Methods to Assess Landscape-Scale Risk of Bark Beetle Infestation to Support Forest Management Decisions

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Abstract

The objective of our paper is to provide practitioners with suggestions on how to select appropriate methods for risk assessment of bark beetle infestations at the landscape scale in order to support their particular management decisions and to motivate researchers to refine novel risk assessment methods. Methods developed to assist and inform management decisions for risk assessment of bark beetle infestations at the landscape scale have been diverse, ranging from simple empirical correlations to complex systems models. These approaches have examined different bark beetle species, forest types and systems, and management questions, and they differ in spatial and temporal precision, the types of processes included, and the form of output. Bark beetle risk assessment methods, however, share a common theme: they aim to quantify expected levels of attack and loss due to beetles. By focusing on this commonality, we present a gradient in which methods can be classified and ranked, ranging from more structural, pattern-oriented methods to more functional, process-oriented methods. Our objective is to describe a framework for comparing methods in terms of how risk is represented and in terms of the complexity of application. To illustrate how diverse methods can be cast within a common frame of reference, we describe and provide brief examples of four types of methods that we have used in British Columbia, Canada, to examine landscape-scale risk of mountain pine beetle attack in lodgepole pine forests. We then provide some guidance on how to select an appropriate method for a given system and set of questions. The most appropriate method is the simplest one that can address the questions, minimize uncertainty, and inform the decision process in the required timeframe. It is important that researchers and practitioners can view bark beetle risk-assessment methods as a toolkit and select appropriate tools for a given task, as no single method is best for all situations.

Introduction

A variety of risk assessment tools have been designed to help managers quantify expected losses from bark beetles, losses which can be quite severe. We present a framework to help managers choose the tools that are most appropriate to their needs.

Several bark beetle species, mostly in the family Curculionidae, subfamily Scolytinae, have the potential for dramatic population increases under favorable forest and climate conditions, which can result in landscape-scale mortality to the host tree species (e.g., Wood and Unger 1996). For example, the mountain pine beetle (MPB, *Dendroctonus ponderosae* Hopk.) has killed much of the mature lodgepole pine (*Pinus contorta* Dougl. ex. Loud.) over an area of approximately 9 million hectares in British Columbia in recent years (Westfall 2005), and the spruce beetle (*D. rufipennis*) has infested several hundred thousand hectares of spruce forest in southwestern Yukon, Canada (R. Garbutt, pers. comm.). These events have widespread implications for current and future forest management, ranging from effects on timber supply and operations, wildfire-urban interface, wildlife habitat, and aesthetics.

Landscape-scale risk assessment of bark beetle infestation aims to quantify the spatial and temporal likelihood of attack extent and severity. Methods to assess risk can range from structural risk (i.e., strictly assessing patterns) to functional risk (i.e., assessing interactions and feedbacks between pattern and process). Susceptibility and risk rating systems (Bentz and others 1993) generally classify stands without a temporal dimension in a relatively simply spatial context and are useful for a quick overview of landscape state and general patterns. Landscape connectivity methods (O'Brien and others 2006) can join stands of higher susceptibility into a network that can help give an integrated landscape perspective but are still temporally static. Connectivity assessments have been useful in areas with limited current attack to provide an assessment of the spatial pattern of hosts and likely pathways of attack. Empirical projection models explicitly model outbreak dynamics based on historical temporal patterns and have been useful to assess very broad-scale dynamics and potential interactions with management (Eng and others 2005). Population models capture system dynamics and feedback between host patterns and beetle demographics in detail (Dunning and others 1995) and can help to gain insight into likely trends of outbreak development and to explore management alternatives in relatively fine detail.

These methods, and others in the literature, share a common theme: they aim to quantify expected levels of attack and loss due to beetles. Although the way in which risk is quantified may differ among methods, risk can always be cast in terms of a probability distribution that represents likelihood of losses or impacts. This provides a common frame of reference with which methods can be compared on a gradient from simpler, structure-based methods to more complex, process-based methods, allowing methods to be assessed in terms of tradeoffs between data required, difficulty of application, and precision of results. To demonstrate this framework, we examine a diverse suite of tools useful to assess risk of bark beetle attack at broad spatial scales. For each, we provide an overview of the method as applied to bark beetle infestation risk, with a focus on data requirements and outputs. We highlight the pros and cons and outline the types of management questions that can be addressed and present an example of management application.

Management Implications of Bark Beetle Infestations

There are three main management strategies for major bark beetles in forestry: prevention, direct control, and salvage (Shore and others 2006b). Preventive management is used when beetles are at, or below, endemic levels, and managers have the opportunity to be proactive in making trees, stands, and landscapes less susceptible to large infestations (Whitehead and others 2006). Direct control is used in the situation when an infestation is underway and management efforts are reactive and primarily directed at killing beetles in order to reduce population size and spread (Carroll and others 2006). Salvage occurs either during or following those outbreaks that are too large for effective control (Eng and others 2005).

Bark beetle management requires decision-support tools to provide information on which to base decisions, including identification of infested trees and susceptible stands. Many decisions are involved in resource allocation including budgets, risk to surrounding stands, access to the infested trees, other resource constraints, allowable harvest levels, and treatment efficacy to name a few. Landscape-scale risk assessment can provide information to support some of these decisions.

What Is Risk Assessment in This Context?

Risk can be defined as the likelihood of an undesirable outcome combined with the magnitude of impact. Events with low likelihood of occurrence (e.g., meteorite impact) are not classified as high risk, nor are events with minor negative impacts (e.g., attack by secondary bark beetles on weaker, smaller trees in a stand). We define landscape-scale risk of bark beetle infestation as the probability of a given magnitude of loss of standing timber due to attack and concurrent management response. That is, conceptually, it is a probability distribution that quantifies the potential of attack at broad spatial scales (Figure 1). The specific shape and expected values of this distribution will depend on the landscape under study (e.g., the configuration and composition of hosts and beetles), and the method used to assess risk (e.g., the quantity reflected by the method, such as proportion of stand volume at risk or proportion of stands that may be attacked within a given timeframe). In general, this distribution cannot be fully mapped owing to uncertainties in future events (e.g., weather) and data (e.g., infestation locations and severity). In addition, management

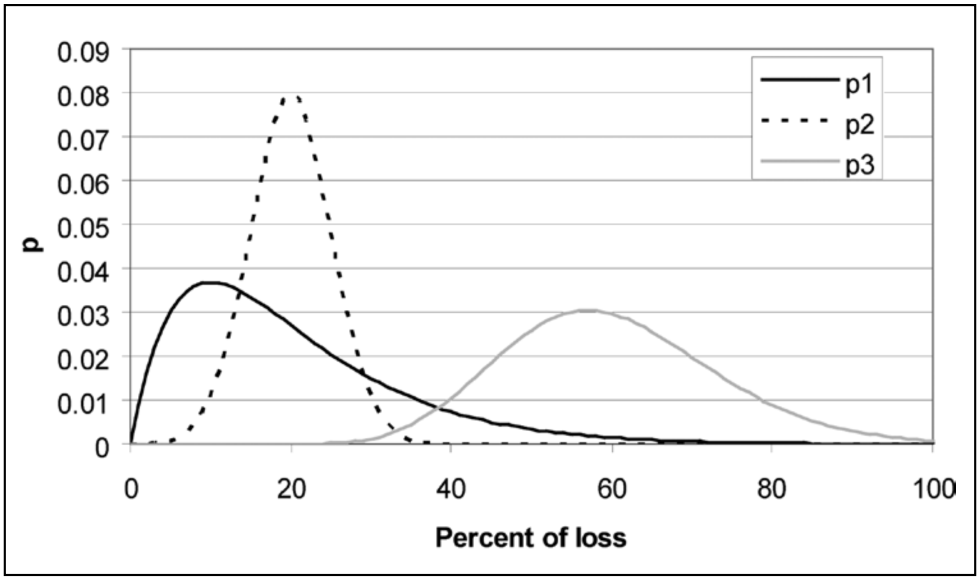

Figure 1—Conceptual diagram of landscape-scale risk of bark beetle infestation. Landscape-scale risk of bark beetle infestation can be conceptualized as a probability distribution of loss of standing timber owing to attack and management response (where probability of loss within a given range is the area under the probability density function curve, p, within the specified range). Loss may be quantified as area attacked, volume killed, or volume lost owing to decay. Variance about the mean may be due to the source data (e.g., if the distribution was formed from frequency information) or uncertainty in future processes (e.g., weather). Three example risk distributions are shown. The first two (p1 and p2) have lower overall risk relative to the third (p3). Based on a 67 percent confidence interval, p1 has an expected loss of between 3 and 24 percent (mean of 20 percent), p2 has an expected loss of between 16 and 24 percent (mean of 20 percent), and p3 has an expected loss of between 45 and 70 percent (mean of 59 percent).

decisions influence risk, so each management option results in a different risk probability distribution. Often, however, risk focuses mostly on the mean, or expected, value of the distribution (Fall and others 2004). Hence, a high-risk scenario is one with a high probability of large levels of loss (e.g., example distribution p3 in Figure 1). A medium-risk scenario may be due to a high probability of medium levels of loss (e.g., example distribution p2 in Figure 1), or a medium probability of high levels of loss (e.g., example distribution p1 in Figure 1) (Shore and Safranyik 1992).

Why Landscape-Scale Risk Assessment Is Needed

Forest management decisions in the context of potential or existing bark beetle infestations require practical information in a timely manner (Maclauchlan and Books 1994, Safranyik and others 1974). Forest managers want to know the most likely outcomes of a range of alternative choices, both to help select an option and to communicate rationale. When a landscape has no current infestation, managers want to know the likelihood of an infestation starting (e.g., if one is imminent or a more remote possibility), and which stands are most likely to be affected first. In landscapes with a current infestation, managers want to know the impact of different types and levels of management effort (e.g., harvest levels, fell and burn treatment levels, global positioning system [GPS] surveys), on the timing, location, and magnitude of loss (Shore and others 2006b). In essence, the choices involve appropriate resource allocation and how to deal with uncertainty in order to assess tradeoffs and costs/benefits. Landscape-scale risk assessment provides key information to support this decision process.

