# Rating the susceptibility of forests to mountain pine beetle infestations: the impact of data

**T. Nelson, B. Boots, M.A. Wulder, T. Shore, L. Safranyik, and T. Ebata**

**Abstract:** British Columbia is currently experiencing the largest mountain pine beetle (*Dendroctonus ponderosae* Hopkins) epidemic on record. The spatial extent of this infestation highlights the need for large-area forest management. We explore the use of three large-area data sets for implementing a stand-scale model of forest susceptibility that quantifies the probability of loss of pine basal area because of attack by the mountain pine beetle. Using these data sets, we investigate the impact of surrogate variables, which is necessary when variables required for the susceptibility model are not present in a data set. The impact of the source data information content on the susceptibility model output is also analyzed. Results indicate that the susceptibility model is sensitive to both surrogate variables and data sources and suggest that landscape level application of the susceptibility model, which was developed using stand-scale relationships, is problematic. Of particular concern is the use of photointerpreted data sets for model parameterization. The information content in photointerpreted data sets is much different than data on similar forest characteristics collected in the field and provides an inadequate substitute for implementing the forest susceptibility model.

**Résumé :** La Colombie-Britannique connaît présentement la plus importante épidémie de dendroctone du pin ponderosa (*Dendroctonus ponderosae* Hopkins) jamais rapportée. L'étendue spatiale de cette infestation fait ressortir la nécessité d'aménager la forêt sur de vastes superficies. Nous examinons l'utilisation de trois jeux de données couvrant de vastes superficies pour implanter un modèle de vulnérabilité de la forêt à l'échelle du peuplement qui quantifie la probabilité des pertes en surface terrière de pin dues à une attaque par le dendroctone du pin ponderosa. À l'aide de ces jeux de données, nous étudions l'impact de variables subrogatives dont l'utilisation est nécessaire lorsque des variables requises par le modèle de vulnérabilité ne sont pas présentes dans un jeu de données. L'impact de l'information contenue dans les données de base sur le modèle de vulnérabilité est également analysé. Les résultats indiquent que le modèle de vulnérabilité est sensible aux variables subrogatives et aux sources de données, ce qui signifie que l'application à l'échelle du paysage du modèle de vulnérabilité, qui a été développé à partir de relations à l'échelle du peuplement, est problématique. L'utilisation de jeux de données obtenues par photo-interprétation pour paramétrer le modèle est particulièrement préoccupante. L'information contenue dans les jeux de données obtenues par photo-interprétation est très différente de celle que procurent les données collectées sur le terrain au sujet des mêmes caractéristiques de la forêt. C'est pourquoi les données obtenues par photo-interprétation ne peuvent adéquatement servir de substitut pour implanter un modèle de vulnérabilité de la forêt.

[Traduit par la Rédaction]

## Introduction

The mountain pine beetle (*Dendroctonus ponderosae* Hopkins; Coleptera: Scolytidae) is endemic in pine (*Pinus* spp.) stands throughout western North America (Safranyik et al. 1974). Currently, British Columbia is experiencing the largest infestation on record. From 1994 to 2004, the mountain pine beetle infested $7 \times 10^6$ ha of British Columbia's forest (Westfall 2004). One tool frequently used for management of the mountain pine beetle in British Columbia is the Shore and Safranyik forest risk model (Shore and Safranyik 1992; Shore et al. 2000). This model combines much of the current knowledge of mountain pine beetle biology into a probabilistic measure of the likelihood of loss in stand basal area (volume) due to mountain pine beetle infestations.

There are two components to the stand-based Shore and Safranyik model. The first is beetle pressure, which is defined as the magnitude of a beetle population affecting a stand. Beetle pressure is related to both the number and proximity of infested trees to the stand being rated. The second component of risk is forest susceptibility, which is the focus of this research. Forest susceptibility reflects the conditions that predispose a stand to attack by mountain pine beetle, such as age, location, and stand density (Shore and Safranyik 1992). Susceptible stands have only low risk when there are no beetles in the vicinity of the stand. The risk associated with a susceptible stand will increase when moun-

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tain pine beetles occur in close proximity. Calculation of forest susceptibility requires data on the mean basal area of pine and nonpine stands, the average age of pine stands, stand density, and a location factor generated from latitude, longitude, and elevation.

The forest susceptibility model relies on relationships that have been observed at a stand scale. However, during an epidemic, landscape level management becomes increasingly important because extensive areas are infested, thus requiring management models that can be applied to landscapes. There are two fundamental issues to applying the forest susceptibility model at a landscape scale. The first is conceptual and reflects the inherent difficulty of aggregating or changing scales when modelling processes. Biological processes are inherently tied to a specific spatial scale (Levin 1992). Therefore, observations of behaviour made at one spatial scale cannot necessarily be applied at other scales. Only recently are large-area studies of mountain pine beetle being conducted, and it is unclear how well processes relate across spatial scales.

The second issue associated with applying the susceptibility model to large areas is that the detailed data sets, acquired at a stand scale, do not typically exist for landscapes. Often, the large-area data sets that are available do not have the attributes necessary to implement the model as specified, resulting in a need for surrogate variables. Surrogate variables and the uncertainty associated with large-area data sets will influence the susceptibility model output.

Although there are issues with the application of the susceptibility model to large areas, in response to the large spatial extent of the current mountain pine infestation and in the absence of existing landscape scale models, the susceptibly model is being used for landscape level management. Only through large-area research will it be possible to understand that validity of modeling large-area mountain pine beetle processes using stand-scale observations. This work is ongoing and in the future large-area models may be developed (e.g., Nelson and Boots 2005; Nelson et al. 2006). At present, it is possible to better understand data issues impacting the large area application of stand-scale models. In this paper, we investigate the impact of using differing large-area data sets when modelling forest susceptibility. Three data sets are used for this exploration. The first is a detailed field data set collected for a sample of sites in the Vanderhoof Forest District as part of the vegetation resource inventory (VRI) (SRMTIB 2004*a*). These data are considered to be an accurate representation of forest conditions. The second data set is also part of the VRI data collection program, but is generated for the entire forest district via aerial photograph interpretation (SRMTIB 2004*b*). The third set, forest inventory polygon (FIP) data, which are also produced through air photograph interpretation, have attributes that are different than those available from the VRI photointerpreted data set. Using these three data sets, we explore the impact of the surrogate variables on the susceptibility model output.

## Study area and data

The study area is the Vanderhoof Forest District located in central British Columbia, west of Prince George and east of Burns Lake (Fig. 1). As with many locations in British Columbia, the Vanderhoof Forest District is experiencing epidemic levels of mountain pine beetle and the infestation is having a substantial impact on lodgepole pine (*Pinus contorta* Dougl. ex Loud. var. *latifolia* Engelm.) forests and communities. The Vanderhoof Forest District was chosen for this study because of the availability of recently interpreted VRI data that consistently represents a large area (18 500 km$^2$). It is one of the few districts that have both a complete set of photointerpreted VRI (PVRI) data and field VRI (FVRI) data. Also available for the Vanderhoof Forest District are FIP data and a digital elevation model (DEM) required for calculating the location factor used in the Shore and Safranyik susceptibility model.

