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Determination of the compositional change (1999–2006) in the pine forests of British Columbia due to mountain pine beetle infestation

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Abstract The current mountain pine beetle (*Dendroctonus ponderosae* Hopkins) outbreak in British Columbia and Alberta is the largest recorded forest pest infestation in Canadian history. We integrate a spatial hierarchy of mountain pine beetle and forest health monitoring data, collected between 1999 and 2006, with provincial forest inventory data, and generate three information products representing 2006 forest conditions in British Columbia: cumulative percentage of pine infested by mountain pine beetle, percentage of pine uninfested, and the change in the percentage of pine on the landscape. All input data were formatted to a standardized spatial representation (1 ha minimum mapping unit), with preference given to the most detailed monitoring data available at a given location for characterizing mountain pine beetle infestation conditions. The presence or absence of mountain pine beetle attack was validated using field data ($n = 2054$). The true positive rate for locations of red attack damage over all years was 92%. Classification of attack severity was validated using the Kruskal gamma statistic ($\gamma = 0.49$). Error between the survey data and field data was explored using spatial autoregressive (SAR) models, which indicated that percentage pine and year of infestation were significant predictors of survey error at $\alpha = 0.05$. Through the integration of forest inventory and infestation survey data, the total area of pine infested is estimated to be between 2.89 and 4.14 million hectares. The generated outputs add value to existing monitoring data and provide information to support management and modeling applications.

Keywords Mountain pine beetle · Mapping · Data integration · Monitoring · Infestation

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Introduction

Forest health monitoring and mountain pine beetle in western Canada

The mountain pine beetle (*Dendroctonus ponderosae* Hopkins) is endemic to forests of western North America. Periodically, beetle populations rise to epidemic levels, causing extensive and intensive tree mortality in pine forests (Safranyik and Carroll 2006). Depending on the stage of the mountain pine beetle population cycle and the spatial scale of interest, there may be a variety of management options available to forest managers to limit beetle-caused pine mortality (Nelson et al. 2006a). Monitoring programs allow forest managers to track the status of beetle populations, and several different data sources have been used for monitoring purposes, with each data source providing a level of detail suitable for a particular information need (Wulder et al. 2006a). The various monitoring approaches used in British Columbia form a survey hierarchy that informs three distinct management objectives: strategic, tactical, and operational. Each level of this hierarchy is characterized by the extent and detail of the spatial data provided (e.g., a synoptic, landscape level survey or a detailed forest stand level survey), relative accuracy, and cost. This hierarchy extends from broad, provincial scale forest health surveys conducted using a fixed-wing aircraft to detailed, stand level surveys conducted using a helicopter equipped with GPS; as one moves through the hierarchy from a coarse overview to increasing levels of detail, surveys cover smaller geographic areas and provide more detailed information, while relative accuracy and costs increase.

To identify areas with mountain pine beetle infestation, aerial survey programs rely on the characteristic fading of an infested tree's crown foliage. Trees are attacked during beetle emergence, which occurs in mid- to late summer throughout most of British Columbia (Safranyik et al. 1974). After a successful attack by mountain pine beetles, the infested tree will die and the crowns will gradually fade from green (green attack), to yellow, to red (red attack). Eventually, the tree will lose all of its foliage, a condition referred to as gray attack. It is estimated that after 1 year, over 90% of trees successfully attacked by mountain pine beetle will have red needles (British Columbia Ministry of Forests 1995). Variability in the rate of foliage discoloration may be attributed to partial and full multivoltinism (more than one brood of beetles per year; Reid 1962), semivoltinism (the extension of one life cycle over more than 1 year; Amman 1973), and other site and tree characteristics, such as drought (Wulder et al. 2006b).

At the provincial scale, aerial overview surveys (AOS) are conducted annually using fixed-wing aircraft and are designed to capture information on a wide range of forest health issues. Observers record the location of visible forest health issues, including mountain pine beetle infestations, onto 1:100,000 or 1:250,000 base maps (British Columbia Ministry of Forests 2000). Given the life cycle of the beetle and the rate at which the foliage of attacked trees fade, the AOS data typically captures trees killed by the beetle in the previous year. Small groups of red attack trees are recorded as points, while larger areas of infestation are delineated as polygons on the basemap. Infestations are coded with a severity rating indicating the percentage of the total area of each delineated polygon that is composed of mountain pine beetle-caused pine mortality (Table 1) for severity classes.

The AOS provides the greatest spatial coverage at the lowest cost when compared with other monitoring initiatives (Wulder et al. 2006a). There has not been a comprehensive ground validation of AOS data to current standards. The primary purpose of the AOS data is to aid strategic level planning by capturing trends in forest health from year to year.

At a more detailed spatial scale, helicopter GPS surveys have been conducted in areas of British Columbia impacted by the mountain pine beetle. These helicopter-based surveys record the location (using GPS) and number of infested trees at a specified location. These detailed surveys are generally only conducted in areas where the spatial extent of the infestation is limited and, therefore, where suppression is still viable. In this context, detailed surveys provide important information

Table 1 Severity class ratings used in aerial overview survey (AOS) mapping in British Columbia

Description	Code	Range (%)	Mid Point (%)
Trace[a]	T	< 1	0.5
Light	L	1–10	5
Moderate	M	11–29	20
Severe	S	30–49	35
Very severe[b]	V	50+	55

[a]Code introduced in 2004

[b]Code introduced in 2005

for mitigation planning. Once the size of the beetle population expands and occupies large, contiguous areas, control becomes increasingly difficult (Carroll et al. 2006). Film-based color aerial photography, collected at a scale of 1:30,000, has also been used as a surrogate for helicopter GPS surveys. Softcopy photogrammetry is used to generate points and polygons representing spot infestations or larger areas of infestation, respectively. The estimated accuracy and costs of the resultant datasets are thought to be similar to those of the helicopter GPS data (Wulder et al. 2006a).

At endemic and incipient population levels, beetle damage typically occurs as single trees or small groups of trees (Geiszler et al. 1980; Safranyik et al. 1992), and therefore, points can be a useful representation of infestation conditions for detailed surveys. However, geographically dispersed, low-density spatial patterns of infested trees over large areas are phenomena that are poorly captured by a point representation. Additionally, intensive landscape infestations are difficult to visualize with point representations, and data require enhancement, such as smoothing (e.g. kernel density estimation, see Nelson et al. 2006b).

