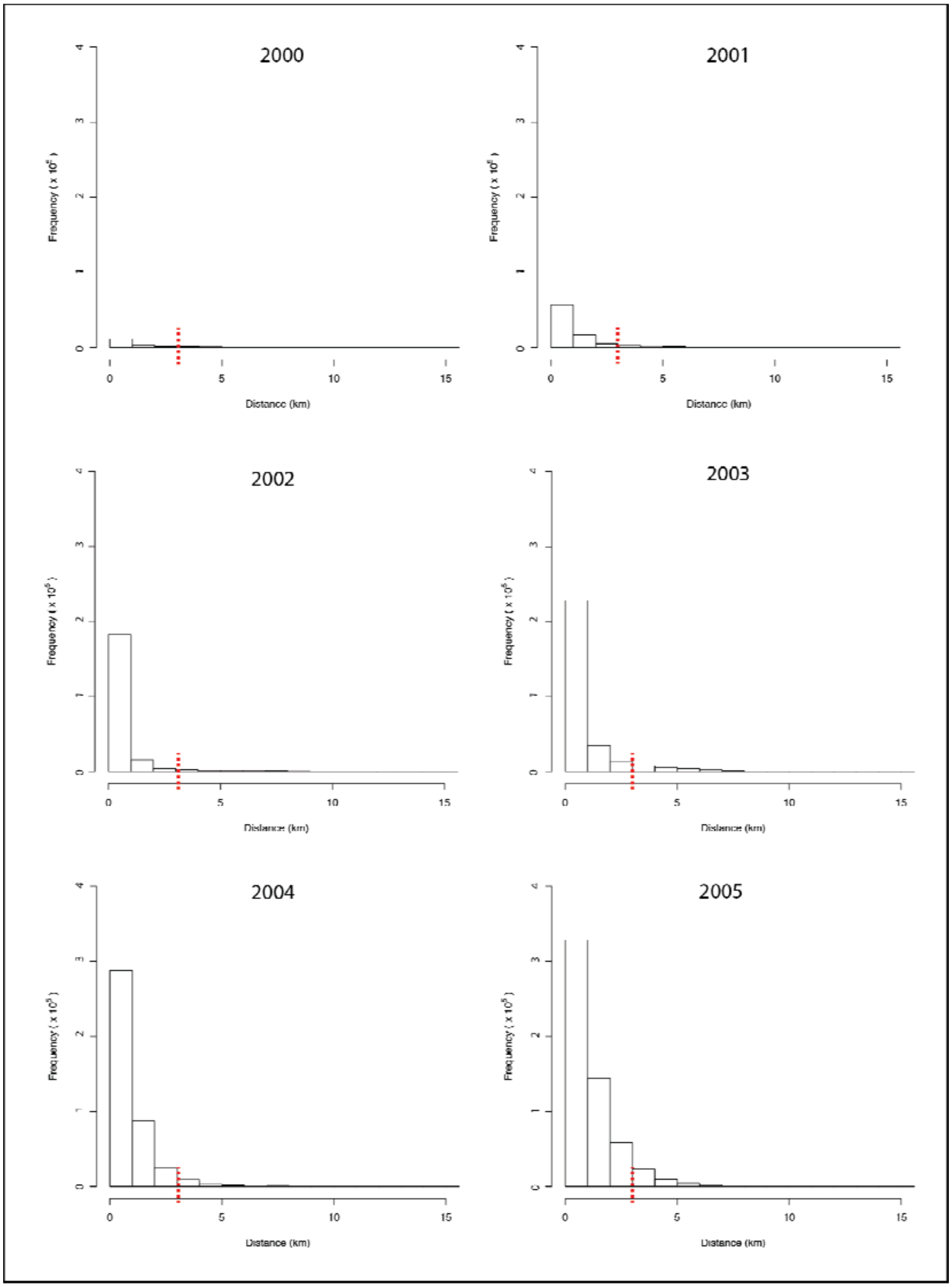

Figure 4. Frequency of nearest neighbor distances between locations that exhibited attack in a specific year (i.e. the year represented in the title of the graph) and locations that exhibited attack for the first time in the subsequent year. The red dotted line represents the 3 km distance selected to define the neighborhood for the bivariate local Moran's I_i.