### Field vegetation resource inventory

Detailed ground sampling was undertaken for 68 locations in the Vanderhoof Forest District in 2001. Field data sites are circular plots having a radius of 5.64 m (SRMTIB 2004*a*). All forest conditions necessary for the forest susceptibility model are measured in the field. These are stand age, stand density, and basal area. An attractive feature of these data is that the attributes for each species are recorded for five diameter at breast height (DBH) classes. For example, mean age is reported for all pine trees and pine trees with DBH ≥ 7.5 cm, DBH ≥ 12.5 cm, DBH ≥ 17.5 cm, and DBH ≥ 22.5 cm. The benefit of DBH classes for this application will be explained when the susceptibility model is described.

For FVRI data, age measurements (reported in years) are derived from ring counts or DBH measurements. Regardless of the technique used, age is reported as a mean and equals the sum of tree age divided by the number of trees. During field sampling, density is recorded as the total number of trees per hectare and usually includes trees with a DBH > 4 cm.

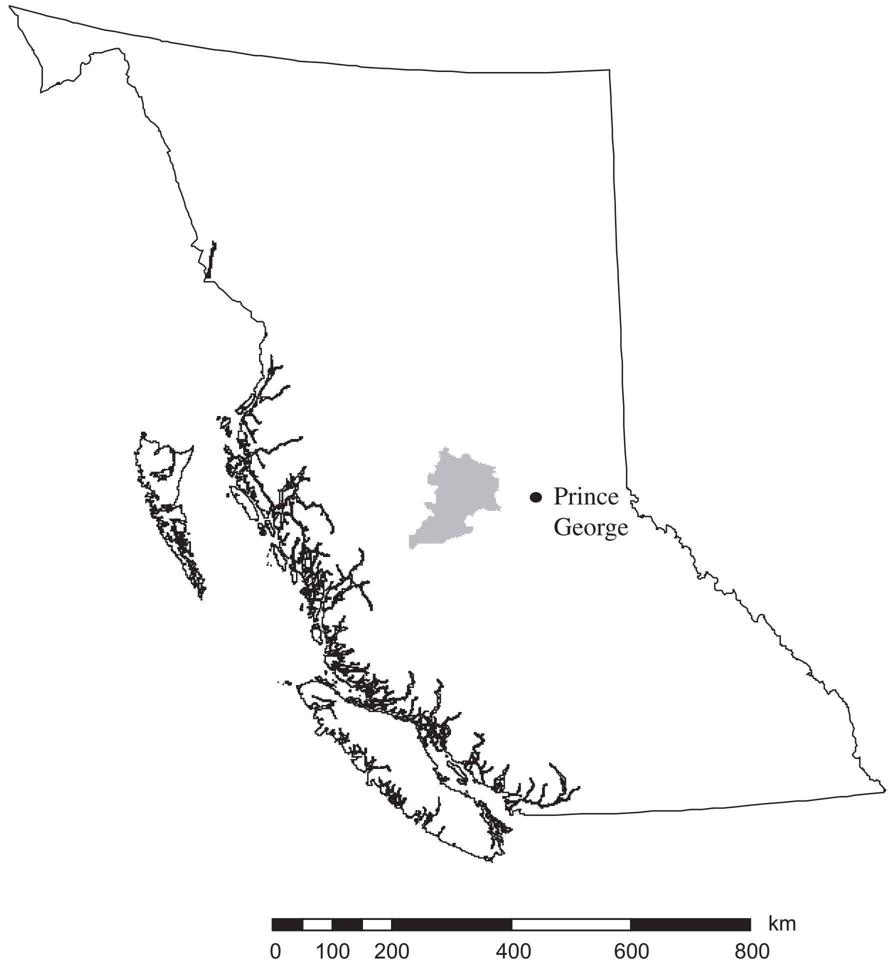
### Photographic vegetation resource inventory

The PVRI data are initially interpreted from aerial photography (1 : 15 000); however, attribute values are adjusted using FVRI data. PVRI data reflect forest conditions in 2001, and the spatial unit for PVRI is a stand. Like the FVRI data, the PVRI data include information on all forest conditions considered by the susceptibility model. Pertinent attributes are stand age, stand density, and basal area. Attributes are reported for all visible dominant and codominant trees and are not summarized by DBH classes (SRMTIB 2004*b*). As well, the percentage of the stand composed by each tree species is reported.

For PVRI data, stand age is the mean estimated age, weighted by basal area, of the dominant and codominant trees, and age field measurements are used to adjust photo-interpreted values. Stand density is reported as the mean number of living dominant and codominant trees that are visible to the photograph interpreter. Stand density is expressed as stems per hectare and, when possible, is informed by FVRI data (SRMTIB 2004*b*).

Also based on dominant and codominant trees, basal area is typically estimated directly from the aerial photographs and reported as square metres per hectare. The basal area of all visible dominant and codominant trees is estimated. Where FVRI are available, PVRI basal area is calculated us-

**Fig. 1.** Location of the Vanderhoof Forest District.




ing a combination of FVRI basal area and density measurements.

### Forest inventory polygons

The FIP data are also generated via aerial photograph (1 : 15 000) interpretation and reflect 2001 forest conditions. The FIP data do not have density and basal area attributes that are necessary for computing a measure of forest susceptibility. Hence, surrogates are used for these variables. FIP attributes employed when computing susceptibility are age, DBH, and species percentage, which are interpreted from trees estimated to have a DBH ≥ 7.5 cm (Howse 1995). Like PVRI data, the spatial unit for FIP data is the stand. Although PVRI data sets delineated stand boundaries more finely in some cases, the majority of stand boundaries in FIP and PVRI data sets are the same.

Stand age is the mean age, in years, of the forest stand and is typically estimated indirectly from aerial photographs. This estimate is not weighted. Diameter at breast height is the quadratic mean stand DBH and is calculated based on forest age and site index (Curtis and Marshall 2000; Stearns-Smith 2001). Tree species and percentages are also provided in the FIP data (Leckie and Gillis 1995).

### Digital elevation model

A DEM was used to calculate the location factor, reflective of climate conditions. The elevation model had 25 m × 25 m grid cells and was created from 1 : 20 000 scale terrain research information management data (British Columbia Ministry of Sustainable Resource Management 1996). The data were interpolated using a linear interpolation process, and the DEM is reported to be accurate within 10 m (British Columbia Ministry of Sustainable Resource Management 1996). The same DEM was used throughout this study; thus, the location factor is held constant for all analysis.