Ground surveys are also conducted to identify mountain pine beetle-killed trees. These surveys rely less on foliage discoloration to identify infested trees; rather, evidence of entry and exit holes on the bole, boring dust, and pitch tubes are indicators of beetle infestation (British Columbia Ministry of Forests 1995). Ground surveys are the only means of detecting recently attacked trees that have not yet undergone visible foliage discoloration (green attack). Due to the costs associated with field data collection, ground surveys are done on a sample basis and are designed to be representative of the encompassing forest.

Depending on the objective of the ground survey, different types of field plots and survey strategies are employed. Permanent sample plots provide forest managers with long-term data on the growth, mortality, and changes in stand structure. Typically, one center plot and four subplots are constructed for each stand being sampled. Stands are selected for sampling based on a probability proportional to size with replacement sampling design. Center plots are located randomly within each stand (British Columbia Ministry of Sustainable Resource Management 2002). Normally, one center plot is used per stand; however, multiple center plots can be used when stands are very large. Ground surveys for mountain pine beetle detection and validation generally employ detailed systematic star probes (circular plots with radii of 50 or 100 m) or walk-through surveys (Wulder et al. 2006b) and may collect a variety of information. At a minimum, ground surveys will typically enumerate the total number of pine trees and the number of trees attacked by mountain pine beetle (all attack stages) along a transect or within a plot.

Mountain pine beetle information products

Monitoring data are often used to create information products that facilitate decision support for forest management and planning. For example, AOS data are used for the synoptic characterization of the extent and severity of the mountain pine beetle infestation on an annual basis (e.g., Westfall 2007). This information is subsequently used to allocate provincial resources for more detailed surveys and mitigation and is also used to adjust timber supply projections and alter the annual allowable cut (British Columbia Ministry of Forests 2003). Helicopter-GPS data and air photo interpretations provide detailed information used to inform map production and modeling for operational planning such as block layout for sanitation logging.

In order to address scientific questions regarding mountain pine beetle spatial processes at landscape scales, data are required that have the large aerial extent afforded by the AOS data, but with the level of spatial detail provided by the helicopter-GPS surveys. By integrating the AOS data with more detailed survey information, the advantages of the entire survey hierarchy may be leveraged. Furthermore, if integrated survey data are then incorporated with provincial inventory data, which provides information on the location and extent of suitable host species for the mountain pine beetle (i.e., pine), several information products may be generated, including: the percentage of pine infested, the percentage of pine that remains uninfested, and the change in the proportion of pine present between 1999 and 2006. By integrating available monitoring data sources, we are able to characterize the current state of British Columbia's forests, providing an up-to-date indication of where pine remains, and the impact of the current mountain pine beetle epidemic on forest composition.

Often the most difficult questions about ecological processes require detailed information across large geographic areas (Levin 1992). Integrating the data collected through the various mountain pine beetle monitoring programs provides value-added information products of benefit to both forest managers and scientists. For example, by documenting the amount of pine that remains on the landscape, scientists are able to characterize processes such as landscape scale beetle dispersal or changes in landscape pattern associated with large area disturbance. In this paper, we demonstrate an approach for integrating disparate datasets for the purpose of generating new information products that are both spatially extensive and detailed. The validity of these products are assessed and reported in a transparent manner, enabling end-users to judge the suitability of the information products generated for their particular application.

Data

Mountain pine beetle monitoring data

AOS data characterizing the location and severity of mountain pine beetle infestations in the province of British Columbia for each year from 1999 to 2006 were obtained from the British Columbia Ministry of Forests and Range (Fig. 1). For each year, one point layer representing spot infestations and one polygon layer representing patch infestations were obtained, resulting in 16 layers. In addition to the AOS data, detailed survey data were obtained from helicopter GPS surveys and interpreted aerial photography. These datasets varied in their spatial coverage by year