A key role of researchers providing decision support is to help decisionmakers frame their specific questions in terms that can be addressed using risk assessment methods. Getting at the fundamental question helps to identify the best methods to apply that can balance information desires with the limitations of data availability, system knowledge,

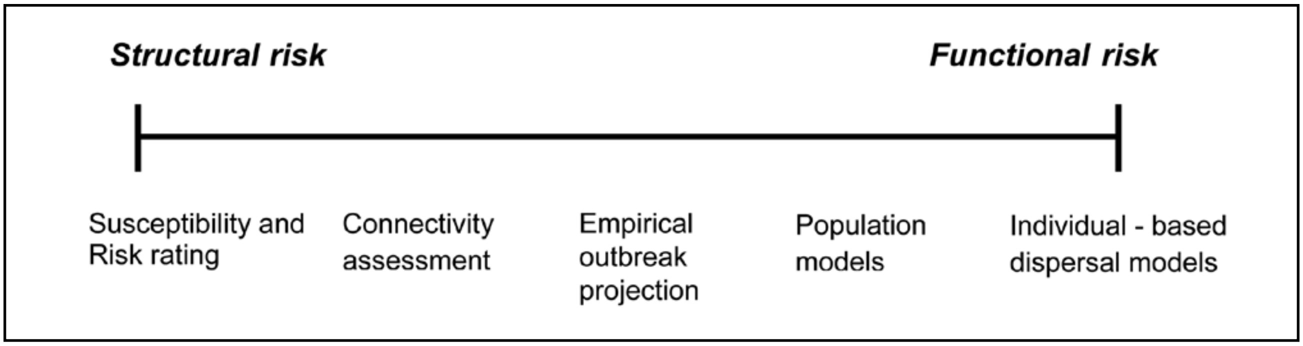

Figure 2—Gradient of landscape-scale methods for assessing risk of bark beetle attack. Landscape-scale methods for assessing risk of bark beetles can be placed on a gradient from structural to functional risk. Structural risk methods focus on patterns, such as stand susceptibility or connectivity networks. Functional risk methods focus on process, such as demographics and movement.

and timeframe. Researchers also need to recast risk assessment results back into a language and format that can be communicated to decisionmakers in a comprehensible and useful manner (Gustafson and others 2005).

Risk-Assessment Methods

This section provides information and example applications for categorizing risk methods, susceptibility/risk rating systems, graph-based connectivity assessments, empirical outbreak projections, population modeling, and other risk-assessment methods. The examples provided in this section illustrate how we categorize risk methods. These examples are based on a range of tools we have used to assess potential impacts of MPB at scales from stands to the entire province of British Columbia. Although the specific details of the methods differ substantially, they are essentially just different approaches to assessing risk. They differ fundamentally in terms of the degree to which ecological and management processes are taken into account and can be viewed along a gradient (Figure 2). **Structural** approaches to risk focus mostly on landscape patterns and correlations between past outbreak behaviour and stand structure, whereas **functional** approaches focus on underlying processes and interactions in the system (cf. distinction between structural and functional habitat connectivity, Taylor and others 1993).

Susceptibility/Risk-Rating Systems

Susceptibility and risk rating systems classify each stand or location in a landscape according to local characteristics (e.g., forest age, distance to nearest attack). We define susceptibility in terms of conditions inherent to a stand (i.e., how suitable is the stand for the beetle species) and risk rating as a function of susceptibility and beetle pressure (Shore and Safranyik 1992, Shore and others 2006a). Stand susceptibility rating systems provide the forest manager with a tool that identifies the likelihood of damage to a stand should a beetle infestation occur in it. When implemented on a map, these tools form the starting point for setting management priorities by identifying stands and landscapes that are more susceptible than others. When combined with maps of beetle locations a manager can look at the risk of loss. Highly susceptible stands in closer proximity to large numbers of beetles can be given management priority.

Data Requirements—
To apply an existing rating system requires basic digital spatial forest cover data on attributes such as stand age, basal area, percentage of host and other tree species. Data on the location of each stand (elevation, latitude, longitude) and infested tree locations are also required. To develop a rating system, however, requires substantial fieldwork to identify correlations between beetle biology and stand characteristics (e.g., Perkins and Roberts 2003).

Output—
The main output is a spatial map of relative or absolute susceptibility rating, defined as the likely proportion of susceptible volume that would be killed **if** beetles arrived in the stand. Structural risk rating systems output a spatial map of

the estimated loss and likelihood of attack based on proximity to existing attack. These maps can be cast as frequency distributions, creating a form consistent with Figure 1.

Pros and Cons—
This method has the distinct advantage of simplicity of application and minimal data requirements. The mountain pine beetle susceptibility and risk rating system (Shore and Safranyik 1992; Shore and others 2000, 2006a) remains one of the most widely used MPB landscape risk assessment tools. On the other hand, these approaches are temporally static. Likely pathways cannot be identified with this method, and there is a limited ability to incorporate management. Susceptibility and risk rating have a limited capacity to use spatial information of known outbreak locations. In general, distances are simply Euclidean (i.e., do not account for direction or intervening land types), and the magnitude of pressure from nearby outbreaks is difficult to incorporate.

Management Application—
Susceptibility rating systems are best used to help prioritize harvest in landscapes without current or imminent attack (preventative management). Risk-rating systems are designed for landscapes with some attack but are best used in the early stages of an outbreak and are of limited use during epidemics (Shore and others 2006a).

Example Application—
We contrasted two landscapes of approximately equal size (Figure 3): Nadina Forest District in west-central British Columbia is approximately 3.0 million ha in size, and Dawson Creek timber supply area (along with a portion of Tree Farm License 48) is approximately 2.6 million ha. The general pattern of susceptibility differs substantially in these two landscapes (Figure 4). Nadina has larger areas of high susceptibility and more continuous cover, whereas Dawson Creek has overall lower susceptibility, but with a substantial amount of moderate susceptibility in the southeast. In terms of the present outbreak, Nadina has experienced very high levels of impact and mortality, whereas Dawson Creek, being east of the Rocky Mountains, is more isolated from the predominate outbreak populations in British Columbia, and population buildup is more recent (Eng and others 2005). We can quantify these differences as a frequency distribution of susceptibility (Figure 5). The percentage of forested area with very low susceptibility is higher in Dawson Creek than Nadina, whereas Nadina has more area with higher susceptibility rating for most cases above 25.

Graph-Based Connectivity Assessment

Examining the network of inter-connections between susceptible host patches can provide a broad perspective of landscape patterns. A variety of methods are available for assessing habitat connectivity (Gustafson 1998, Schumaker 1996, With and others 1997), which is defined as the degree to which a landscape facilitates or impedes movement of organisms among habitat patches (Taylor and others 1993, Tischendorf and Fahrig 2000). Graph-based methods are emerging as an effective approach that supports multiscale analysis and that provides a good balance between field-intensive studies that aim to directly measure functional connectivity, but are limited to small areas and less vagile species (Tischendorf and Fahrig 2000) and pattern analysis methods that focus on structural connectivity (Calabrese and Fagan 2004, Urban and Keitt 2001). We have developed an extension to graph theory (Harary 1972) that we call **spatial graphs**, which captures features relevant to geospatial ecological analysis (Fall and others, in press; O'Brien and others 2006). Unlike conservation situations, management of bark beetles generally aims to reduce connectivity of host habitat. Hence, a key objective of connectivity analysis is to help identify where opportunities exist in a landscape to increase the level of fragmentation. This can be done by analyzing the spatial scales at which patches of susceptible hosts are well-connected, in particular, connected to areas with existing attack.

Data Requirements—
Digital spatial forest cover data and information on beetle movement and current infestation locations are required. Spatial graph connectivity assessment requires two spatial inputs: a patch layer (e.g., areas of high susceptibility) and a **cost surface** (e.g., relative difficulty or speed of movement or spread through different cover types). These require a

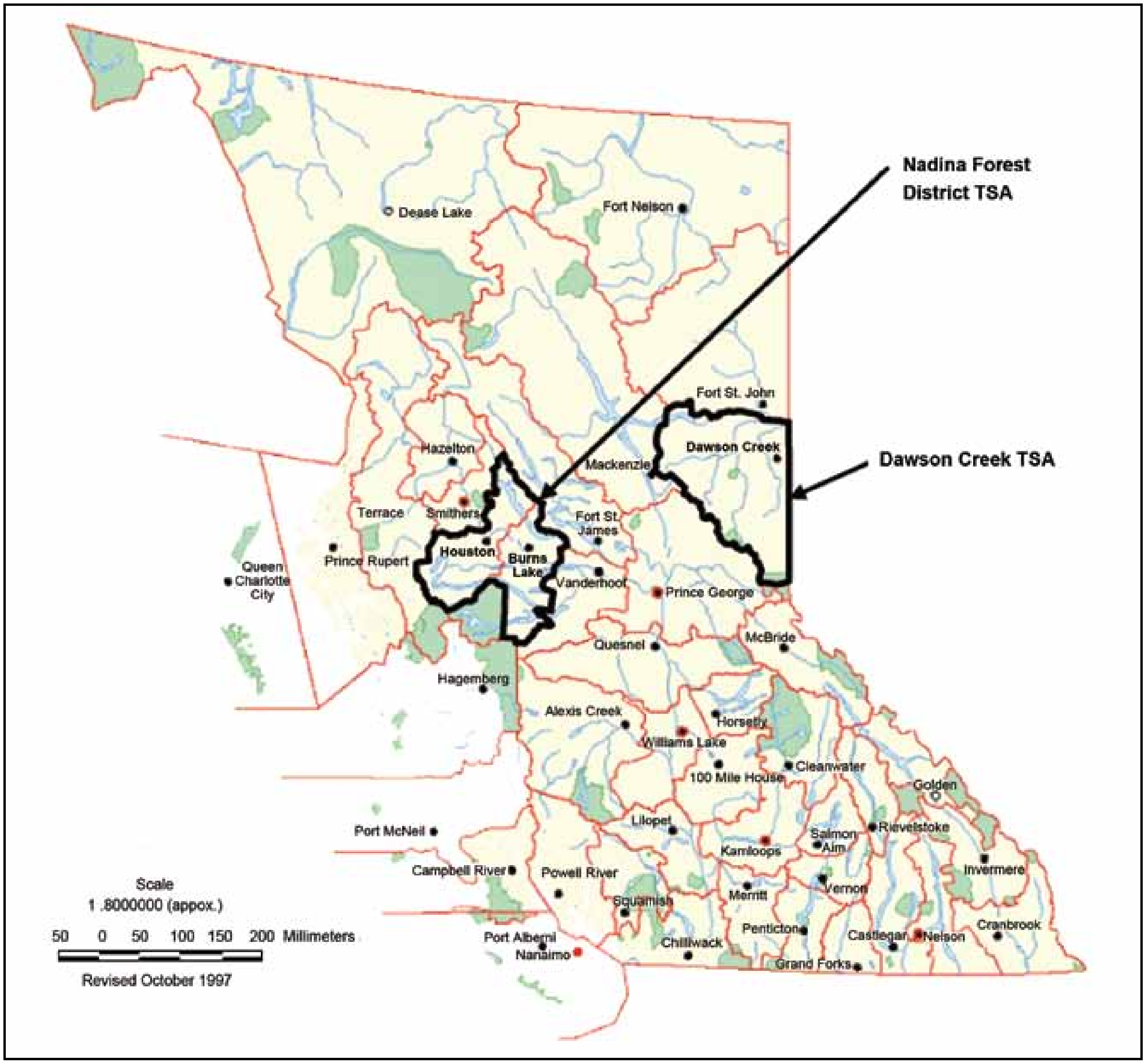

Figure 3—British Columbia, Canada, showing the Nadina Forest District (Lakes and Morice timber supply areas [TSA]) and Dawson Creek TSA.