### Susceptibility model

Based on an understanding of mountain pine beetle biology, stand susceptibly reflects the inherent characteristics of a stand that affect the likelihood, or probability, of attack and damage (Shore and Safranyik 1992; Shore et al. 2000; Dymond et al. 2006). In this context, a stand is defined as a homogenous aggregate of trees. Stand susceptibility ($S$) ranges from 0 to 100 and is based on the percentage of susceptible pine basal area ($P$), a pine age factor ($A$), stand density ($D$), and a location factor ($L$). Stand susceptibility is calculated as

$$[1] \qquad S = PADL$$

The percentage of susceptible pine basal area, which we refer to as the basal area factor ($P$), considers tree size and stand composition. $P$ is calculated as

$$[2] \qquad P = \frac{(\text{average basal area/ ha of pine} \geq 15 \text{ cm DBH})}{(\text{average basal area/ ha of all species } \geq 7.5 \text{ cm DBH})}$$

In eq. 2, the 15 cm DBH threshold reflects mountain pine beetle preferences for larger trees (Hopping and Beall 1948). Under epidemic conditions, smaller trees may be attacked, but fewer beetles will emerge than were required to attack the tree (Safranyik et al. 1974). The lower threshold of 7.5 cm is a practical limitation, as smaller trees are not typically visible from aerial photography and are usually not included in ground surveys for inventories (Leckie and Gillis 1995). The use of DBH classes, when calculating the basal area factor, is one reason the FVRI is the optimal data source for generating susceptibility. FVRI data does not have measurements partitioned at 15 cm, but the 12.5 cm threshold is a close approximation. The FVRI DBH classes ≥12.5 cm and ≥7.5 cm were used when computing the susceptibility for the 68 locations in the Vanderhoof Forest District.

Forest age relates directly to a pine tree's ability to resist a mountain pine beetle attack. Older trees, which tend to be larger and less able to resist attack, are more susceptible (Safranyik et al. 1974). The age factor (ranging from 0 to 100) is calculated as a continuous variable using the equations in Table 1 (Shore and Safranyik 1992; Wulder et al. 2004).

The relationship between tree mortality and stand density reflects factors such as tree vigour and the microclimate (wind, light, and temperature). The highest pine mortality occurs when stand density is between 750 and 1500 stems/ha. Stand density is converted to a density factor ranging from 0 to 100 using the equations in Table 2 (Shore and Safranyik 1992, Wulder et al. 2004).

The location factor is an indicator of climate and is based on latitude, longitude, and elevation. At locations where these characteristics suggest that the temperatures are colder, the value of $L$ is lower. Warmer microclimates are associated with higher values of $L$. To determine $L$, first, a parameter ($Y$) is calculated as follows

$$[3] \qquad Y = (24.4 \times \text{longitude}) - (121.9 \times \text{latitude}) - \text{elevation} + 4545.11$$

where elevation is in metres. Using $Y$, the location factor can be generated using the equations in Table 3. The location factor is computed for the geographical centre of the plot or polygon.

## Model implementation

The susceptibility model outputs generated from each data set are shown in Fig. 2. The FVRI data were used to implement the susceptibility model as described above. One modification was required to generate the susceptibly model from PVRI data. In this scenario, the basal area factor was computed using all visible dominant and codominant trees, rather than DBH classes.

More substantial modifications were required to implement the susceptibility model with FIP data. Using FIP data, DBH becomes a surrogate for density and the stand percentage of pine replaces basal area (Howse 1995; Wulder et al. 2004). Based on methods published by the former Cariboo Forest Region in British Columbia (Howse 1995), DBH was converted to a density factor using thresholds (Table 4) and when DBH values were missing, age was used as a surrogate for density (Table 5). In Vanderhoof, 96% of pine stands have associated DBH values.

**Table 1.** Equations for calculating the forest susceptibility age factor.

| Mean pine age (years) | Age factor calculation |
|---|---|
| ≤40 | 0 |
| >40 to ≤80 | $100\left(0.1 + \{0.1[(\text{age} - 40)/10]^{1.585}\}\right)$ |
| >80 to ≤120 | 100 |
| >120 to ≤520 | $100\{1 - [0.05(\text{age} - 120)/20]\}$ |
| >520 | 0 |

**Table 2.** Equations for calculating the forest susceptibility stand density factor.

| Stand density (stems/ha of trees ≥7.5 cm DBH) | Stand density calculation |
|---|---|
| <650 | $100[0.082(\text{density}/250)^2]$ |
| ≥650 to <750 | $100\left(1 - \{0.7[3 - (\text{density} / 250)]^5\}\right)$ |
| ≥750 to <1500 | 100 |
| ≥1500 | $100\left[1/\left(0.9 + \{0.1e^{0.4796[\text{density}/250)-6]}\}\right)\right]$ |

**Table 3.** Equations for calculating the forest susceptibility stand location factor.

| $Y$ | Location factor calculation |
|---|---|
| >0 | 1 |
| ≤0 | $1/\{0.9 + [0.1e^{-0.8(Y/250)}]\}$ |

## Comparison methods

### *Surrogate variables*

The only surrogate used to compute the susceptibility model with the FVRI data is the DBH threshold of ≥12.5 cm rather than 15 cm. In contrast, both the PVRI and FIP data necessitate the use of more surrogate variables. To investigate the impact of such variables independently of the data-collection methods, we derived from the FVRI data those surrogate variables required for implementing the susceptibility model with PVRI and FIP data. To derive the surrogate basal area factor used with PVRI data, the basal area of pine trees having DBH values ≥7.5 cm was divided by the basal area of all trees with DBH values ≥7.5 cm. Trees with DBH sizes <7.5 cm were not used because it is unlikely that these are visible from aerial photographs. Although deriving the surrogate basal area factor value from dominant and codominant species would better reflect the PVRI surrogate variable, dominance is not specified in the FVRI data.

Similarly, surrogate variables required for implementing the susceptibility model with FIP data were also derived from the FVRI data. Again, the FVRI DBH category of ≥7.5 cm was used to reflect the size threshold applied during