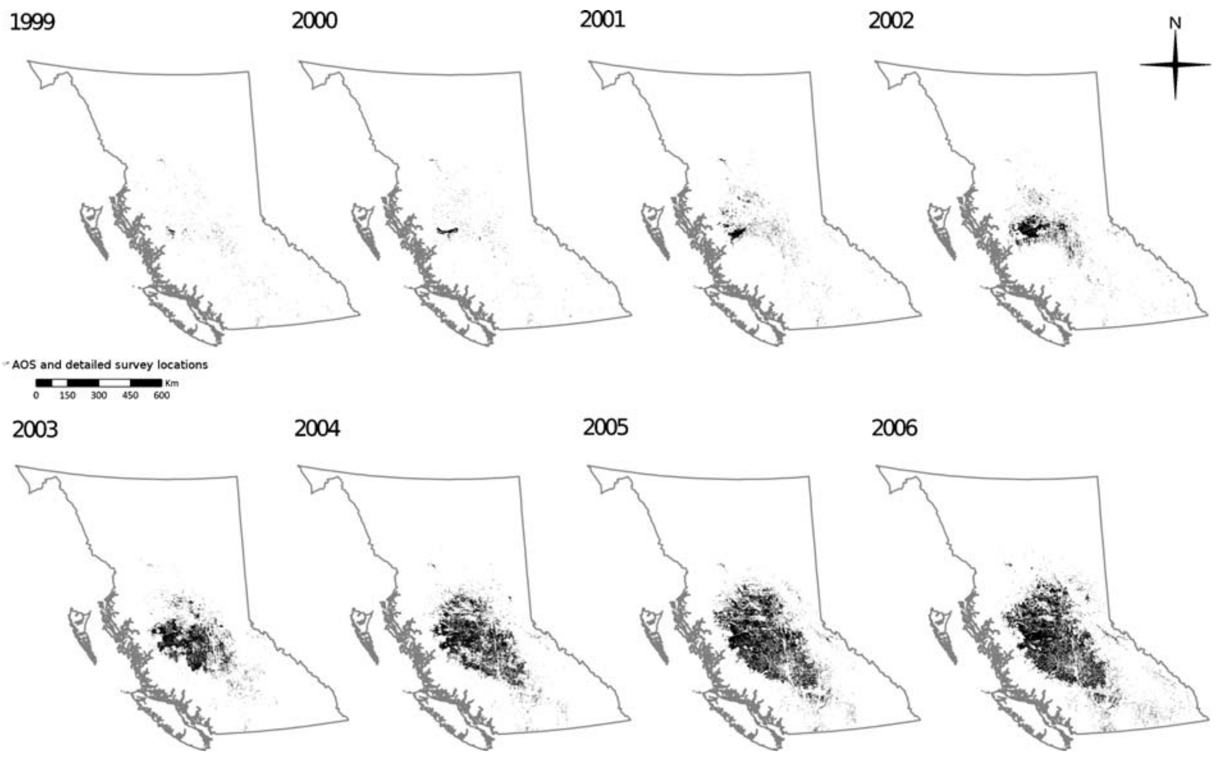

Fig. 1 Locations of AOS and detailed survey, by year for 1999–2006

(Fig. 1). Detailed datasets were either polygon representations with a severity rating or point datasets with either a severity rating or a count of the number of infested trees. We utilized 14 detailed datasets (eight point, six polygon) across the temporal span of our study. The annual areal coverage of these detailed datasets had an average area of 68,430 ha with most years covering under 100,000 ha.

Field data

Ground survey data were obtained from several sources for accuracy estimation of the derived information products. Vegetation Resources Inventory (VRI) permanent sample plot data were obtained from the British Columbia Ministry of Forests for each year from 1997 to 2005 ($n = 948$). VRI field plots are circular variable radius plots. Additionally, field plots were obtained from forest licensees throughout British Columbia ($n = 724$). An assessment of beetle damage was made for an initial plot, and the plot was extended radially outward in increments of usually 100 m.

The locations of field plots are presented in Fig. 2. The temporal distribution of field data is approximately uniform until 2006, when a larger amount of field data became available due to research and operational interest in the spread of beetles northward and eastward. The spatial distribution is fairly uniform, with concentrations in west central British Columbia near Houston and in the interior plateau area. Regions where existing field data could not be found were supplemented with high resolution air photo interpretation ($n = 325$) and new field surveys conducted by the authors in the summer of 2007 (southeast British Columbia, $n = 57$). The total number of field plots obtained for all years was 2,054.

Auxiliary and derived datasets

A seamless forest inventory dataset was obtained for the entire province of British Columbia.

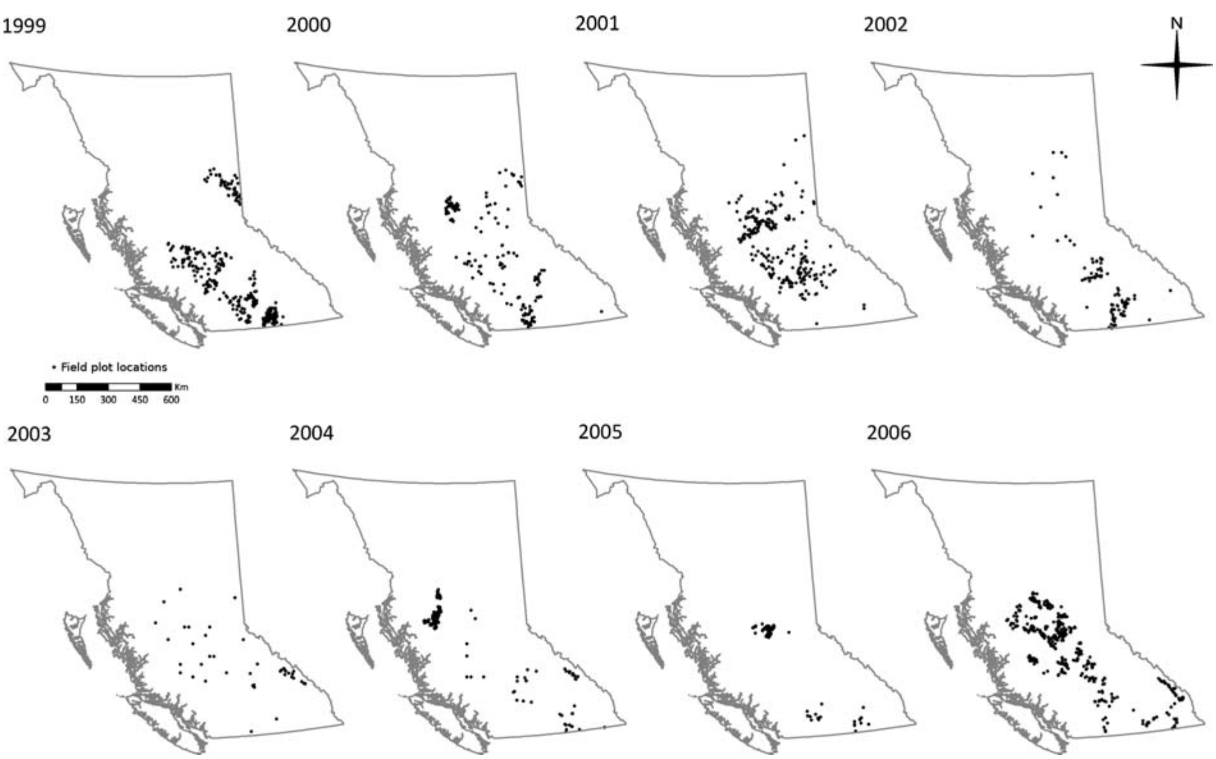

Fig. 2 Locations of field plots per year. Each year displays the locations of field plots conducted in that year. The year 1999 includes plots from 1997 to 1999, 2006 includes plots from 2006 and 2007

The Vegetation Resources Inventory (VRI) provides full spatial coverage of the status of forest conditions in British Columbia in a particular year (British Columbia Ministry of Sustainable Resource Management 2002). Forest stands are mapped as polygons with attributes attached describing stand characteristics such as age and composition. Attributes are derived from both photointerpretation and field validation.

A digital elevation model (DEM) was obtained from the Government of Canada portal Geobase (http://www.geobase.ca), extracted from the National Topographic Database (NTDB). The dataset was reprojected to BC Albers Equal Area projection, using the North American Datum 1983 (NAD83) horizontal datum, and the Canadian Vertical Geodetic Datum 1928 (CVGD28) vertical datum. The data scale was 1:50,000 which had a grid cell resolution of maximum of 3 arc seconds, and was resampled to 100 m grid cells.