susceptibility rating to define habitat patches and information on the permeability of different cover types in the matrix between patches (O'Brien and others 2006). Current infestation locations can be used to analyze the resulting connected network of patches in terms of effective distances from susceptible hosts to current attack.

Output—

The main output of graph-based connectivity analysis is a spatial graph that shows the location of connections between host patches and the cost of those links, derived from the patch map and cost surface. Analysis of this graph can identify scales (effective distances) at which large increases in host connectivity occur—these can be examined spatially using the graph to draw connections at those scales. Given infestation locations, the graph can be reoriented to identify scales at which hosts become connected to current attack. The results can then be cast as a distribution of high susceptibility stands according

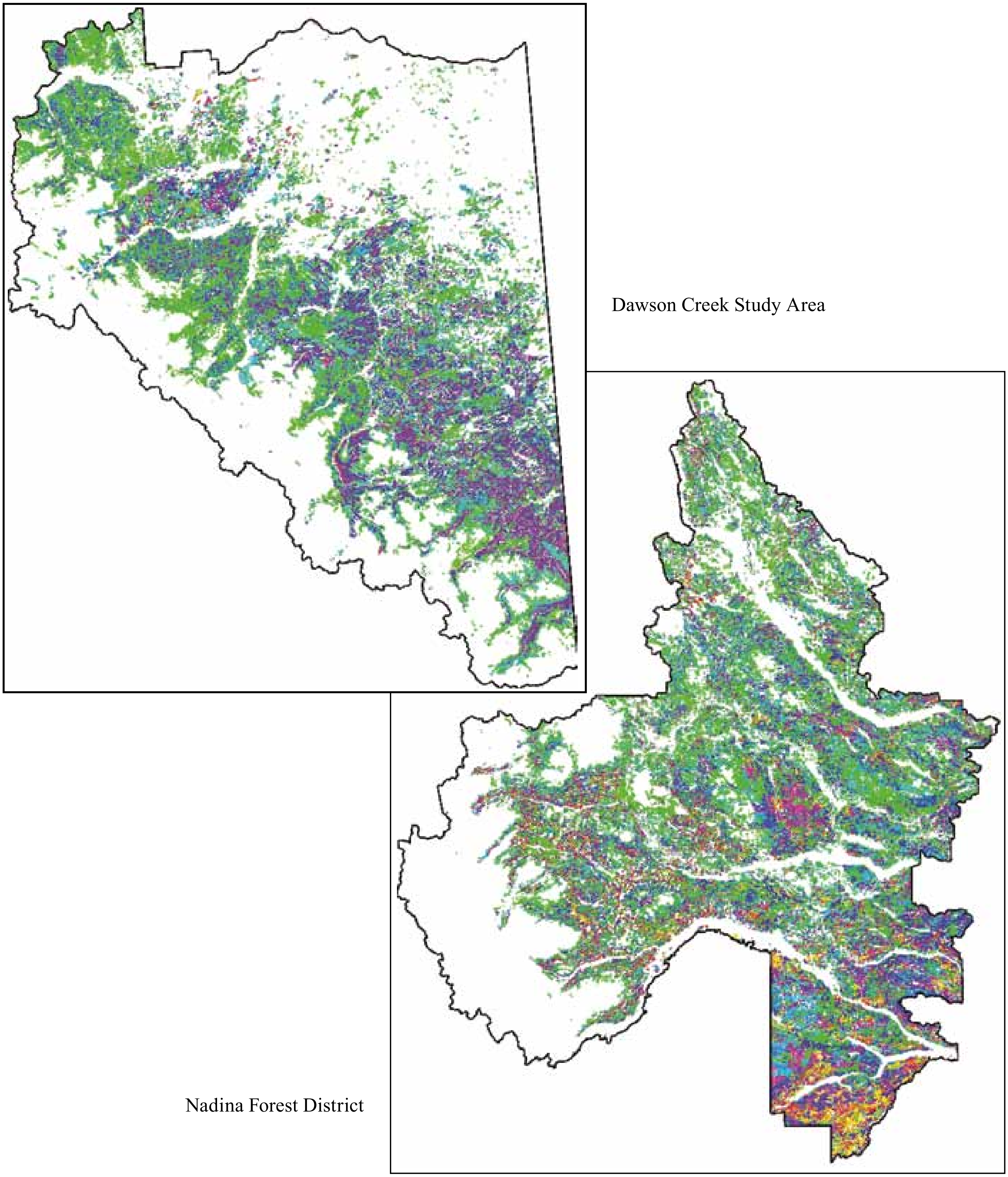

Figure 4—Susceptibility of stand loss owing to mountain pine beetle attack in the Nadina and Dawson Creek study areas (based on Shore and Safranyik 1992). The Nadina forest district (right) has high overall susceptibility and large contiguous areas of moderate to high susceptibility. Susceptibility in the Dawson Creek study area (left) is more moderate and fragmented.

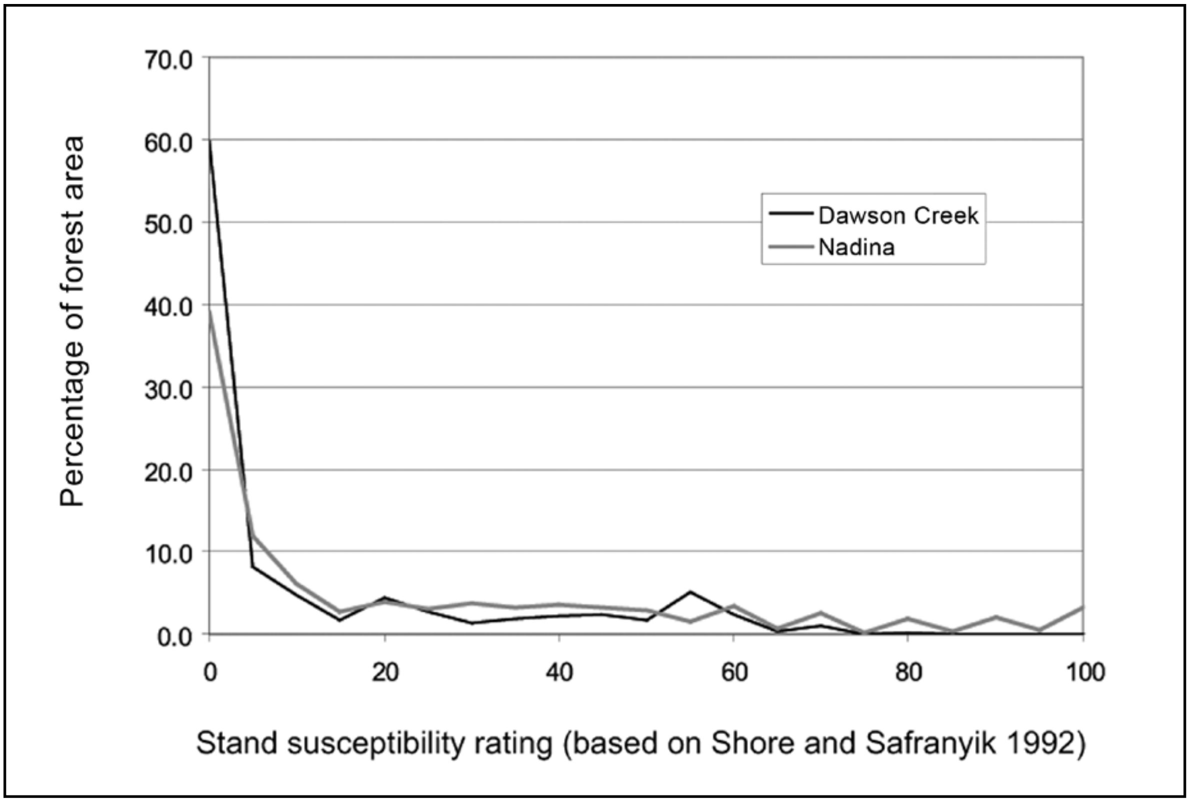

Figure 5—Frequency distribution of stand susceptibility rating for mountain pine beetle in Nadina and Dawson Creek study areas as percentage of forested area. Susceptibility was defined on a range from 0 to 100 as an index of potential basal area mortality according to Shore and Safranyik (1992) and Shore and others (2000). The Nadina distribution has a mean of 23.3 and a standard deviation of 28.8. The Dawson Creek distribution has a mean susceptibility of 12.9 and a standard deviation of 20.0.

to distance from current attack. One key benefit of using spatial graphs is the ability to translate from a graph back to the landscape, which is critical for effective communication and decision support.

Pros and Cons—

These methods required a low to moderate effort to apply, and data requirements are modest. The required information on movement cost/impedance can be challenging to parameterize with statistical confidence (O'Brien and others 2006), but cost surfaces derived using simpler methods, such as expert opinion, can be used for some less precise analysis. Although still static in nature, likely pathways can be identified as well-connected corridors, especially between areas with current attack and areas with clusters of high susceptibility. In addition, large areas can still be processed efficiently. However, it provides a static perspective on a dynamic problem and has a limited ability to incorporate management.