**Fig. 2.** Susceptibility model output generated using (A) FVRI, (B) PVRI, and (C) FIP data.

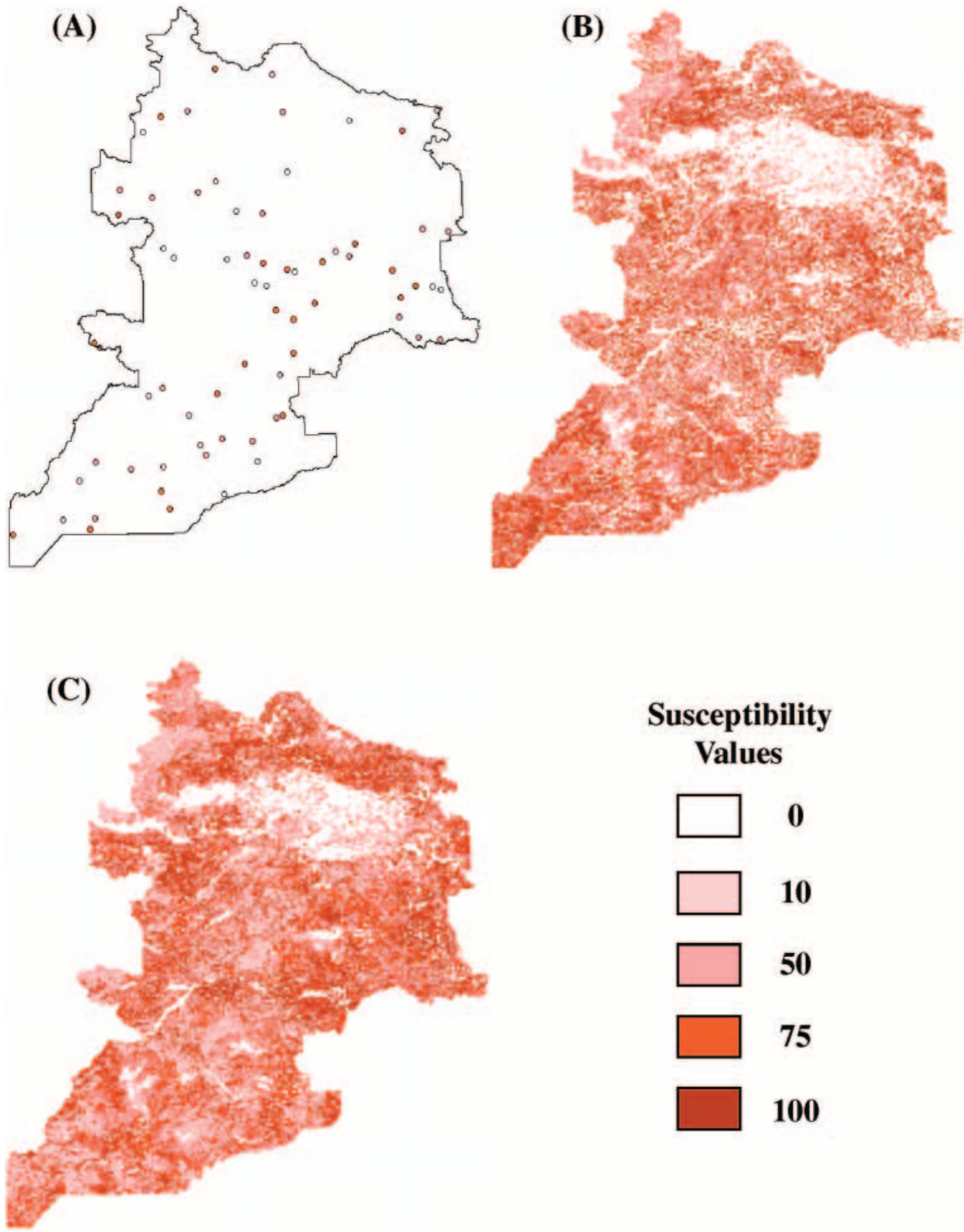



**Table 4.** Diameter at breast height (DBH) surrogate density factor.

| DBH (cm) | Density factor |
|---|---|
| ≤20 | 0.1 |
| >20 and ≤22.5 | 0.6 |
| >22.5 and ≤25 | 0.8 |
| >25 | 1 |

**Table 5.** Age-based surrogate density factor.

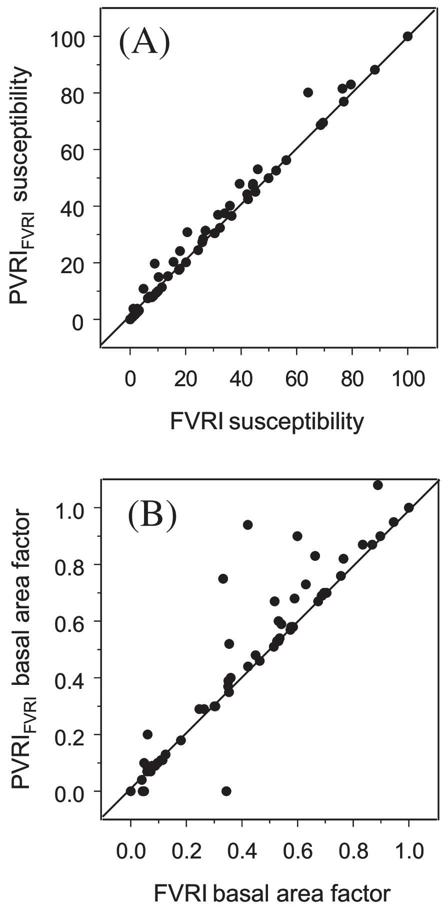
| Age (years) | Density factor |
|---|---|
| <60 | 0.1 |
| 60–79 | 0.8 |
| ≥80 | 1 |

air photograph interpretation to generate the FIP data. Using the quadratic mean DBH of all trees ≥7.5 cm, the equations in Table 4 were applied. The proportion of pine in each stand, which is available from the FVRI data, was used to derive the surrogate measure of the basal area factor. In the remainder of the paper, FVRI-derived measures will carry the subscript FVRI. For example, PVRI susceptibility values that are derived from FVRI data will be designated $PVRI_{FVRI}$.

### *Comparisons*

Comparisons were made between the FVRI data and the two derived data sets ($PVRI_{FVRI}$ and $FIP_{FVRI}$) and between

**Fig. 3.** Comparison of FVRI and $PVRI_{FVRI}$ (A) susceptibilities and (B) basal area factors.




all pairs of the three data sets (FVRI, PVRI, and FIP). Relationships between susceptibility values and between susceptibility factors (basal area, age, and density) were explored using scatterplots and bivariate correlation. Relationships were tested for statistical significance using a significance level of 0.05.

Susceptibility models produced from the FVRI data were compared with those from the PVRI and FIP data using the values at the FVRI sites and those for the PVRI or FIP polygons in which the FVRI sites were located.