The impacts of varying climatic and terrain factors on survey error (see Modeling survey error with covariate auxiliary variables) were considered by calculating direct clear-sky shortwave radiation (SWR) using the methods of Kumar et al. (1997). Consideration of terrain through solar radiation was deemed useful given the complex nature of the terrain in British Columbia, combined with the large area of the province. Elevation ranges from approximately 0 to 3,978 m. Previous research has used SWR as a significant variable for predicting red attack damage at the landscape scale (Coops et al. 2006). Calculations for SWR require parameters for terrain (DEM), latitude, day of the year, and a time interval at which to make calculations. Kumar et al. (1997) suggest that short time intervals have greater accuracy, so calculations were made every 120 min. These calculations were conducted for a single mid-month day for each month, in order to derive a mean estimate of SWR for the entire year.

Methods

Data preprocessing

The first step toward data integration was standardizing all of the input data to a compatible spatial representation and resolution and a common scale of infestation severity. Previous research has indicated that spatially continuous representations of forest conditions, such as raster grids, are useful for visualization and landscape scale analysis of mountain pine beetle infestations (Nelson et al. 2006b). To facilitate continuous data representation and subsequent modeling, a raster representation was selected with a grid cell resolution of 100 m by 100 m in order to accurately capture the stand attributes in the forest inventory.

Data preprocessing included conversion of the polygon and point survey data to raster format with a 1-ha minimum mapping unit (MMU). For polygonal data, we followed the recommendations of the British Columbia Model for Outbreak Projections and used the midpoint of the severity classes (Eng et al. 2004), as indicated in Table 1. We assumed that the percentage of area infested applied homogeneously throughout the entire polygon and, therefore, assigned the appropriate midpoint value as an attribute to the polygon. This was repeated for each of the eight AOS polygon data layers and the six detailed survey (i.e., helicopter GPS and interpreted aerial photography) data layers. These polygonal layers were then converted to raster format.

For point data in both the AOS and detailed datasets, each point represents an area of infestation ranging from 0.25 to 1 ha. If a severity class was associated with the point, we used the full severity rating, assuming that spots represent small but intensely infested areas. Some point data had infestation severity indicated by a count of infested trees. Tree counts were converted to severity classes (percentage infested ratings) by considering the number of infested trees relative to the number of noninfested trees and the area of the spot. Stem density, was based on VRI stem density estimates. Using the area of the spot infestation, we multiplied the percent infested associated with the new severity classes by the area of the spot to arrive at the area of infestation for each point. This allowed us to convert the point layers from both the AOS and the detailed surveys to raster grids, where the resultant raster values indicated the percentage of each cell that represented mountain pine beetle-caused pine mortality. The result was 30 separate rasters (14 AOS and 16 detailed), each with a 1-ha spatial resolution, where each cell represents the proportion of infestation.

The percentage of pine (by area) within each forest inventory polygon was calculated and assigned to an attribute in the forest inventory. Similar to the process described above, the proportion of pine was assumed to apply to the entire forest inventory polygon uniformly, and this polygonal data was converted to raster format with 1 ha resolution. The result was a raster for the province indicating how much pine was found within each MMU.

Spatial data integration

Due to the large variety of input data sources, we used the survey hierarchy to inform the data integration procedure. We define data integration as the combination of data from different sources (Lenzerini 2002). In order to combine rasters for each year of our study, we considered point data to be more accurate than polygon data and detailed surveys to be more accurate than AOS surveys (Fig. 2). Therefore, when values from multiple data sources occurred at the same location, the raster representing the detailed point value had highest priority, followed by rasters representing detailed polygons, AOS points, and finally AOS polygons. As indicated in Fig. 3, when a MMU had multiple values, the value with highest priority took precedence. This produced one final hierarchical spatially integrated (HSI) layer, for each year, representing the percent of area infested within each MMU, for the entire province of British Columbia.

Generation of information outputs

Three distinct information products were generated from the annual HSI layers: percent pine infested, percent pine uninfested, and change in percent pine on the landscape. The HSI layers for all the years considered for this study were combined to determine the cumulative area of the infestation within each MMU from 1999 to 2006. This was done by summing the values at each location, from each HSI layer. The percent pine raster was then used in conjunction with the cumulative percent area raster to produce an

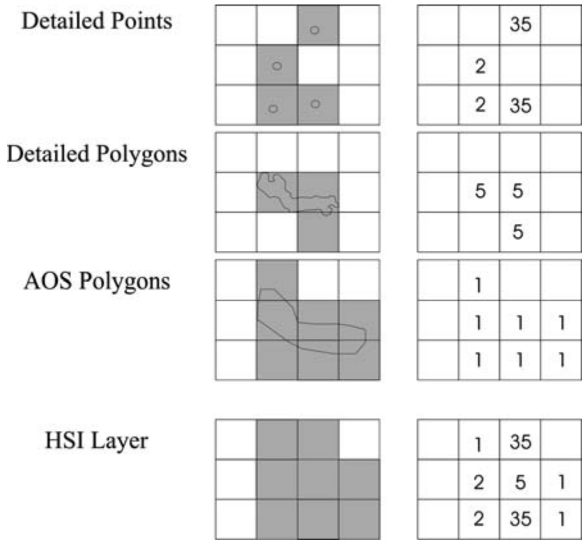

Fig. 3 Hierarchical spatial integration of mountain pine beetle survey data from multiple sources. The order of greatest to least accuracy was detailed points, detailed polygons, AOS points (not shown) and AOS polygons

estimate of the percent pine infested (PPI) within each MMU (Eq. 1):

$$\mathrm{PPI} = \frac{\%\ of\ 1\ \text{ha unit infested}}{\%\ \text{pine in 1 ha unit}} \tag{1}$$

The percent pine uninfested (PPU) or the percent pine remaining on the landscape was estimated by subtracting the PPI from the total percent pine (Eq. 2):

$$\mathrm{PPU} = \left(\%\ \text{pine in 1 ha unit}\right) - \mathrm{PPI} \tag{2}$$

Our estimates of total pine mortality for British Columbia are based on the difference between PPU and the original pine raster, so locations identified as having mortality in the HSI that do not have pine are excluded from the results. In this way, our calculations of pine mortality are constrained to known locations of pine forests, thereby reducing the likelihood of overestimation. This situation could occur due to both interpreter error and errors in the forest inventory. The spatial constraint also factored into our calculation of percent pine change (PPC) defined as the difference between the original percent pine and the remaining percent pine (Eq. 3):

$$\text{PPC} = \left(\%\ \text{pine in 1 ha unit}\right) - PPU \quad (3)$$

Validation

Locations of red attack damage were validated with field data using an error matrix. For each field plot in British Columbia, the PPI value for the corresponding year was extracted. PPI values greater than zero indicated that mountain pine beetle attack was present, while values of zero indicated beetle absence. Overall map accuracy was assessed by computing the correct classification rate, or the sum of the true positive and true negatives divide by the total number of observations. We also evaluated the false-positive rate, false-negative rate, and the kappa statistic. To examine temporal fluctuation in the level of accuracy in the HSI data, we examined all error matrix statistics partitioned by survey year.