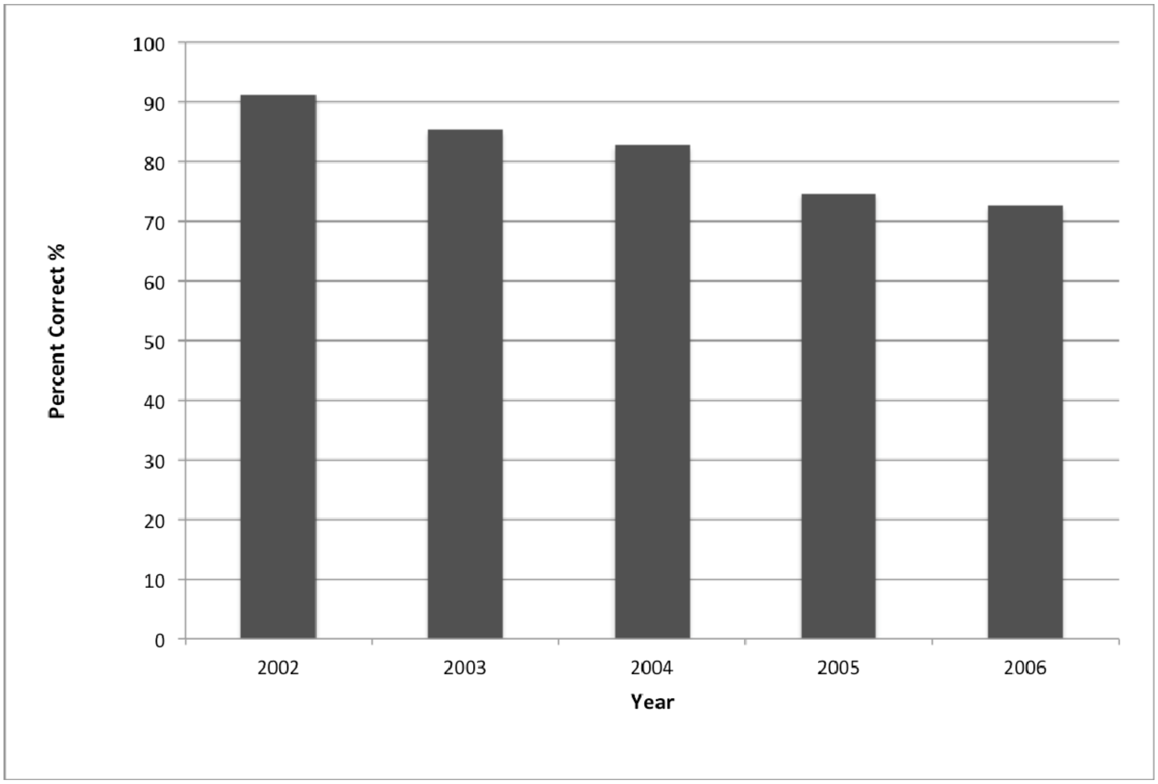

Figure 5. Accuracy of the risk classes derived from the bivariate local Moran's I_i in predicting the change in mountain pine beetle severity.