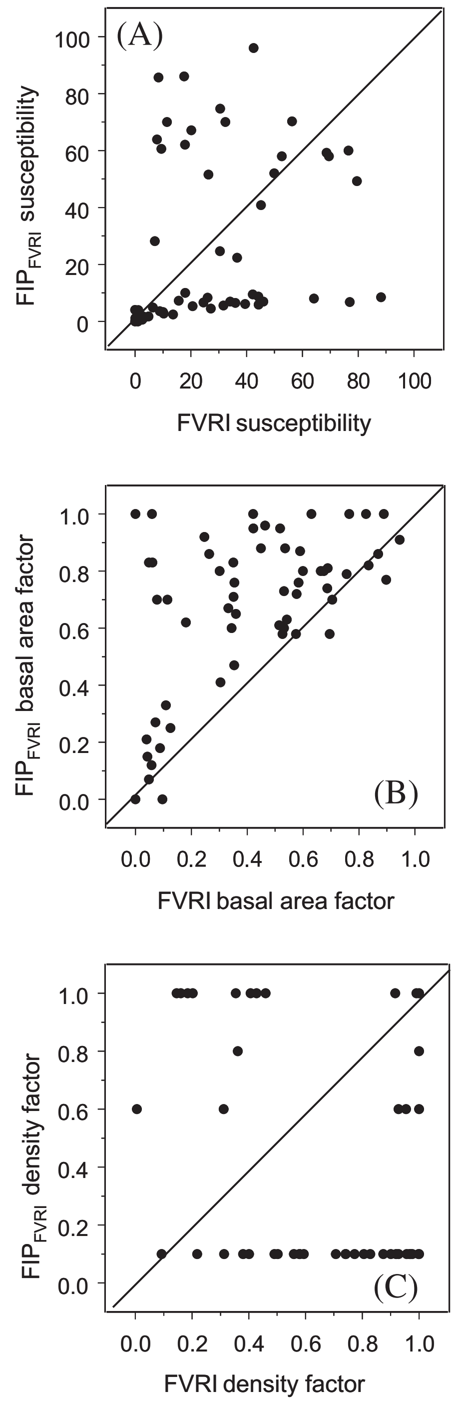
Only the PVRI and FIP data sources are available for the entire Vanderhoof Forest District. Given that most of the PVRI and FIP units are similar, the data sets were represented by polygon centroids and overlain. Because the number of PVRI polygons is slightly larger (90 997 versus 87 303), the PVRI centroids were used as the spatial anchor, and their associated values were compared with those at the nearest FIP centroids. Typically, when the polygons do not overlap, it is because the PVRI have been more finely delineated.

## Results and discussion

### The impact of surrogate variables

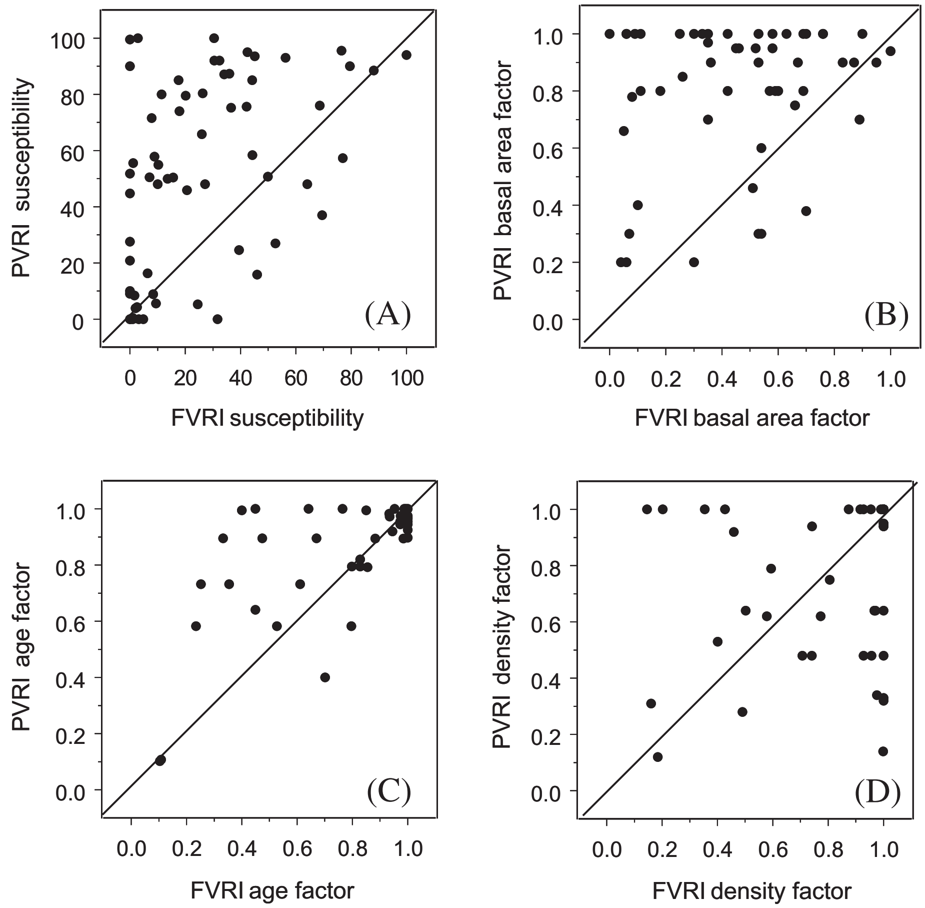
Figures 3A and 4A show the relationships between the susceptibility values computed using the FVRI model variables and those obtained using surrogate variables associated

**Fig. 4.** Comparison of FVRI and $FIP_{FVRI}$ (A) susceptibilities, (B) basal area factors, and (C) density factors.




with the PVRI and FIP data, respectively. There is a strong correlation between susceptibility values calculated with the FVRI and $PVRI_{FVRI}$ surrogate variables ($r$ = 0.993, $p$ < 0.001) (Fig. 3A). It is noteworthy that, using Moran's $I$, we found no significant spatial autocorrelation in the model factors generated from the field data. Consequently, in those relationships involving these variables, we do not expect the estimate of the magnitude of $r$ or its test of significance to be biased (see Haining 1993, p. 279). Minor variability in the susceptibility values is related to the basal area factor be-

**Fig. 5.** Comparison of FVRI and PVRI (A) susceptibilities, (B) basal area factors, (C) age factors, and (D) density factors.




cause the only difference in the inputs to the FVRI and the $PVRI_{FVRI}$ susceptibility models is the numerator in the basal area factor. Using FVRI, the numerator is the basal area of pine trees with DBH values ≥12.5 cm, whereas, the numerator is generated from trees with DBH values ≥7.5 cm for $PVRI_{FVRI}$. Although there is a strong correlation between the two basal area factors ($r$ = 0.949, $p$ < 0.001) (Fig. 3B), the $PVRI_{FVRI}$ basal area factors tend to be larger. The mean DBH associated with the FVRI basal area factor numerator is larger and the numbers of stems per hectare are fewer than that of the $PVRI_{FVRI}$, resulting in an overall reduction in basal area.

When susceptibility values are compared for the FVRI and $FIP_{FVRI}$ data, the overall relationship is statistically significant, although much weaker ($r$ = 0.408, $p$ = 0.001) than for the FVRI and $PVRI_{FVRI}$ data (Fig. 4A), reflecting the variable associations between the pairs of values in the two data sets. However, there are a number of locations with low magnitude $FIP_{FVRI}$ susceptibility values, most of which have much higher corresponding values when susceptibility is generated using FVRI data. This is likely a result of the $FIP_{FVRI}$ density factor, which has a value of 0.1 for 59.4% of locations. In contrast, only 2.8% of FVRI locations have density factors ≤0.1 (Fig. 4C). Further details on the density factor are provided in the following.