Severity of red attack damage, or PPI, was assessed using an ordinal measure of association, the Goodman–Kruskal gamma statistic (Goodman and Kruskal 1954). The PPI values in the field data and the HSI were classified back into severity classes (see Table 1), and the gamma statistic was computed for these ordinal classes. The Goodman–Kruskal gamma measure of ordinal association is defined as below:

$$\gamma = \frac{(P - Q)}{(P + Q)} \quad (4)$$

Where P is the number of concordant pairs, and Q is the number of discordant pairs. Gamma ranges from 0 to 1 and can be interpreted as the percentage contribution of the predictor in reducing errors incurred when predicting the response randomly.

We calculated absolute residuals (observed–predicted) between the field and HSI-derived PPI. Positive residuals therefore indicate HSI underestimation, and negative residuals indicate overestimation. Residual patterns were explored by partitioning data into severity classes and plotting distribution of residuals for different severity classes using boxplots.

Modeling survey error with covariate auxiliary variables

We examined the underlying characteristics of survey error to investigate if there were any systematic landscape conditions contributing error in the PPI layer. Spatial models were used as we expect errors to be spatially structured across large areas. We selected four variables that have previously been associated with mountain pine beetle processes: quadratic mean diameter (Mitchell and Preisler 1991), age (Safranyik et al. 1974), percentage pine (Nelson et al. 2007), and shortwave radiation (Coops et al. 2006). Stand quadratic mean diameter, age, and composition make are three of four variables commonly used in forest susceptibility rating in British Columbia (Shore and Safranyik 1992). Shortwave radiation has been a predictor of landscape-scale red attack damage in a number of studies (Coops et al. 2006; White et al. 2006). The forest and environmental conditions that impact the severity and likelihood of mountain pine beetle infestations may also influence the ability of surveyors to map the infested landscape.

Estimation of a linear multiple regression model ($Y = X\beta + e$) where Y is survey error, X is a vector of independent covariates, β is a vector of regression coefficients and e is a vector of independently and identically distributed (iid) residuals was first conducted using ordinary least squares (OLS) regression. Due to the nature of our dataset, spatial autocorrelation in both the dependent variable (survey error), and the explanatory variables could violate the assumption of iid residuals (Cliff and Ord 1981). Therefore, spatial autocorrelation was incorporated by estimating spatial autoregressive (SAR) models (Cressie 1993; Haining 2003). Three types of SAR models were tested: the spatial error model ($Y = X\beta + \lambda Wu + e$), where spatial autocorrelation (inherent or induced) is modeled as the product of an estimated spatial autocorrelation parameter λ, a neighborhood weights matrix W, and u, the neighborhood error matrix. The remaining error term, e is iid. The spatial lag model ($Y = \rho WY + X\beta + e$) models the spatial autocorrelation parameter ρ as a lag on the dependent variable Y. The SAR mixed model ($Y = \rho WY + X\beta + WX\gamma + e$), includes terms for spatial autocorrelation in ρWY, the dependent variable and $WX\gamma$, the error terms of model (Kissling and Carl 2008).

The weights matrix, the most important component of spatial model specifications (Aldstadt and Getis 2006), was kept constant for all models as a k-nearest neighbor symmetric neighborhood with $k = 5$. The k parameter was set to ensure a symmetric weights matrix and as an estimate to make sure that plots that are part of the same survey design included a measure of spatial dependence. Since sampling schemes tend to follow natural landscape boundaries, we expect autocorrelation in errors for neighboring field plots under similar survey programs. The mean distance to the fifth nearest neighbor was 10.5 km.

Model assessment was based on two criteria. First, we examine the residual spatial autocorrelation using spatial correlograms constructed using 20 distance classes and Moran's I coefficients using the spdep package in R (Bivand 2002; Ihaka and Gentelman 1996). Second, models were assessed using the Akaike information criterion (AIC) which allows assessment and comparison of spatial models based on model fit and model complexity (Burnham and Anderson 1998).

Results

Percent pine and percent pine infested

A summary of the cumulative infestation in the infestation data indicates that the total cumulative amount of red attack damage in British Columbia by 2006 was 4.16 million hectares (Fig. 4). When we constrained this estimate to areas of known pine forest in the VRI data, the estimate was 2.89 million hectares. The current distribution (as of 2006) of uninfested pine (PPU) in British Columbia is presented in Fig. 5. Knowledge of where the pine remains, as opposed to the more common representation of where pine has been lost, supports tactical- and strategic-level planning. The impact of the mountain pine beetle on forest composition is shown in Fig. 6, where the percent pine infested on the landscape between 1999 and 2006 is depicted. Compared with typical provincial maps of the spatial extent of the mountain pine beetle infestation, this representation includes variations in infestation intensity and differences in regions where the infestation is having severe impacts on the landscapes from areas where the effects are moderate or light.