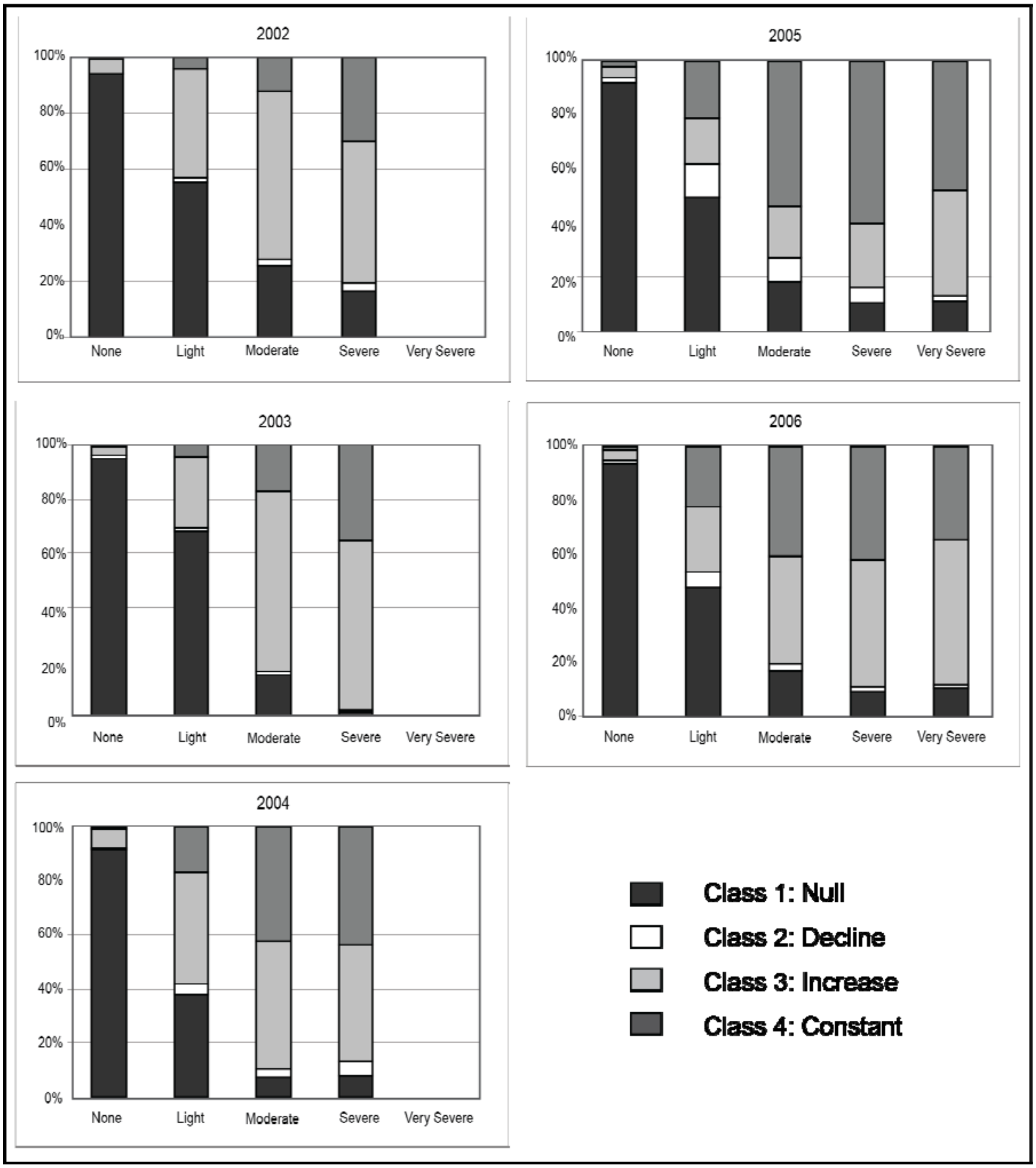

Figure 6. The percentage of locations within each risk class (represented by percentages inside the bars) and their corresponding observed severity class as defined in table 1.