Management Application—

Graph-based connectivity assessment is best used in situations with low or no attack. In a sense, this approach can be viewed as increasing the spatial dimension of susceptibility and risk-rating systems. The results can help to focus management effort on stands to reduce connectivity within management limits. The utility is based on the premise that the most important stands to treat in a landscape are not necessarily just the most susceptible, but the susceptible stands that are most connected. This is especially important in landscapes for which the area of susceptible stands greatly exceeds management capacity.

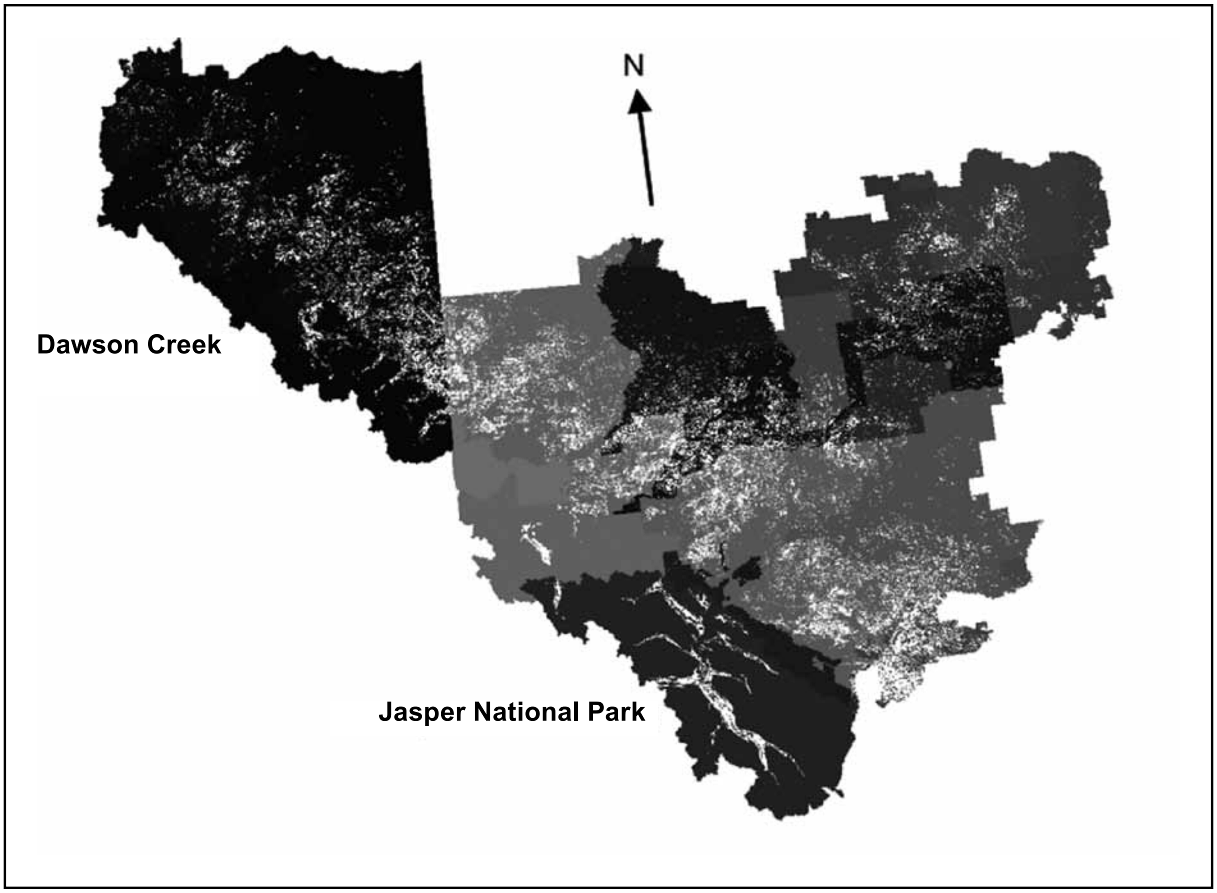

Figure 6—Patches with high susceptibility to mountain pine beetle attack and loss used for connectivity analysis. High susceptibility patches (those with greater than or equal to 65 on the Shore and Safranyik [1992] susceptibility rating system) for the Dawson Creek and west-central Alberta study area for which connectivity analysis was performed (white areas in the Figure). The area east of Dawson Creek and north of the Alberta portion of the study area is farmland. The southwest boundary is the Rocky Mountain divide. The different shades of grey in the underlying map denote different management units (national parks, provincial parks, timber management areas called forest management units in Alberta and timber supply areas or tree farm licenses in British Columbia).

Example Application—

We used spatial graphs to assess the potential of the current mountain pine beetle outbreak in British Columbia to spread into the boreal forest of northern Alberta. The study area consists of about 11.2 million ha, with Dawson Creek (Figure 3) on the western side and extending east to Slave Lake in central Alberta, north of Edmonton. Susceptibility was defined on a range from 0 to 100 according to Shore and Safranyik (1992). High susceptibility patches were defined as contiguous areas of susceptibility greater than, or equal to, 65 (Figure 6). The cost surface was produced using the reverse of susceptibility (i.e., increasing cost with decreasing susceptibility), based on the assumption that beetles will spread more effectively through higher susceptibility stands, and that this increases linearly with susceptibility. The base graph extracted joined host patches into a network (Figure 7). This graph was reoriented, so that costs,(which can be interpreted as effective distance), through the graph correlated with distance to the nearest infested patch.

This resulting graph was analyzed by thresholding: at each threshold from 0 to 600 km in units of 100 m (effective distance in cost units), all connections longer than the threshold were discarded, and only patches connected to current attack in Dawson Creek and western Alberta (mapped by heli GPS, M. Duthie-Holt, pers. comm.) were

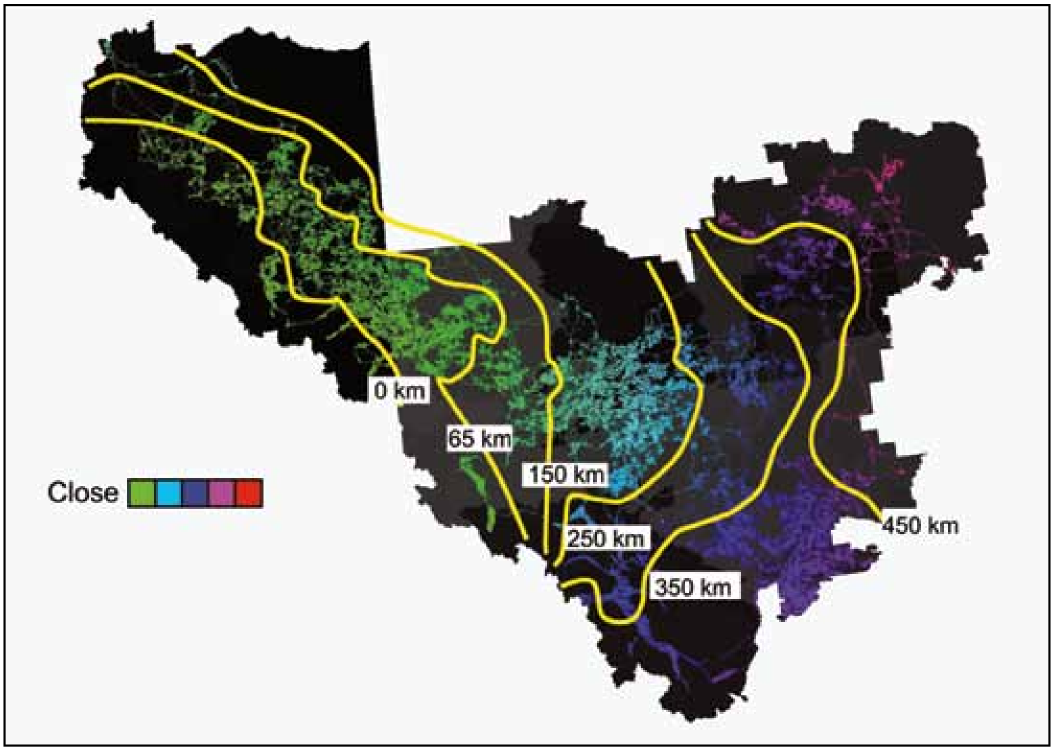

Figure 7—Isolines (of the results of graph thresholding. Mapping the results of graph thresholding in Dawson Creek/west Alberta study area by drawing isolines lines of equal effective distance from current attack) at the critical scales identified in Figure 8. Effective distance is the cost through the graph from infested patches to other patches.

retained (Figure 8), (Fall and others, in press). Hence, at a threshold of 0, only patches containing current attack were retained. As thresholds increase, the area of host joined to current attack increases until all host area is included. The pattern of these increases provides insight into pattern across spatial scale. Steep areas indicate scales with rapid increases in connectivity to current attack. These critical scales can then be cast back onto the original map of susceptible patches using isolines (Figure 7). Areas corresponding to more gradual increases in connectivity likely represent areas with higher likelihood that management can reduce connectivity, and, hence, risk in a timely manner. In this example, the areas corresponding to thresholds 65 to 150 km and 250 to 350 km appear to provide the best opportunity to reduce the risk of spread across this landscape.