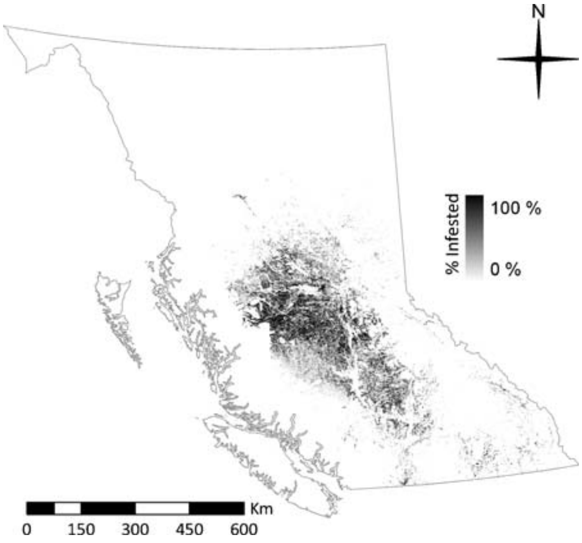

Fig. 4 Percent pine infested (PPI) as of 2006

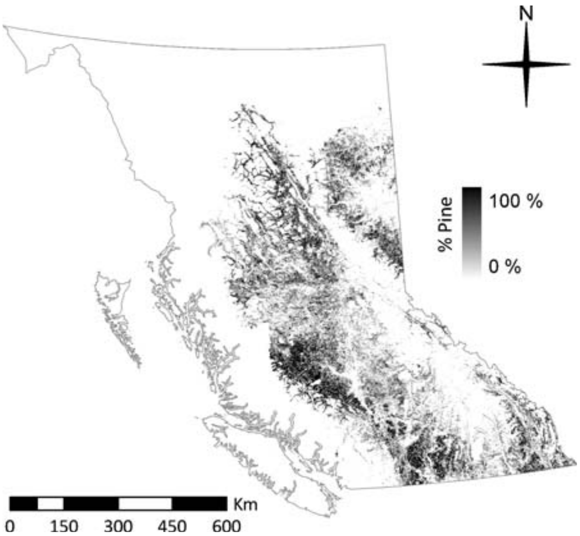

Fig. 5 Percent pine uninfested (PPU) as of 2006

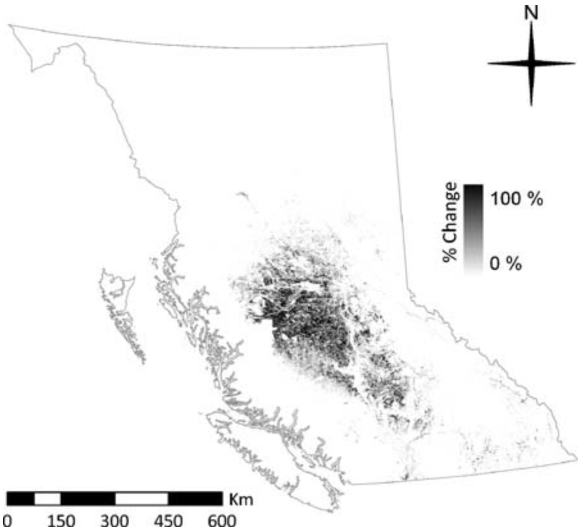

Fig. 6 Percent change in pine (PPC; 1999–2006)

Validation results

Of the 2,054 field plots used in this analysis, 1,620 (79%) had red attack damage present. Accuracy summary statistics for the HSI validated against the field plots are presented in Table 2. The accuracy of the HSI layer in detecting red attack identified in the field data was high, with an average of 93% (true positive) of field verified red attack sites being correctly identified in the HSI layer. True negatives were less accurately predicted, with 33% of field plots without red attack damage were correctly identified as such in the HSI layer. The total number of true negatives was 434, and as time progressed, more plots (proportionally) had red attack damage. The overall accuracy of the map red attack classification was 60%, while the false-positive rate was 14%, and the false negative rate was 46%. The kappa statistic for the all field plots validating the HSI was 0.25.

Examining the temporal trend in correspondence between the HSI and the field plots (Fig. 7) revealed that the false-negative rate or the plots where red attack was found in the field but missed in the HSI, declined markedly with time. False negatives were very high initially, likely due to the fact that infestations were spotty and unexpected by aerial surveyors. As the infestation increased in magnitude and spatial extent, the false-negative rate declined. The false-positive rate showed a large increase in 2004, and a moderate increase in 2005. The overall correct classification rate declined from 1999 to 2001, but thereafter steadily increased to 87% in 2005.

We calculated the absolute deviance as the HSI PPI subtracted from the field PPI. Figure 8 shows the deviation partitioned by severity class. More severe classes are associated with high positive deviation, demonstrated by the distance of the median bar in each of the boxplots from zero. This corresponds to an underestimation of the amount of pine infested in the HSI layer. When field PPI values are low, the deviance is negative. This becomes more apparent at more severe levels of infestation, which is not surprising as estimates of infestation magnitude will tend to vary more when infestations are larger (Nelson et al. 2006b).

Modeling survey error results

The OLS model of the HSI survey errors yielded the estimates presented in Table 3. Overall, the independent variables explained approximately 10% of the variation in the error between field values of percent pine infested and HSI percent pine infested. Variables that were significant predictors

Table 2 Error matrix summary statistics for the field plot validation of HSI locations of red attack damage by mountain pine beetles

		Field Plot		Producer's accuracy	User's accuracy
		Red attack	No red attack		
HSI	Red attack	868	61	54%	93%
	No red attack	752	373	86%	33%
Correct classification rate		60%			
Kappa statistic		25%			
False-positive rate		14%			
False-negative rate		46%			

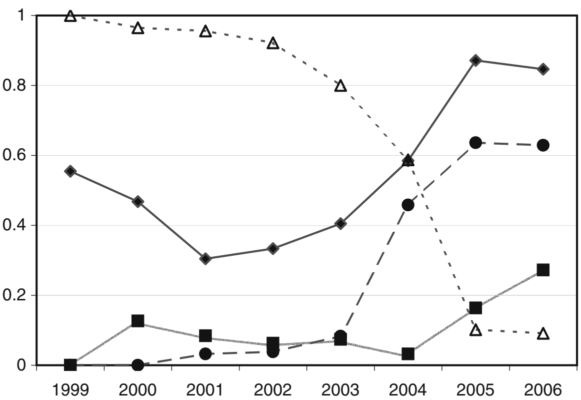

Fig. 7 Temporal trend in accuracy statistics for the field plot validation of HSI locations of red attack damage by mountain pine beetle

of error included percent pine, year of the sample, and stand age class. Shortwave radiation and diameter at breast height were not significant variables for predicting variation in the error between field and HSI PPI. Model coefficients with the greatest impact on the model were year of data collection and percentage pine. For more recent surveys, survey error declined, while for higher percentages of pine survey, error increased.