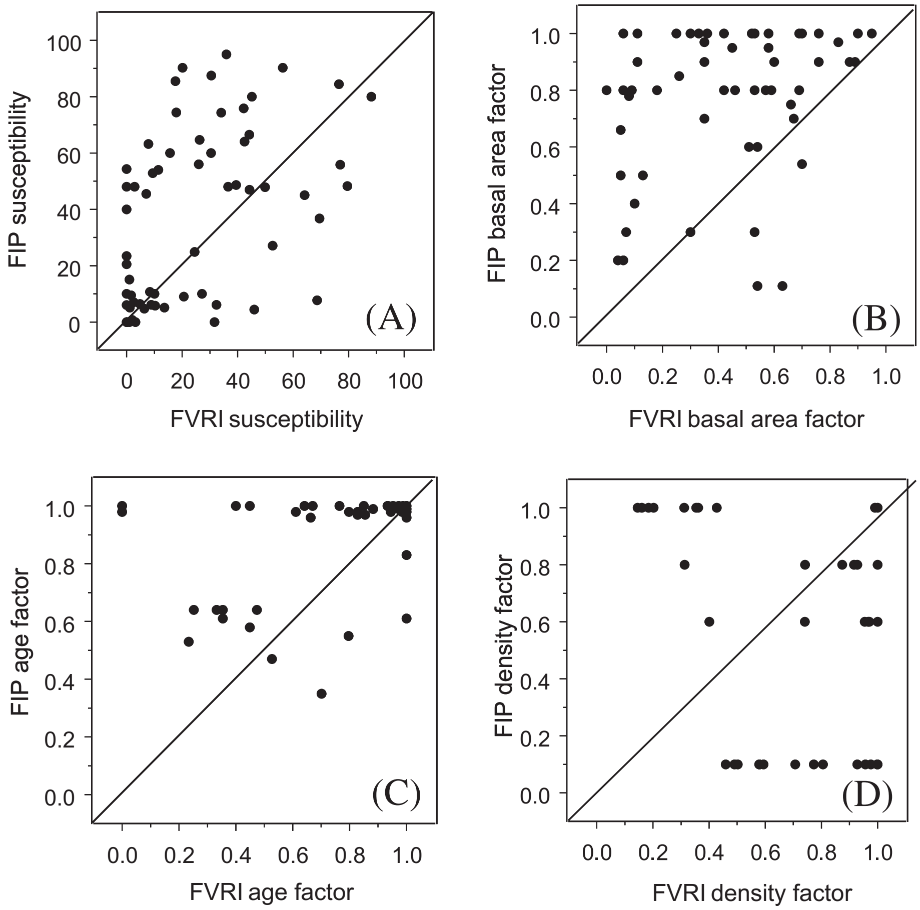
The correlation between basal area factors, computed from FVRI and $FIP_{FVRI}$ measures, is low and nonsignificant ($r$ = 0.137, $p$ = 0.281). In virtually all cases, the magnitude of the $FIP_{FVRI}$ basal area factor is larger than if calculated from FVRI data (Fig. 4B). This is because all detectable pine, rather than that with a DBH ≥ 7.5 cm is considered susceptible when using $FIP_{FVRI}$ data.

The linear correlation ($r$ = 0.206, $p$ = 0.090) between the density factors generated from the FVRI (density) and $FIP_{FVRI}$ (DBH) data sets indicates no relationship, primarily because the discrete nature of the DBH to density conversion results in density taking on only four values for the $FIP_{FVRI}$ data (Fig. 4C). Because of the categorical nature of the density factor, correlation values and their associated significance tests are best interpreted as indicators of the general nature of relationships for density factors generated using different parameters and data sets. Another element contributing to the lack of correlation is that, while the majority of density factors values are 0.1 when calculated from $FIP_{FVRI}$, few values ≤0.1 are generated using the FVRI data.

## Comparing FVRI and PVRI data

For the FVRI and PVRI data, there is a significant but modest correlation between susceptibility values ($r$ = 0.508, $p$ < 0.001) (Fig. 5A). This correlation is considerably less than that generated from comparing FVRI and $PVRI_{FVRI}$ susceptibility values (see the previous text). This reduction indicates that the data collection method has an impact above and beyond that of the surrogate measures. Also, as Fig. 5A shows, PVRI susceptibility values are more likely to be higher than FVRI values.

**Fig. 6.** Comparison of FVRI and FIP (A) susceptibilities, (B) basal area factors, (C) age factors, and (D) density factors.




To further investigate the nature of differences in susceptibility values, we focus on the susceptibility factors. Of the 68 FVRI sites used in the comparison, four had no pine in either data set, six had no pine in FVRI but pine in the FIP, and three had pine in the FIP but not in the FVRI, leaving 55 locations having pine in both data sets. The following comparisons are limited to those 55 locations. The correlation between the basal area factors for the FVRI and PVRI data is weak and nonsignificant ($r$ = 0.224, $p$ = 0.107) (Fig. 5B) and smaller than that computed from FVRI and $PVRI_{FVRI}$ data sets. As with FVRI and $PVRI_{FVRI}$ data, PVRI basal area factors are more likely to be larger than their FVRI counterparts, perhaps reflecting that all detectable pine are considered susceptible, rather than only those having a DBH = 12.5 cm.

Although there is a significant, moderate correlation between FVRI and PVRI age factors ($r$ = 0.748, $p$ < 0.001) (Fig. 5C), the tendency for one set of values to be larger or smaller than the other is not strong.

There is a weak correlation between the density factors for the two data sets ($r$ = 0.362, $p$ = 0.008) (Fig. 5D), which suggests that the numbers of stems per hectare estimated from aerial photographs do not consistently replicate field measurements.

## Comparing FVRI and FIP data

Comparisons between susceptibility input factors and susceptibility values generated from FVRI and FIP data are shown in Fig. 6. Although the correlation between susceptibility values is moderate ($r$ = 0.527, $p$ < 0.001) (Fig. 6A), it is higher than when susceptibility was computed using $FIP_{FVRI}$. This is unexpected and may be attributable to differences in the relationships between the susceptibility factors for the data sets. Comparisons of factors focus on sites where pine is reported in both the FVRI and FIP data sets (56 of 68 locations). The correlation between FVRI and FIP basal area factors (Fig. 6B) is similar to that observed when $FIP_{FVRI}$ data are used ($r$ = 0.307, $p$ = 0.022). Again, there is a marked tendency for the FIP basal area factor to be larger than its FVRI counterpart. The age factor, for which $r$ = 1.000 for the $FIP_{FVRI}$ data, has $r$ = 0.641 ($p$ < 0.001) (Fig. 6C). The density factors are uncorrelated ($r$ = 0.015, $p$ = 0.911), primarily because the FIP density factors are limited to four values (Fig. 6D). Although the density factors are poorly correlated, they likely explain the improvement in the correspondence in susceptibility values relative to comparisons between FVRI and $FIP_{FVRI}$. The percentage of sites in the 0.1 density class is lower when real data are used rather than derived FIP data (25.0% versus 59.4%). Therefore, using $FIP_{FVRI}$, the frequency distribution of basal area factor values is more similar to the FVRI frequency distribution of values, as only 2.8% of FVRI density factor values are ≤0.1.