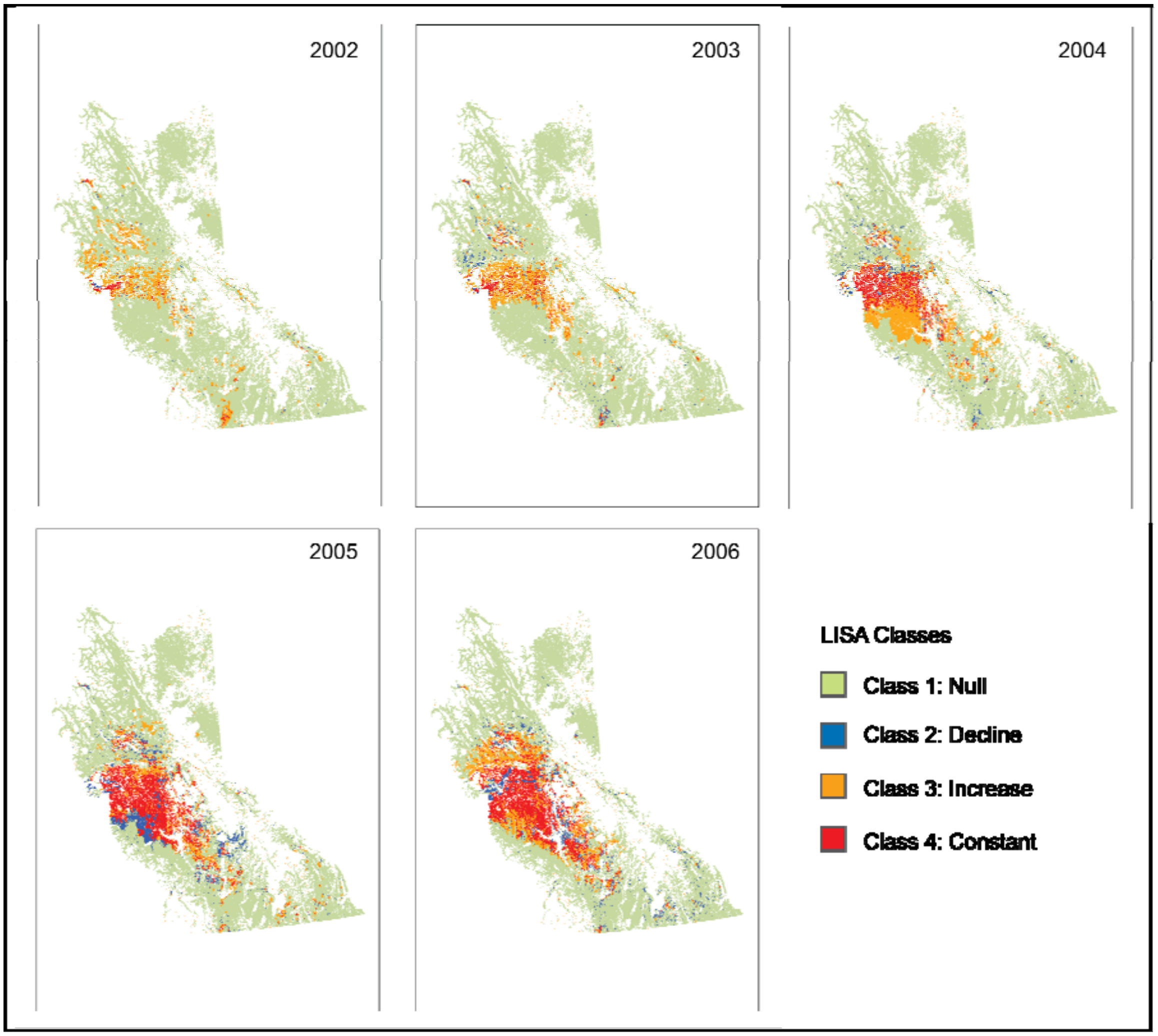

Figure 7. The spatial distribution of risk classes for each year of the analysis.

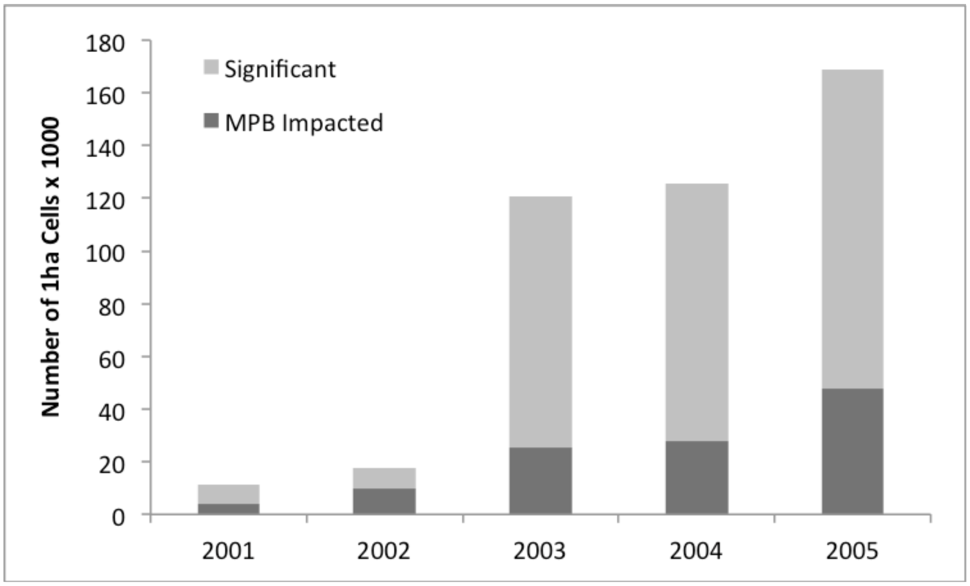

Figure 8. The number of 1-hectare cells that were impacted by mountain pine beetle contrasted the number of 1-hectare cells in which the bivariate Moran's I_i values were deemed significant.

Severity Class	Area Infested (%)	Area Infested in 2000 (ha)	Area Infested in 2006 (ha)
Light	1-10	77, 746	2,933,172
Moderate	11-30	92, 554	2,933,172
Severe	31-49	114, 889	1,230,869
Very Severe	$\geq$ 50	n/a	516,894

Table 1. Severity class as defined by the percentage of area infested by mountain pine beetle. Table also provides information on the total area infested in each class for the years 2000 (Westfall and Ebata 2001) and 2006 (Westfall and Ebata 2007). Note that the Very Severe and Trace classes were added in 2004. However, the Trace class is omitted here as no area in the study site was allocated to this class.