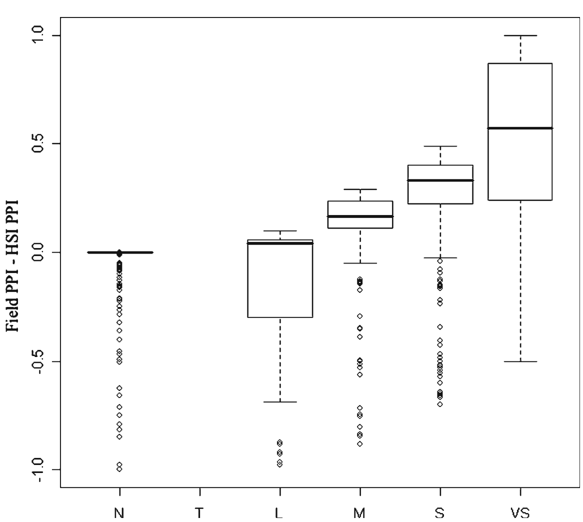

Fig. 8 Deviation (actual–predicted) from field measured percentage pine infested (PPI) by severity classes, summarized by BMU. Severity class codes are as follows: T: <1%, L: 1–10%, M: 11–29%, S: 30–49%, VS: >49%

Table 3 Results of linear model estimation using ordinary least squares(OLS) regression (multiple $R^2 = 0.10$)

Variable	Coefficient	SE	*P*
Constant	8,274	647.600	0.000
Diameter	0.1371	0.101	0.174
Age	0.001	0.000	0.000
Shortwave radiation	0.000	0.000	0.851
Year	−4.122	0.324	0.000
Percent pine	0.183	0.030	0.000

Of the three spatial models estimated, the greatest improvement was attained using the spatial error model. Results for the spatial error model are presented in Table 4 which shows an improvement over the OLS model fit (ΔAIC = 102) and a significant ($p < 0.000$) spatial autocorrelation coefficient ($\lambda = 0.311$) with a fairly large impact on the model. In Moran correlograms computed for all models, the spatial error model resulted in the least amount of residual spatial autocorrelation. All subsequently reported results from the spatial models are for the spatial error model.

Discussion

In British Columbia, AOS data are collected on an annual basis to provide a synoptic assessment of forest health across the province. The amount of area impacted by mountain pine beetle is reported from the AOS data, with the total area impacted reported, regardless of severity code. The estimates of pine mortality estimated from our analysis (2.89–4.16 million ha) output differs strikingly from the 9.2 million hectares reported from the AOS data in 2006 (Westfall 2007). There

Table 4 Results of spatial error model estimation using maximum likelihood regression ($\Delta AIC = 102$)

Variable	Coefficient	SE	*P*
λ	0.311	0.029	0.000
Constant	8837.900	772.450	0.000
Diameter	0.092	0.100	0.353
Age	0.001	0.000	0.001
Shortwave radiation	0.000	0.000	0.515
Year	−4.401	0.386	0.000
% Pine	0.190	0.031	0.000

are a number of reasons that explain the differences in these estimates. First, the AOS data are designed to be synoptic—the data are collected at a coarse spatial scale, and observers are trained to delineate broad areas of damage. Harris and Dawson (1979) compared the amount of red attack damage estimated from an AOS to estimates made from the interpretation of aerial photography. The total area identified as red attack from the AOS was 34% larger than the area of attack interpreted from air photos, while the number of red attack trees estimated from the AOS was 39% less than the number of red attack trees estimated from the photos (with the underestimation of attacked trees increasing with increasing density of red attack trees). This discrepancy is largely a function of scale—the field of view of the AOS interpreter is much larger than that of a photo interpreter; the AOS interpreter may see large areas of red attack damage, while not being able to readily discern individual trees. Conversely, the increased spatial resolution afforded by the air photos allows the photo interpreter to delineate units of impact that are more spatially discrete than is possible for the AOS interpreter.

The AOS data are appropriate for characterizing the general location of damage, to approximate the gross area of damage, and indicate general trends in damage from one year to the next. Shortcomings of the AOS data include the lack of positional accuracy, large errors of omission when damage is very light, and inconsistencies in the estimates of attack magnitude (Wulder et al. 2006a). Location inaccuracies result from off-nadir viewing, variations in lighting conditions, and interpreter experience and fatigue, among others (Aldrich et al. 1958; Leckie et al. 2005). Harris and Dawson (1979) found that among several AOS interpreters, estimates of red attack damage varied from the actual amount of red attack damage by a range of 42% to 73%.

The method by which the HSI layer was assembled gave priority to more detailed survey results (Fig. 3). In our analysis of change in forest composition, areas that did not contain pine in the forest inventory were excluded from our computation of pine mortality, and the variable intensity of the infestation is incorporated into the estimate. As such, the PPI may be viewed as a refinement of the AOS, created using the best available data in order to deliver the most precise estimate possible.

With a growing emphasis on managing the post mountain pine beetle landscape (British Columbia Ministry of Forests and Range 2006), knowledge of the current forest conditions is a necessary prerequisite for planning. While there are many techniques available for large area mapping, such as remote sensing, our approach, which combines a wide range of datasets, adds value to existing monitoring data and enables the production of timely and cost-effective information products for large areas. However, when detailed data on the severity of infestation are needed, additional data, such as those available through remote sensing, are required.

The inverse of the PPI is the PPU (Fig. 5) or the percent of pine which remains uninfested (as of 2006). This layer provides information useful for management of a variety of forest resources, as well as providing new information for forest modelers tasked with predicting future forest conditions and assessing the impacts of the infestation on processes such as the hydrological systems and wildlife. Such data may also be useful for assessing timber supply scenarios, which are often based on assumptions of the level of pine mortality in any given stand.

The change in the proportion of pine on the landscape from 1999 to 2006 characterizes the impact that mountain pine beetle infestations have had in British Columbia by quantifying changes in forest cover (Fig. 6). As a tool for assessing the broad impact of beetles on the forests of British Columbia, Fig. 6 demonstrates how the interior plateau landscape has been transformed by beetle infestation. Less impact has been experienced in the pine forests of northern and southeastern British Columbia. By examining the difference between the PPU and PPC, it becomes evident that there still exists a large component of viable pine in British Columbia forests that is capable of sustaining the epidemic in the near future. This supports the findings of other researchers that regional variations exist in the factors governing the growth of local beetle populations (i.e., climate; e.g., Logan et al. 2003; Taylor et al. 2006; Régnière and Bentz 2007). Thus, assuming these regional variations persist, connectivity to the main infestation area in the interior plateau region may be the critical determinant of future large-scale spread of mountain pine beetle.