## Comparing PVRI and FIP

Although the spatial boundaries of both data sets are simi-

**Table 6.** Characteristics of photographic vegetation resource inventory (PVRI) and forest inventory polygons (FIP).

| | PVRI All | FIP All | PVRI pine | FIP pine |
|---|---|---|---|---|
| No. of polygons | 90 997 | 87 303 | 66 121 | 61 202 |
| Mean polygon size (km$^2$) | 0.15 | 0.16 | 0.16 | 0.17 |
| Minimum polygon size (km$^2$) | ~0.00 | ~0.00 | ~0.00 | ~0.00 |
| Maximum polygon size (km$^2$) | 40.03 | 78.19 | 18.82 | 19.95 |
| CV of polygon size | 2.78 | 3.32 | 1.85 | 1.86 |

lar, PVRI polygons are more finely delineated. While there are 4% more PVRI polygons than FIP polygons (Table 6), when only pine polygons are considered, there are 8% more PVRI polygons than FIP polygons. Thus, in comparison with all polygons, pine polygons are twice as likely to be finely delineated in the PVRI data set. Mean polygon sizes are similar for PVRI and FIP polygons. When only pine polygons are considered, the coefficients of variation are also similar; however, the FIP data have more variability in polygon sizes when all polygons are investigated. Differences in the depiction of spatial boundaries may explain, at least in part, why susceptibility values generated from the FIP data appear smoother and more generalized, than those produced from the PVRI data (Fig. 2). However, the majority of differences in output are related to variation in the attribute data.

A caveat to results involving PVRI and FIP data is that statistical significance is influenced by the large number of observations and by the possibility of spatial autocorrelation in both variables. Although there is a moderate significant correlation in susceptibility values ($r$ = 0.713, $p$ < 0.001), a number of FIP locations have low susceptibility values for the entire range of PVRI values (Fig. 7A). This is similar to the trend between FVRI and FIP$_{\mathrm{FVRI}}$ output and is related to the high percentage of FIP density factor values of 0.1. While 34.8% of density values equal 0.1 when generated from FIP data, only 12.4% are ≤0.1 when derived from PVRI data.

Although the pairs of age and basal area factors appear to have good correspondence ($r$ values of 0.898 ($p$ < 0.001) and 0.860 ($p$ < 0.001), respectively), Figs. 7B and 7C show that there is no obvious tendency in these relationships. In spite of a significant correlation, the relationship between the PVIR and FIP forest density values shows no obvious correspondence ($r$ = 0.565, $p$ < 0.001) (Fig. 7D) because of the limitation in the number of possible FIP values. As with investigations of the correspondence between FVRI and FIP generated susceptibility models, correlations are stronger between PVRI and FIP models when actual, rather than derived data, are used.

## Conclusions

In this research, we have investigated the impact of using surrogate variables and large-area data sets when computing the susceptibility component of the Shore and Safranyik forest risk model (Shore and Safranyik 1992). The use of surrogate values enables susceptibility to be generated for the entire spatial extent of the forest inventory. By using a field data set collected as part of FVRI, we were able to compare susceptibility values calculated using the original model factors with those resulting from the use of surrogate variables. By comparing results from the FVRI data with two spatially extensive data sets (PVRI and FIP) and by comparing the PVRI and FIP, we were able to explore the impact of using the model to determine susceptibility values at a landscape level.

The results indicate that, in all but one situation examined, the susceptibility values calculated with the Shore and Safranyik forest risk model are highly sensitive to adjustments in the model input factors. This holds whether or not the same observational units are used. The small adjustment required when using PVRI data (changing the numerator of the basal area factor) did not result in any marked difference in susceptibility values. However, the more extensive change involved in using surrogate variables from the FIP data results in less correspondence in susceptibility values, thus foiling any prospect of using the FIP derived values to estimate the original ones in this instance.

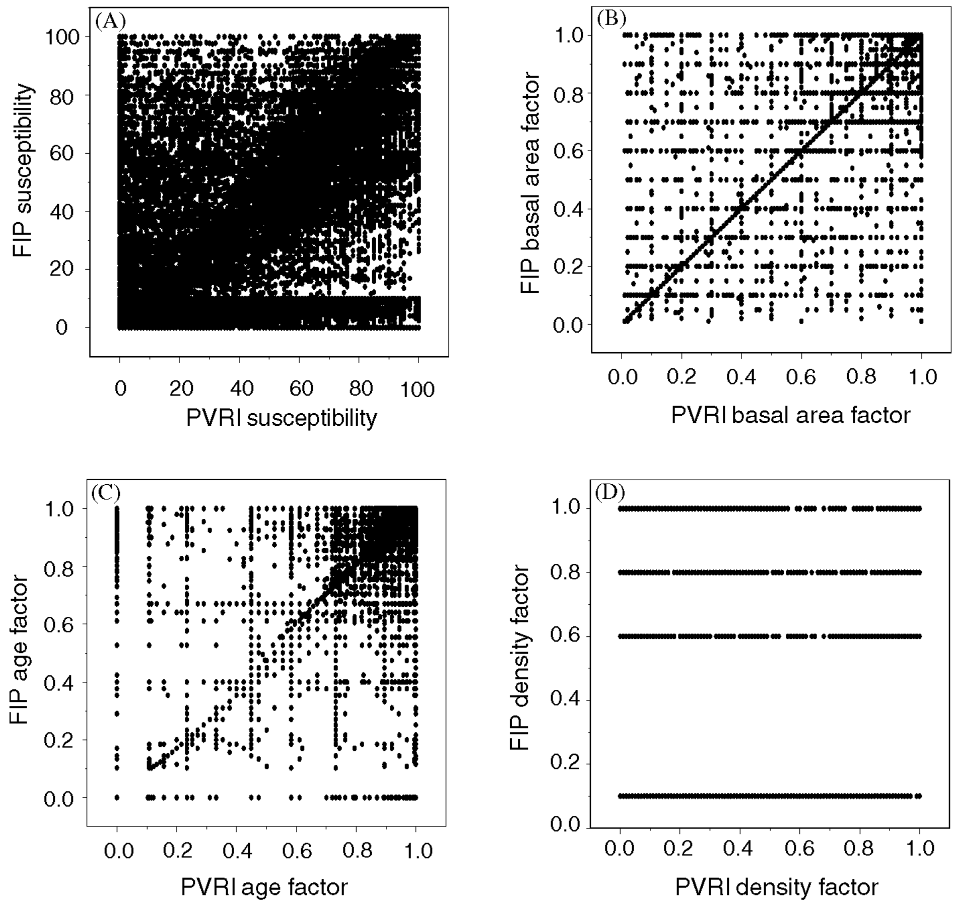
At the landscape level, both the susceptibility values generated using the PVRI data and those generated using the FIP data show only a modest correspondence with the values generated using the original model variables (FVRI). In addition, the finding that the FIP values were slightly more correlated with the FVRI values ($r$ = 0.527) than were the PVRI ($r$ = 0.508) was unanticipated. Theoretically, the PVRI values should have a stronger relationship because fewer surrogate factors are involved. This may be an indication that the limitations to using large-area data sets for susceptibility modelling are more related to the nature of air photograph interpretation than to the lack of optimal attributes or surrogate measures.