Empirical Outbreak Projection

The development of methods for modeling and analyzing spatially and temporally autocorrelated data such as the historical spread of a bark beetle outbreak across a heterogeneous landscape is a current and active area of research (e.g., Augustin and others 2007, Wikle 2003, Zhu and others 2005). However, appropriate statistical modeling techniques are not yet sufficiently well developed or disseminated for timely and practical application in many situations. Semi-Markov models are a standard method of projecting vegetation dynamics (Acevedo and others 1995, Baker 1989). Where data are abundant, the statistical challenge of modeling transition probabilities may be avoided by categorizing observations and using observed transition probabilities directly. Until robust statistical methods are available, this direct approach is reasonably well suited for practical and timely decision support. The approach can be extended to include multiple predictive factors in a probabilistic state-transition table. A time series of infestation progression is collected and categorized into infestation intensity classes. That time series is combined with spatial data about the physical environment. All of the data are

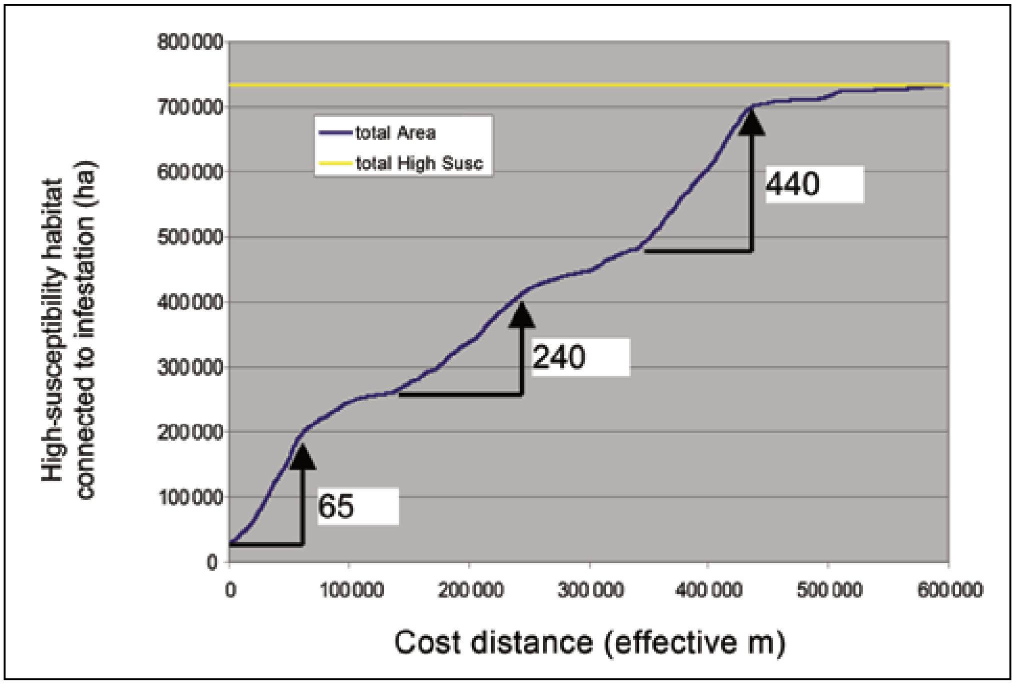

Figure 8—Results of graph thresholding in Dawson Creek/west Alberta study area. The total area of high susceptibility to mountain pine beetle attack and loss (greater than, or equal to 65, according to the Shore and Safranyik [1992] rating system) habitat is just over 700 000 ha (yellow line). The amount of high-susceptibility habitat connected to current attack in Dawson Creek through the graph increases as cost thresholds increase (blue line). At a threshold of 0, only host patches containing current attack are connected. As the threshold increases, more patches are joined at distances less than or equal to the threshold. At an effective distance of just under 600 km, all habitat is connected in a single cluster. Arrows indicate scales over which there are rapid increases in connectivity indicated by changes in slope.

cast in a grid cell (raster) environment. Two kinds of factors determine the state of a cell:

1. Factors based on the state of the infestation itself such as the history of the infestation in a particular cell, and some measure of the influence of infestations in other parts of the landscape. Simple neighborhood rules (e.g., number of infested cells within some distance) are a common method of characterizing spatial effects, but we have found a more biologically informed model of dispersal pressure to be more useful.
2. Factors based on the nature of the physical environment such as forest age, species com-- position, and elevation.

Transition probabilities, from one state to another, are calculated directly from the observed transitions. Care must be taken not to over-specify the model (ensure adequate sample sizes for probability calculations). The model may be refined somewhat by introducing hierarchy into the transition table. For example, the factors that best predict the probability of infestations starting in cells with no previous infestation history may be different than the factors that predict how infestations proceed once they have arisen. The state transition table is used to project an infestation through time.

Data Requirements—

Spatially explicit information about infestation history is required, categorized into states that represent the level of damage caused. In addition, information about the physical environment relevant to the progression of the infestation, such as forest cover mapping, must be available in digital form.

Output—

The principal output is a spatially explicit projection of the effect of an infestation on the forest resource. The spatial resolution of the output will be the same as the resolution of the input layers, whereas the precision (e.g., the level of the effect) will depend on the resolution of the historical outbreak information. Output is in the form of the state of the infestation (in terms of severity classes) in a given year and grid cell, based on the states represented by the input infestation maps. Numerous other outputs can be derived from the projection of the state; for example, spatially explicit projections of the volume of timber that is killed and tabular summaries of the area affected. As such models are stochastic, each scenario can be used to generate an expected distribution of attack, such as the form illustrated by Figure 1. However, mean values are generally used to communicate spatial and temporal dynamics and compare alternative scenarios.

Pros and Cons—

This approach is relatively data intensive, and a significant amount of analysis is required to develop the state transition tables. The approach will not provide new insights into the behavior of an infestation. As a strictly empirical approach, a key assumption is that the future behavior of the outbreak will resemble the behavior in the past. This approach, however, is one of the simplest ways to provide a spatially and temporally explicit dynamic projection. Although the data requirements are reasonably onerous, there is only a limited requirement for understanding the processes that govern the progression of the outbreak. A key advantage of the approach is that the spatially and temporally explicit projection can be integrated with other management or planning models to explore interactions between the effect of the infestation and the management response.

Management Application—

This approach could be applied over an area of any size. It is only applicable in situations where there is enough historical data on all outbreak phases to develop a useful state transition table. Its primary use is to project potential infestation trajectories, which can be used to clarify management options and consequences and guide strategic policy development.

Example Application—

British Columbia is currently in the midst of the biggest MPB outbreak in recorded history. We used an empirical outbreak projection to forecast the possible impact of the outbreak over the entire province for the next 20 years (Eng and others 2005, Figure 3). We obtained 7 years of infestation history collected through the Provincial Aerial Overview of Forest Health (Ebata 2004, Figure 9). Forest cover information and a host of other data regarding the physical environment and management regime were collected primarily from the Province of British Columbia's Land and Resource Data Warehouse (http://lrdw.ca). An outbreak projection model along with a forest management response model was implemented using the SELES (Spatially Explicit Landscape Event Simulator) spatio-temporal modeling tool (Fall and Fall 2001). SELES combines a spatial database for a landscape with a high-level, declarative modeling language used to specify key processes and a discrete-event simulation engine that interprets and executes such models.

Based on the most recent infestation mapping, we estimate that approximately 25 percent of the merchantable pine volume in the province was observed to be dead (red or grey crowns) during the summer of 2005 (Figure 10). Because trees killed during the summer cannot be detected through aerial surveys (their crowns are still green), we rely on the projection model to estimate that an additional 10 percent of the pine volume was killed during that summer. The difference between the two projections is due to the dramatic increase in infestation in 2005. We show both to illustrate how empirical projection models are driven by observation, but focus on the one driven with a more complete data set (i.e., including 2005 data). This difference, however, does not alter the primary conclusions. We project that by 2010 over 60 percent of the merchantable pine volume in the province will be observed as dead, and that about 80 percent will be killed (Figures 10 and 11) by 2013 when the infestation will have largely run its course. Further maps of the input data and the projections can be found at http://www.for.gov.bc.ca/hre/bcmpb.

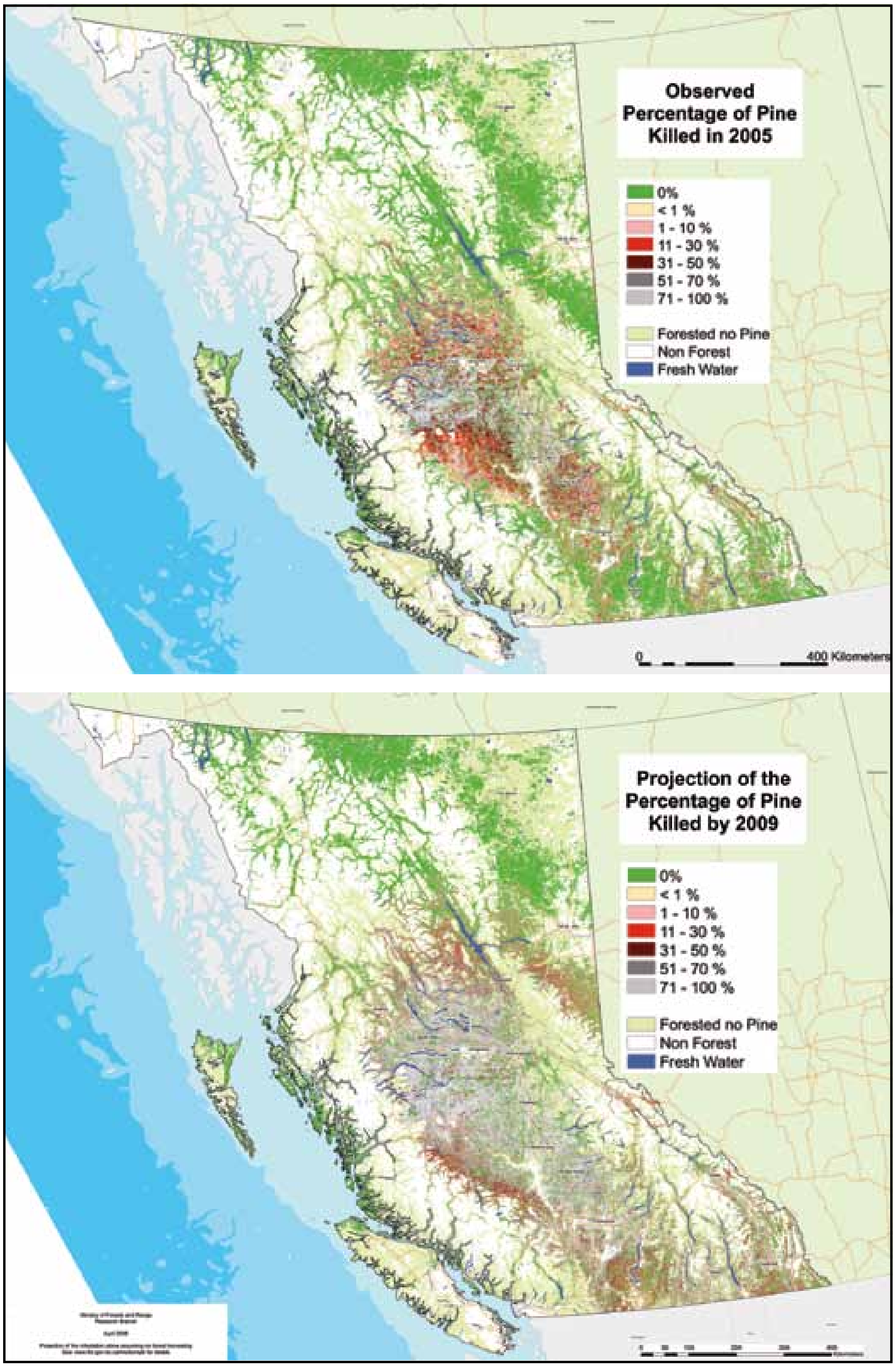

Figure 9—Mountain pine beetle attack from 2005 observation and projected at 2009. Comparison of patterns of mountain pine beetle attack from 2005 aerial overview surveys (top) and projected at 2009 using an empirical model (bottom) (from Eng and others, unpublished, found at http://www.for.gov.bc.ca/hre/bcmpb).