The amount of beetle-caused pine mortality estimated in this analysis has implications for a sustained infestation. The PPU map indicates that 8.79 million hectares of pine remain on the landscape in 2006, out of a base level of 11.68 million hectares in the percent pine raster. However, outside of harvesting, this analysis did not account for the effects of other disturbance types in our estimations. Thus, the effects of fire and other disturbances will likely reduce the actual amount of pine remaining markedly. To determine how these disturbances influence our results, we examined the estimates of abiotic disturbances (e.g., fire) for all of the Summary of Forest Health reports in British Columbia from 1999 to 2006. The total estimate of abiotic disturbance over this time period was 600,955 ha. Thus, even if all of the abiotic disturbances had occurred only in pine forests, the final estimation of pine remaining on the landscape would still be 7.75 million hectares.

The HSI cumulative percentage pine-infested layer performed well in determining locations of beetle presence, and accuracy increased with time (Fig. 7). The number of omissions declined with time, as more areas became infested, and forest health monitoring efforts intensified. While difficult to quantify, over the period of the outbreak under consideration, omissions are expected to have declined based upon an increase of reference points on the land base for the interpreters to build upon (e.g., salvage and mitigation locations). Additionally, Landsat imagery is increasingly used as an information underlay when sketch mapping. Inclusion of the sketch information from previous years also aids in providing context for depiction of new infestations. When the HSI is used for predicting severity, the ordinal measure of association indicated a moderately strong association. The error between the HSI and the field plots tended to be overestimation for low intensity infestation and underestimation for high intensity infestation. Thus, for the aspatial accuracy assessment, we have two primary trends, (a) prediction accuracy of infested locations increases with greater amounts of infestation, and (b) prediction accuracy of infestation severity tends toward underestimation.

There are a number of reasons that we think are giving rise to this seemingly contradictory result. Firstly, we expect, based on the nature of aerial surveying that larger infestations are easier to identify from the air, and hence, years when infestations are greater will have fewer omission errors. High omission errors have previously been noted when infestation severity is low (Wulder et al. 2006a). However, once a patch is located, the classification of the infestation severity level is susceptible to greater subjectivity among surveyors (Harris and Dawson 1979).

Examining the results of the spatial modeling of survey error also sheds light onto what may be contributing to the apparent underestimation of infestation severity in the HSI. The regression modeling revealed that, in addition to the percentage of pine, survey year also influenced the amount of error observed between the HSI and field data. A negative coefficient for the sample year supports the notion that survey estimates of pine mortality become more accurate with time, likely due to greater amounts of infestation. However, the low level of variability explained by the models combined with the general underestimation of PPI revealed in the aspatial accuracy assessment suggests that other variables are also determinants of error. Previous research has indicated that the greatest source of error in aerial-based surveys is the temporal variation in the timing of crown foliage discoloration (Nelson et al. 2006b). Other likely sources of error include weather, surveyor variability, and differences in field data collection methods.

The finding that the spatial model outperforms the linear model combined with the presence of significant spatial autocorrelation in the spatial error model (Table 4) reveals that the survey errors are spatially structured. There are two plausible explanations for this. Firstly, the likely missing variables identified above, such as temporal variation in crown discoloration, are themselves spatially dependent. Thus, variability in survey error arising due to spatially dependent variables will also be spatially autocorrelated. Secondly, the field survey designs may also be affecting our field data estimates. Because mountain pine beetles attack trees in clusters (spot infestations), ground surveys are usually nonsystematic. Calculations of PPI derived from field plots located at infestation centers will therefore be artificially high relative to the surrounding forest. These plots, therefore, may not be representative of broader forest conditions. The HSI layer, which enumerates PPI derived from larger-area estimates, would therefore be expected to be lower than the estimates derived from plots located at infestation centers. This problem of scale speaks of the difficulty of accurately measuring forest conditions across large areas, either on the ground or from the air.

Integrating all existing monitoring data provides a new mapping tool for generating timely information on the provincial forest. It also provides an improved cartographic presentation of the impact of mountain pine beetle to the forest, aiding communication with the public and justification for resource allocation and associated activities. The new map products generated through integration of existing data directly benefit decision-makers tasked with the challenge of managing the impacts of the mountain pine beetle on forests. With a growing emphasis on managing a wide range of timber and nontimber (i.e., wildlife habitat and water quality) values in postmountain pine beetle landscape, new map products are needed and have many potential users.

Conclusion

By integrating the existing spatial hierarchy of mountain pine beetle monitoring data from 1999 to 2006, we were able to generate up-to-date information products describing the forest composition of British Columbia. Specifically, we generated three outputs that describe forest conditions as of 2006: the cumulative percentage of pine infested (1999–2005), the percentage of pine uninfested, and the change in the percentage of pine on the landscape. These products provide timely information on the state of the provincial forest and furthermore, by leveraging all the data in the survey hierarchy, we were able to generate a more refined estimate of the total area impacted by the mountain pine beetle than is possible using the AOS data exclusively. Furthermore, we conducted an accuracy assessment using a comprehensive field dataset as ground truth. We also explored the variations in predicted and observed PPI using spatial modeling which revealed significant spatial structuring of survey error.

The information products produced in this research provide an improved cartographic presentation of the impact of mountain pine beetle to the forest, aiding communication with the public and justifying resource allocation and associated activities. These products will also facilitate both strategic and tactical forest management planning. Strategic planning addresses very long time frames and large spatial extents. Refined estimates of infestation severity and the integration with forest inventory data enable more detailed modeling of various forest management scenarios, treatment activities, and timber supply across large areas. Tactical planning, such as harvest scheduling and road construction, may also be facilitated by our refined large-scale estimates of beetle damage and forest conditions. With a growing emphasis on managing the wide range of timber and nontimber (i.e., wildlife habitat and water quality) values in post-mountain pine beetle landscape, new maps products, such as those presented here, are needed and have many potential users.

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