The relationships between FVRI susceptibility values and those generated using the PVRI and FIP data are different from their counterparts for the FVRI sites, with the PVRI being weaker and the FIP being stronger. In general, this suggests that the impacts of using surrogate variables are confounded by the spatial context in which they are used. In particular, surrogate variables designed for use with FIP data appear to be more representative of forest conditions when applied to large area photointerpreted data sets, than when used with detailed data.

The interaction between type of surrogate variables and spatial context is also captured in the lack of a strong correlation between susceptibility values calculated from the PVRI and FIP data sets despite both of them representing a polygonal coverage of the entire study area and being derived from the same photointerpreted material.

To attempt to gain some understanding of the differences in the susceptibility values produced using the different data, we explored the relationships between the three forest factors (age, basal area, and density) incorporated in the Shore

**Fig. 7.** Comparison of PVRI and FIP (A) susceptibilities, (B) basal area factors, (C) age factors, and (D) density factors.




and Safranyik forest risk model. This revealed that the age factor is least affected by the use of surrogate variables, followed by the basal area factor, and the density factor. Density is particularly problematic in the FIP data because it uses DBH values that are converted into just four discrete density values. At the very least, there is a need to derive an expression that converts DBH into continuous density values. This would also help to determine if DBH is an appropriate surrogate measure of density.

Although our findings relate to a specific forest district, there is little to indicate that this district has markedly different characteristics to those of others currently experiencing epidemic infestations (Westfall 2004). Taken collectively, our results suggest that resource managers should be extremely cautious if they use the Shore and Safranyik forest risk model in anything other than an individual-stand context and utilizing the original variables. There are issues to using stand-scale observations to model landscape-scale processes, and theoretical concerns are compounded by lack of appropriate data. In all but one situation we examined, the correspondence between susceptibility values generated from the original data and the modified ones was weak. Strong correspondence was only observed when detailed field data were available and when DBH stratification of basal area was the only missing data characteristic. Although basal area factors tend to be overestimated when large-area data sets and surrogate variables are used, there were no consistent trends in the differences in susceptibility values, with surrogate variables generating susceptibility values that were both over- and under-estimates of those produced by the original model. Thus, true susceptibility values cannot be estimated from surrogates nor can the surrogate values be used in a relative fashion. For the short term, FIP data will remain the most widely available data source making clear the need to develop other models and approaches that can identify risk at the landscape level.

Although our analysis pertains to a specific forest model, results highlight the general issues associated with large-area application of models that require forestry data for parameterization. Particularly in British Columbia where FIP data are frequently used as input for large-area environmental modeling, data uncertainty is likely to complicate results. The information content of large-area data sets is difficult to navigate because large area data will always be both problematic and necessary. Recognizing that data will never be error-free, forest-modelling approaches that incorporate data uncertainty are required.

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## References


British Columbia Ministry of Sustainable Resource Management. 1996. Gridded DEM specifications. British Columbia Ministry of Sustainable Resource Management, Victoria, B.C.

Curtis, R.P., and Marshall, D.D. 2000. Why quadratic mean diameter? West. J. Appl. For. **15**: 137–139.

Haining, R. 1993. Spatial data analysis in the social and environmental sciences. Cambridge University Press, Cambridge, UK.

Hopping, G.R., and Beall, G. 1948. The relation of diameter of lodgepole pine to incidence of attack by the bark beetle *Dendroctonus monticolae* Hopkins. For. Chron. **24**: 141–145.

Howse, K. 1995. A stand susceptibility rating system for bark beetles in the Cariboo Forest Region. British Columbia Ministry of Forests, Cariboo, B.C.

Leckie, D., and Gillis, M. 1995. Forest inventory in Canada with emphasis on map production. For. Chron. **71**: 74–88.

Nelson, T., and Boots, B. 2005. Identifying insect infestation hot spots: an approach using conditional spatial randomnization. J. Geogr. Syst. **7**(3–4): 291–311.

Nelson, T., Boots, B., and Wulder, M.A. 2006. Representing large area mountain pine beetle infestations. For. Chron. **82**(2): 243–252.

Safranyik, L., Shrimpton, D., and Whitney, H. 1974. Management of lodgepole pine to reduce losses from the mountain pine beetle. Canadian Forest Service, Pacific Forestry Centre, Victoria, B.C.

Shore, T., and Safranyik, L. 1992. Susceptibility and risk rating systems for the mountain pine beetle in lodgepole pine stands. Can. For. Serv. Pac. For. Cent. Inf. Rep. BC-X-336.

Shore T., Safranyik L., and Lemieux, J. 2000. Susceptibility of lodgepole pine stands to the mountain pine beetle: testing of a rating system. Can. J. For. Res. **30**: 44–49.

Stearns-Smith, S. 2001, Making sense of site index estimates in British Columbia: a quick look at the big picture. B.C. J. Ecosyst. Manage. **1**: 1–4.

Sustainable Resource Management Terrestrial Information Branch (SRMTIB). 2004*a*. Vegetation resource inventory: ground sampling procedures. Resource Information Standards Committee, Terrestrial Information Branch, British Columbia Ministry of Sustainable Resource Management, Victoria B.C. Available from http://srmwww.gov.bc.ca/tib/vri/vri/ standards/grnd_sample/vri_gs_procedure_2k4.pdf [accessed 25 April 2005].

Sustainable Resource Management Terrestrial Information Branch (SRMTIB). 2004*b*. Vegetation resource inventory: photo interpretation sampling procedures. Resource Information Standards Committee, Terrestrial Information Branch, British Columbia Ministry of Sustainable Resource Management, Victoria B.C. Available from http://srmwww.gov.bc.ca/risc/ pubs/teveg/vri-photointerp2k2/photo_interp2k2.pdf [accessed 25 April 2005].

Westfall, J. 2004. 2004 Summary of forest health conditions in British Columbia. Forest Practices Branch, British Columbia Ministry of Forests, Victoria, B.C.

Wulder, M.A., Seeman, D., Dymond, C., Shore, T., and Riel, B. 2004. Arc/Info Macro language (AML) scripts for mapping susceptibility and risk of volume losses to mountain pine beetle in British Columbia. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Victoria, B.C. Technol. Transfer Note No. 33.