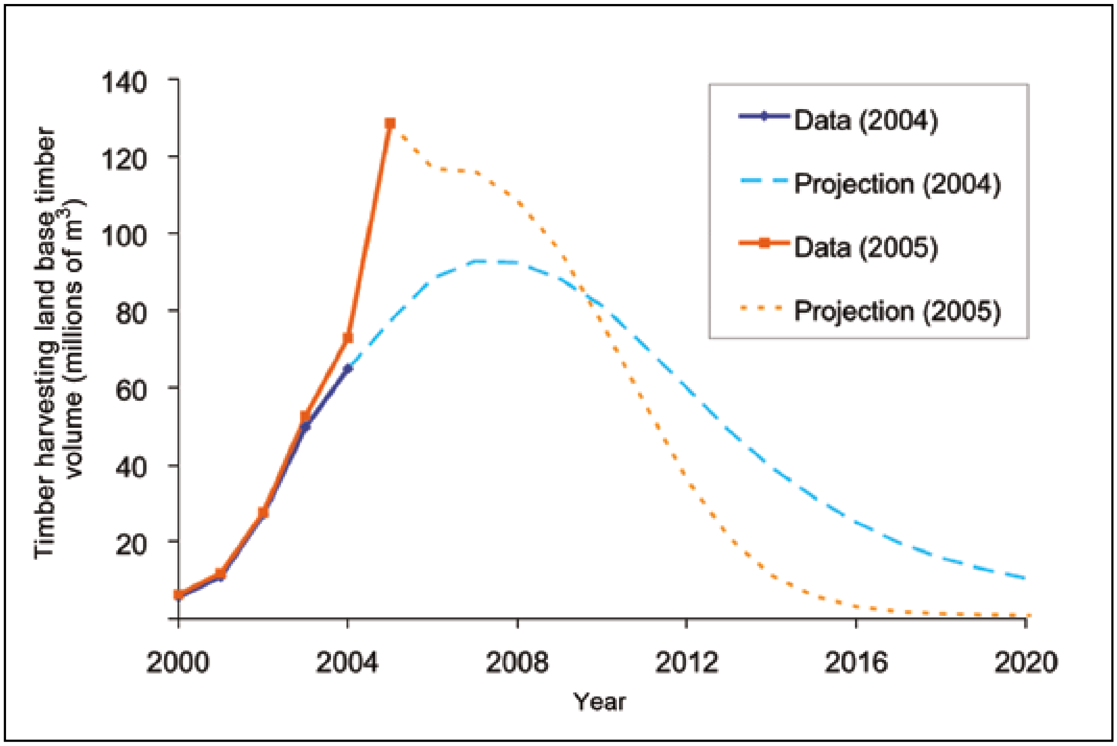

Figure 10—Observed and projected annual kill based on British Columbia mountain pine beetle model runs in the timber harvesting land base (THLB) over the entire province of British Columbia. Based on the 2004 and 2005 Provincial Aerial Overviews (Eng and others, 2005, Eng and others unpublished found at http://www.for.gov.bc.ca/hre/bcmpb/BCMPB.v3.BeetleProjection.Update.pdf).

The results of the projection have been used for a variety of purposes. Notably, they have been widely cited in the press and have been extensively communicated to natural resource managers in an effort to increase awareness about the severity of the problem. The results of the interactions between the outbreak projection model and our forest management model have been used to help direct funding for control efforts, examine the impacts of the forest management response on the transportation system, and to investigate the possibility of developing a bioenergy plant in the most severely affected area. The results of the infestation projection itself have been incorporated into detailed modeling for timber supply analyses.

Population Modeling

Population models capture outbreak dynamics by explicitly modeling demographic changes with processes of mortality, birth, dispersal, etc. (Caswell 1989). We designed a landscape-scale MPB population model to assess impacts at scale of ~1 000 000 ha to explore likely trajectory and broad spatial patterns of an outbreak, to evaluate a range of management options, and to estimate likelihood of different outcomes (Fall and others 2004). The general concept is to project an infestation forward using a landscape model that combines a spatially explicit MPB population model (Dunning and others 1995) with a spatial management model for timber supply, strategic forest management, and fell and burn treatments, so that interactions between management and beetles can be assessed.

The MPB population model scales results from a more detailed stand-level MPB population model, MPBSIM, which projects expected development of a beetle outbreak in a stand of up to several hectares (Riel and others 2004, Safranyik and others 1999). Our approach is to conceptually run MPBSIM in each cell of the landscape. Because it is not feasible or desirable to do this directly, we first run MPBSIM under a wide range of conditions to produce a table linking conditions to consequences. Conditions include stand attributes (e.g., age, percentage of pine),

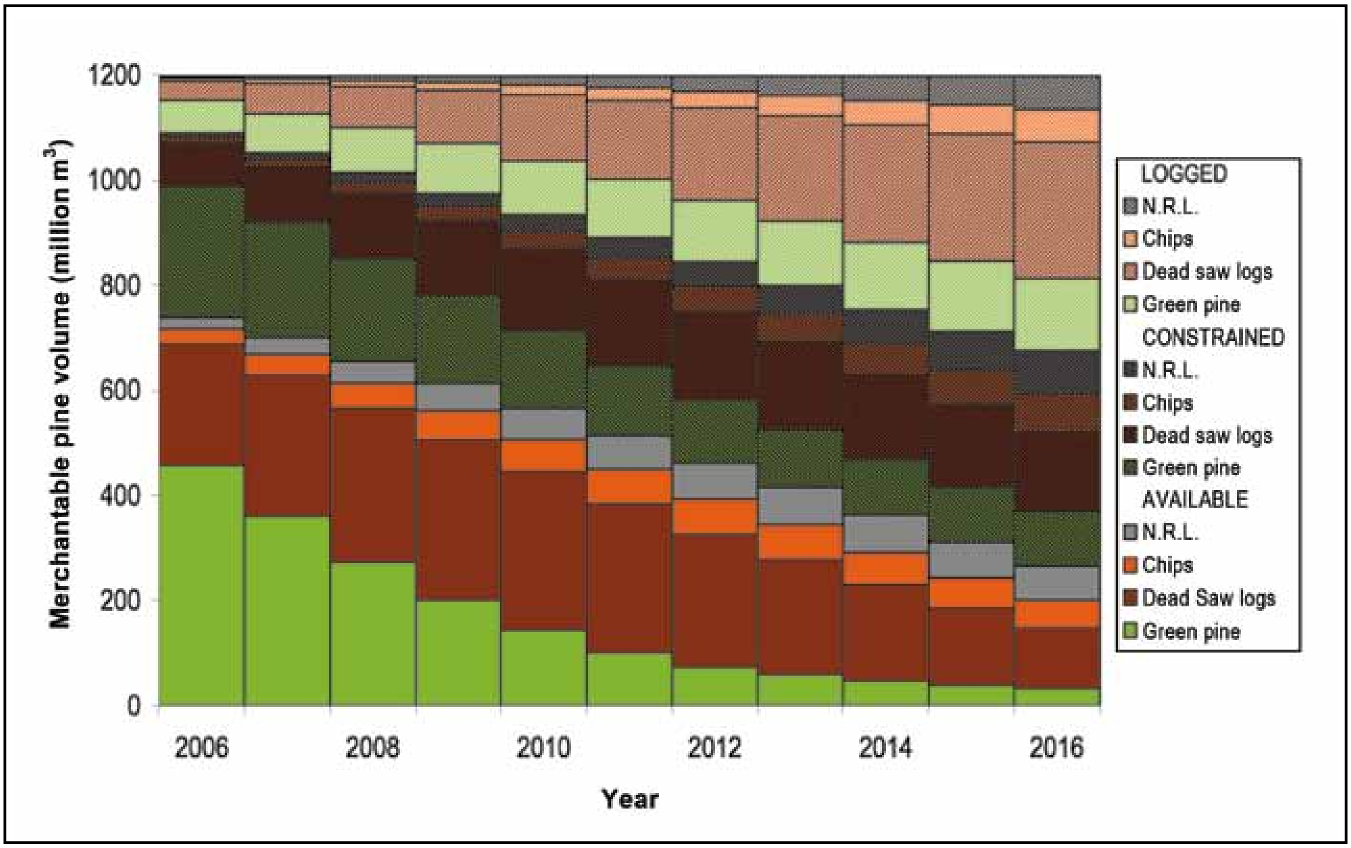

Figure 11—Projection of pine volume from British Columbia mountain pine beetle (MPB) model. This graph indicates the projected proportion of merchantable pine volume on the timber harvest land base in the 20 management units in British Columbia with the highest level of susceptible pine (from Eng and others, unpublished, found at http://www.for.gov.bc.ca/hre/bcmpb/BCMPB.v3.ReferenceScenario.Update.pdf). Left diagonal hatching indicates volume logged during the scenario. Right hatching indicates volume not available for harvest owing to policy constraints (e.g., visual areas) or economic limits (road access, minimum volume). No hatching indicates volume available for harvest (standing live and dead merchantable wood). NRL is nonrecovered loss (volume lost owing to decay). Chips are for products with lower requirements for wood quality (e.g., oriented strand board), whereas saw logs are for products with higher requirements for wood quality (e.g., structural lumber). All pine killed by MPB are covered by the NRL, chips, and dead saw logs category. Pine volume not killed by MPB is in the green pine category.

outbreak status (e.g., number of attacking beetles), etc. (Riel and others 2004). Consequences refer to the effect of 1 year of attack under those conditions (e.g., number of dispersers and number of trees killed). The landscape-level model uses this table to project MPB dynamics in each 1-ha cell containing beetles. The stand table includes stochastic variation in number of emerging beetles, and we control this to capture synchronous annual variation and above-average weather conditions.

Dispersal between cells provides the spatial context for an outbreak, leading to an increased beetle population in cells within a current outbreak, or starting an outbreak in a currently uninfested cell, expanding an existing spot, or starting a new spot. The flight period, including beetle local and long-distance dispersal and pheromone production and diffusion, is modeled as a spatial process. Long-distance dispersal is largely governed by wind speed and direction used to select distance locations for MPB spread, whereas local dispersal is influenced by wind, susceptibility, pheromones, and distance. During attack, beetles kill pine trees, resulting in standing dead volume that may be salvaged by the logging sub-model.

Data Requirements—

Data requirements include detailed digital spatial forest cover data, infestation locations/intensity, beetle population estimates, and demographic parameters. In addition, availability of a stand-level population model to support scaling, or the information required to develop process sub-models is required. This poses substantial effort and a long-term program to obtain the ecological information for parameterization (Fall and others 2004).

Output—
Nonspatial indicators summarize information across space as time-series output that includes:

1. The MPB outbreak indicators such as volume killed.
   number of trees killed, and area attacked
2. Growing stock inventory: cubic meters of live forest.
3. Management indicators such as annual volume and area harvested, volume of nonrecovered loss, volume salvaged, and amount of available salvageable wood.

Because the approach is stochastic, multiple replicates of each scenario are run. We designed several spatial indicators that summarize information across time and replicate:

1. The number of runs in which each 1-ha cell was attacked at least once, which can be roughly thought of as the probability that a cell will be attacked at some point in the 10-year horizon.
2. The cumulative volume killed, which shows areas likely to have the highest timber impacts.
3. The cumulative percentage of pine killed, which shows areas likely to have the higher ecological impacts.

Pros and Cons—
This approach requires substantial effort to develop and has fairly high data requirements, in particular the need for a reasonable understanding of beetle biology and interactions with hosts at relatively fine scales. The main advantage is that a population model takes a process-oriented approach to dynamic projections. This provides a closer match with the ecological process and greater ability to assess interactions with management. These methods can be used to identify likely trends over time and can integrate with management models. The process-based perspective enables emergent (bottom-up) properties not possible in a more strictly empirical (top-down) approach (Korzukhin and others 1996). That is, a population can respond to future landscape conditions that haven't been encountered in the historical record. As with the empirical projection method, each scenario could potentially produce risk information in the form illustrated by Figure 1, but generally mean values are used to facilitate comparison of scenarios and to communicate spatial or temporal dimensions or both.

Management Application—
This method is applicable at landscape scales where cell resolution can be fairly fine (1 ha) and is designed for situations with an existing outbreak. Its strength is the ability to explore dynamic interactions between management alternatives and beetle populations, an approach that we have applied in a number of landscapes across BC (Fall and others 2004, in press). Information on the relative effects of beetle management strategies on area infested and volume killed can be used to assess impacts directly or to serve as input for further analysis of economic, social or ecological cost/benefits.

Example Application—
The MPB attack was first confirmed in the Dawson Creek area in 2002 (Figure 3). The main outbreak in British Columbia was expanding rapidly, and it appeared that there was some long-distance dispersal through the Rocky Mountains. Spots recently detected in Dawson Creek most likely originated from the main outbreak, and were transported over long distance via wind and through mountain passes (A. Carroll, pers. comm.). Growth rates, as indicated by green: red attack ratios have been relatively low (M. Duthie-Holt, pers. comm.), but nonetheless showed potential for population growth. This suggested that recent weather was sufficiently warm to support an outbreak, whereas historical climate likely precluded outbreaks (Carroll and others 2004). There has been substantial effort in Dawson Creek focused on dealing with detection and treatment of spots, with cooperation among licensees, the Forest Service, and parks. A landscape-scale projection of outbreak potential was deemed to be useful to inform this process and to help clarify some tradeoffs between options available (Fall and others, in press).

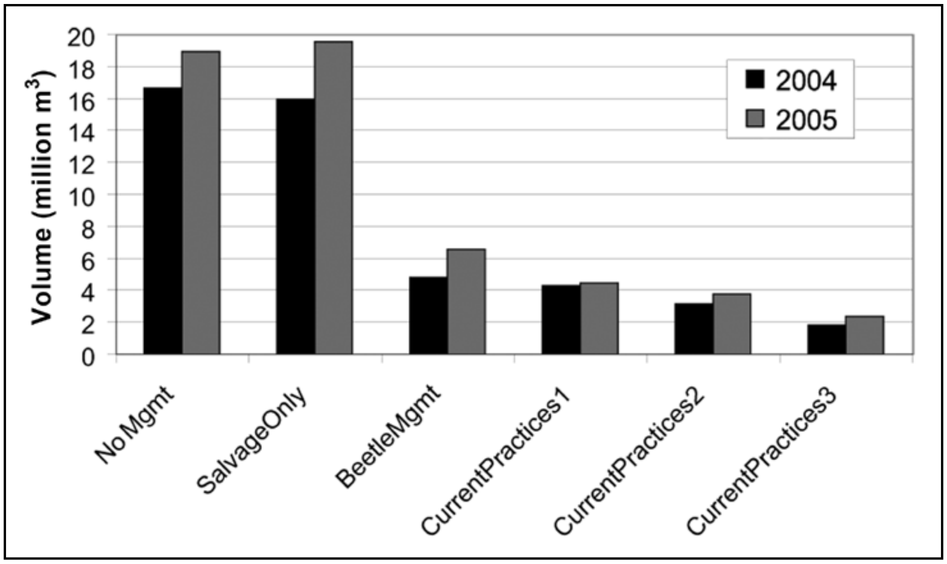

Figure 12—Projected cumulative volume killed in Dawson Creek mountain pine beetle population model over 10 years for the base beetle management scenarios and no harvesting. Initialized using 2004 or 2005 survey information (averages of 10 replicates). These scenarios include estimated changes in climatic suitability (Carroll and others 2004) and immigration from the main outbreak to the west. NoMgmt is no harvesting and no fell and burn. SalvageOnly only allows salvage of dead merchantable timber (i.e., focus is on recovery of dead wood, not population reduction). BeetleMgmt is general beetle management, aimed at reducing populations where possible. CurrentPractices approximates better current management in Dawson Creek, which aims at population reduction as well as reducing risk of spread eastward into Alberta. Three variations were assessed, differing primarily in budget limits on treatment levels.

The main purpose of this study was to apply a population-based model methodology to evaluate the effectiveness of bark beetle management activities in reducing losses to the MPB and to analyze the potential spread, likely trajectory, and impacts of the beetle across the study area. To achieve this goal, we started with the current conditions and projected likely outcomes under various management scenarios representing alternative beetle management regimes derived from workshops held in Dawson Creek with government and industry. We projected system dynamics for 10 years, with 10 replicates per scenario. A wide range of experimental scenarios was also assessed for calibration and sensitivity analysis.

Our results generally showed that this area still has the potential for beetle management to have an impact on population levels, in particular current local practices (Figure 12). In addition to general information to help with strategic planning, this modeling approach can provide spatial outputs to visualize and quantify patterns of the expected outbreak trajectory under different management and weather conditions (Figure 13). This information is important for communicating risk potential in a landscape and can help with tactical planning of areas that may need management focus.

Other Risk-Assessment Methods

It may be possible to interpret other methods for assessing landscape-scale risk of bark beetle outbreaks in the framework presented (Figure 2), such as spatial temporal statistical methods (Augustin and others 2007, Wikle 2003, Zhu and others 2005) and field experiments. An alternative approach is employed in the Westwide Pine Beetle Model in which contagion forms the basis for a spatially explicit spread model (Beukema and others 1997). Another process-based approach to spatio-temporal modeling of MPB dynamics has been taken in the MPBpde model (Powell and others 2000), in which the MPB-pine interaction is represented by a system of partial differential equations that can

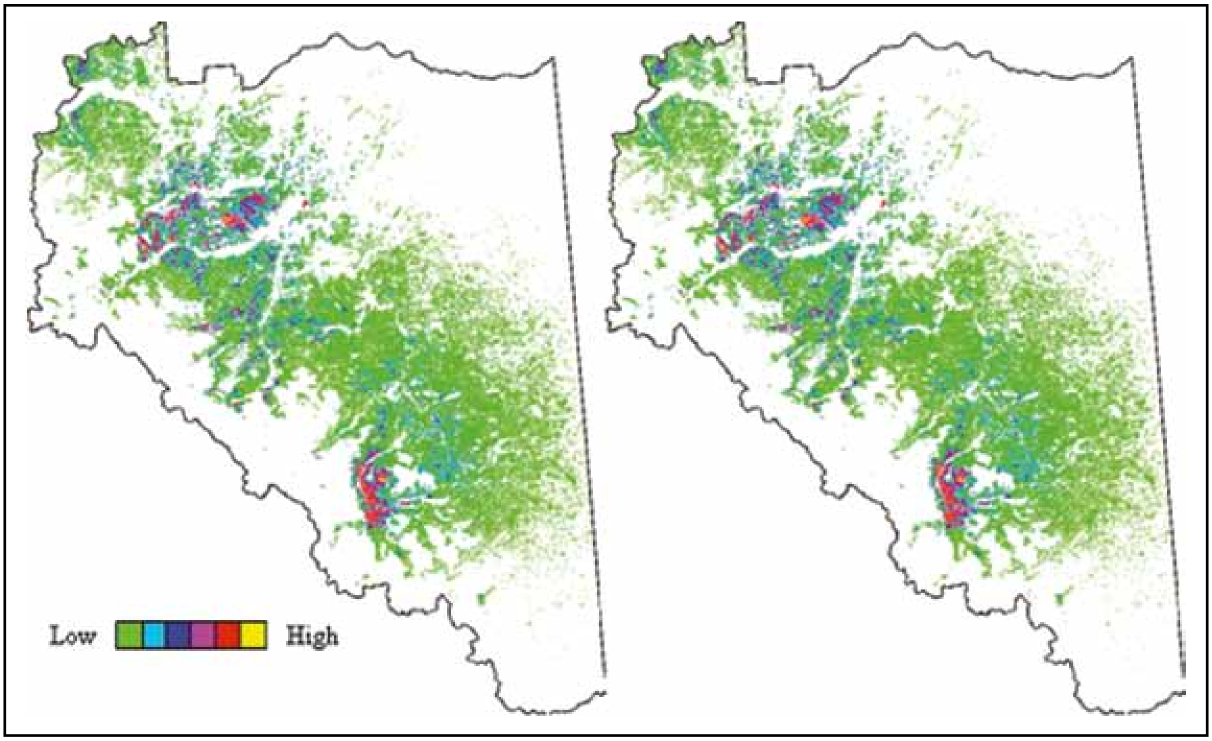

Figure 13—Spatial presentations of landscape risk for the no management scenario in the Dawson Creek study area. Left: projected likelihood of attack (proportion of 10-year runs in which each cell is attacked in projection). Right: projected intensity of attack represented as the percentage of pine killed (average cumulative percentage killed). These include estimated changes in climatic suitability (Carroll and others 2004) and immigration from the main outbreak to the west.

be explored numerically (e.g., Logan and others 1998) and analytically (e.g., Powell and others 2000). Partial differential equation methods can be applied over broad scales, but are challenging to combine with other landscape processes that are more discrete in time and space (e.g., timber harvesting). Hughes (2007) modeled beetles individually at a similar spatial and temporal scale. These models allow detailed exploration of how beetles interact functionally with a landscape. However, individual-based approaches are generally prohibitive at the landscape scale because such models are computationally demanding and because we lack the detailed land cover and beetle data required to parameterize them.

Discussion

In this section, we provide information for use in selecting an appropriate method of risk assessment, provide a discussion on model verification and validation, and discuss future research needs in this area.

Selecting an Appropriate Method

Some key aspects of a given problem can help guide the most appropriate choice of risk assessment method. In general, the best method is the simplest one (Occam's razor) that addresses the desired management questions in the required timeframe, using data available for the study area. The **possible** methods for a given problem are in the intersection of these issues. That is, these issues can help filter infeasible approaches. Generally, management needs emphasize more detailed and precise (more functional) risk assessment methods, whereas timeframe and data/knowledge availability emphasize simpler and coarser (more structural) methods. There is always a tension between the goals of maximizing information and minimizing uncertainty.

The following are some key considerations to help narrow the range of potential methods:

- Identifying management questions: Often, decisionmakers want to "know what will happen" in the future. However, it is essential to clarify in precise terms the nature of the decision problem. What decisions need to be made? What level of information would be sufficient (as opposed to desirable)? It is important to maintain a transparent and collaborative relationship (e.g., Fall and others 2001) to ensure that results are useful. It is also important to communicate the uncertainties associated with different options and different questions to increase confidence in the chosen method.

- Decision timeframe: The timing of decisions plays a key role. For ongoing or long-term decisions, there may be time to collect new field data and develop more complex models. Short timeframes will require the use of currently available information and methods that can be supported by available data. Articulating the timeframe required for different options can help foster a shared understanding of the constraints imposed upon the choices available.
- Defining area of interest: Often, the spatial scale of a decision will determine the study area (e.g., harvest levels and strategies are often specified at the scale of a timber supply area). Sometimes the ecological scale of a process influences this decision. For example, a very broad-scale output may indicate that a larger study area is needed to ensure that adequate context is captured. It is critical to avoid scale mismatch problems (Cumming and others 2006).
- Data availability: Data availability can impose a significant constraint on which risk-assessment method can be employed. Lack of detailed knowledge about beetle demographics and movement may prohibit a population- or individual-based approach. Lack of readily available spatial information on historical outbreak patterns may prohibit an empirical approach. If the available data are not adequate to support a given method, this should lead to serious consideration of its applicability. The apparent precision provided by applying a more detailed method and using inadequate data may be a false benefit compared to the more accurate but less precise results that would be achieved using a coarser method. Additionally, the data requirements to develop a new method or model are often different (and in many cases more onerous) than the data required to adapt an existing method developed elsewhere.

The most important decision is selection of a good team with a broad range of skills. At the outset, the primary focus should be on the questions or issues to address, and then the team should work backwards towards the tools. That is, clarify the issues and constraints of data and knowledge and timing raised in the preceding subsections, while developing and formalizing conceptual models. Flexibility and often an iterative approach are required to shift course as information (or lack thereof) becomes apparent. The simplest method that meets the needs of the study should be chosen. If temporal dynamics or outputs are not required, a static approach can be used. If spatial interactions or outputs are not needed, a non-spatial approach is appropriate. We presented the example methods in order of increasing complexity. Other methods can be fit into this framework at different points. A suite of methods that may be applicable should be identified, filtering out methods that are not adequate to meet the requirements. The remaining methods should then be contrasted to pick the simplest one because higher complexity and data requirements imply higher uncertainty as well as longer timeframes for application.

Model Verification and Validation

We define **verification** as an assurance that the model is implemented as specified, and **validation** as an assurance of the appropriateness of the model for its intended use (Rykiel 1996). That is, validation relates to the level of certainty one can place in model outputs; (i.e., the degree to which model results differ from expectations). Verification is an essential step and must be considered in model selection and application.

Validation is often defined as the degree to which model output matches an independent data set (Rykiel 1996). More structural approaches to risk assessment facilitate validation more easily than more process-oriented approaches (e.g., Cameron and others 1990, Dodds and others 2004). Static methods such as susceptibility rating can be statistically tested in areas with field data on past and current attack (Dymond and Wulder 2006). Empirical and connectivity approaches are driven by observation, and predictions can be compared with actual outcomes as an outbreak proceeds (and such data can then be used to improve the model parameters). Empirical, or data, validation for a spatio-temporal model is only possible in cases with short time lags in system response or for which suitable replicates exist (e.g., for chronosequence-type comparisons). The exact conditions encountered within large landscape systems cannot be found outside the system (Levin 1992). In addition, observational data isn't available for assessing hypothetical management alternatives. In relatively process-oriented approaches, it may be more appropriate to rely on conceptual and logical validation (Rykiel 1996), where we view the model as a hypothesis and model output as a consequence of the hypothesis. That is, the purpose of such models are to make a clear link between the initial conditions, parameter values, and process behavior, and the consequences of those assumptions, which are projected via simulation (which in this sense is akin to theorem proving), and not to predict the real state of the future forest (i.e., projection not prediction). Logical validation inherently relies on the adequacy of the input information regarding initial conditions, model processes, and appropriate parameter values. Refinement of these can occur over time as ecological knowledge is refined.

Future Research Needs

New methods will be developed, and existing methods will be improved in the area of risk assessment. We suggest that using the proposed framework for comparing tools will assist tool selection for a given situation and improve understanding of the differences between tools in terms of precision, uncertainty, and resources required. In addition to ensuring that the set of tools forms a cohesive toolkit, it will also be important to improve the application of tools. That is, evaluating the applicability of a tool in a given situation needs to be easy, and usage of the method should be as straightforward and transparent as possible.

Although the examples we present focus on MPB in lodgepole pine forests, the concepts underlying the risk-assessment methods and the classification gradient apply to other bark beetle species and forest systems. Susceptibility rating systems have been developed for MPB in ponderosa pine, *Pinus ponderosa* Dougl. ex Laws. (Chojnacky and others 2000, Negron and Popp 2004) and whitebark pine, *P. albicaulis* Engelm. (Perkins and Roberts 2003). Dodds and others (2004) and Negron (1998) examined risk rating for Douglas-fir beetle (**Dendroctonus pseudotsugae** Hopk.). Susceptibility rating systems have been developed for spruce beetle (*D. rufipennis* Kby.) in Alaska (Reynolds and Holsten 1996). Connectivity analysis for risk assessment is not very common at present. We have ongoing work to explore risk of spruce beetle (across a large area of southwestern Yukon, Canada, using connectivity methods. In addition to susceptibility rating, statistical methods to examine spatial and temporal autocorrelation of environmental factors (Gumpertz and others 2000) and simulation-based approaches (Mawby and Gold 1984) have been applied to the southern pine beetle (*D. frontalis* Zimm.).

Applying methods in new systems presents a number of challenges and high levels of uncertainty. The MPBs have been expanding the northeastern limit of their range and are approaching boreal jack pine (*P. banksiana* Lamb.) forests in Alberta, Canada (H. Ono, pers. comm.). These changes increase uncertainty owing both to the dynamic character of the changes and because little information is known on MPB—host interactions in these forests. Nonetheless, managers of these systems are faced with challenging decisions, and risk-rating systems can provide some insights. In conjunction with climatic suitability work (Taylor and others 2006), we have ongoing work to adapt and apply susceptibility and connectivity methods in the boreal forest of British Columbia and Alberta, Canada.

Conclusion

We presented a common framework within which methods to assess landscape-scale risk of bark beetle infestations can be classified. This framework has two elements. First, conceptualizing landscape-scale risk as a probability distribution of potential loss provides a common basis to compare methods and allows varying degrees of precision, uncertainty, and stochasticity to be included. Second, viewing methods along a gradient from structural (pattern-oriented) to functional (process-oriented) approaches to risk assessment helps to clarify tradeoffs between precision, uncertainty, data requirements and timeframes for application. A key message is that no single tool or method can address all needs. Viewing methods along a gradient of complexity helps provide a system to classify methods, which, in turn, facilitates comparison and selection for a given set of questions.

Acknowledgments

We would like to acknowledge support for this project from the Mountain Pine Beetle Initiative of the Canadian Forest Service (CFS). We also thank Les Safranyik (CFS emeritus), Adrian Walton (British Columbia Forest Service), and Peter Hall (BC Forest Service). We would like to thank all the people in various regions of BC and elsewhere who have collaborated on projects and methods presented.

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