Augmenting forest inventory attributes with geometric optical modelling in support of regional susceptibility assessments to bark beetle infestations

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Abstract

Assessment of the susceptibility of forests to mountain pine beetle (Dendroctonus ponderosae Hopkins) infestation is based upon an understanding of the characteristics that predispose the stands to attack. These assessments are typically derived from conventional forest inventory data; however, this information often represents only managed forest areas. It does not cover areas such as forest parks or conservation regions and is often not regularly updated resulting in an inability to assess forest susceptibility. To address these shortcomings, we demonstrate how a geometric optical model (GOM) can be applied to Landsat-5 Thematic Mapper (TM) imagery (30 m spatial resolution) to estimate stand-level susceptibility to mountain pine beetle attack. Spectral mixture analysis was used to determine the proportion of sunlit canopy and background, and shadow of each Landsat pixel enabling per pixel estimates of attributes required for model inversion. Stand structural attributes were then derived from inversion of the geometric optical model and used as basis for susceptibility mapping. Mean stand density estimated by the geometric optical model was 2753 (standard deviation ± 308) stems per hectare and mean horizontal crown radius was 2.09 (standard deviation ± 0.11) metres. When compared to equivalent forest inventory attributes, model predictions of stems per hectare and crown radius were shown to be reasonably estimated using a Kruskal-Wallis ANOVA ($p < 0.001$). These predictions were then used to create a large area map that provided an assessment of the forest area susceptible to mountain pine beetle damage.

Keywords: Landsat; forest inventory; mountain pine beetle; susceptibility; geometric optical modelling; western Canada; lodgepole pine; forest health.

1 INTRODUCTION

1.1 Susceptibility mapping of forest insect infestations

Susceptibility mapping can be used to guide preventative measures against forest insect attack by enabling estimates where infestations are likely to occur (Machlauchlan and Brooks 1998). In central British Columbia, Canada, the mountain pine beetle, Dendroctonus ponderosae (Hopkins) has caused mortality of over 13 million hectares of lodgepole pine forest (Pinus contorta Douglas. var. contorta Englemann) (Raffa et al. 2008). Under changing climate these infestations have the potential to expand to the north and east, and into higher elevations (Fall et al. 2006; Robertson et al., 2009; Safranyik et al. 2010) as well as into the boreal forest regions of Canada (Logan and Powell 2001). Recent surveys have recorded the presence of mountain pine beetle well into Alberta, eastward of previous expectations, infesting both lodgepole and jack pine (Cullingham et al. 2011). As a result, there is an increasing need to better understand the susceptibility of stands to the infestation, prioritize management activities to control mountain pine beetle outbreaks, and to provide data for preventative management (Machlauchlan and Brooks 1998).
1.2 Forest inventory data for susceptibility mapping

Typically, susceptibility models have focussed on stand and tree attributes measured in sample plots during field surveys (Shore and Safranyik 1992). More recently, forest inventory data has been used to estimate the likelihood of stands being attacked by insects (Wulder et al. 2004). However data collection for forest inventories is expensive, takes time to acquire and process, and requires expertise from field crews and from aerial photograph interpreters (Leckie 1990; McRoberts and Tomppo 2007). As such, inventory data are not updated frequently and can be subject to spatial and attribute errors due to inconsistent data collection standards and the long time frames involved between data collections (Gillis 2001). Furthermore, due to the expense and labour required portions of the land base are often excluded from inventory programs such as inaccessible forest stands, those not under government jurisdiction, or park and conservation lands. As a result, susceptibility maps derived from forest inventory data can be non-representative of the current infestation as inventory cycles often occur every 10 years. Alterations to the forest resource by insects and management activities are not included within the inventory cycle (Wulder et al. 2006a).

1.3 Forest inventory from satellite remote sensing

Satellite remotely sensed imagery can be used to augment forest inventories (Wulder et al. 2006a) substituting observations otherwise not available from conventional forest inventory techniques. Imagery can be acquired successively over the same geographic location within a short time period, is low cost (in some cases free), and provides spatially accurate information over large areas. As a result, remotely sensed imagery is becoming more widely integrated with forest inventory data collection and a number of programs now either integrate digital remote sensing data, or have plans to integrate remote sensing into inventories (Falkowski et al. 2009; Lund 1998).

Measurements can be derived from digital imagery and used to predict forest inventory variables and include basal area per hectare, stand volume per hectare, site index, stand density, growth and yield, and tree health (Hussin and Bijker 2000; Köhl et al. 2006). These variables can be derived, typically with minimum accuracies of 75% (Hussin and Bijker 2000) either by direct measurement, from relationships to other more easily measured variables, or estimated by modelling. One such method with potential to provide forest information is geometric optical modelling that determines stand level attributes through model inversion based on satellite derived reflectance and shadow proportions within a pixel.

1.4 Objectives

In this research we extract key attributes from remotely sensed imagery to augment and update forest inventories to supply susceptibility information for mountain pine beetle infestation. To fulfill this objective, we invert a geometric optical model using 30m spatial resolution Landsat imagery to estimate biophysical attributes of forests on a per pixel basis including estimates of diameter at breast height (DBH), forest age, and stand
density. The attributes estimated by the model are then combined with location information and an expected proportion of pine to determine the likelihood of attack by the mountain pine beetle over the area covered by an entire 185 x 185 km Landsat scene. Susceptibility will be derived based on the model posited by Shore and Safranyik (1992) where the susceptibility of each pixel is calculated based on the derived data and then used to estimate the likelihood of attack by mountain pine beetles.

2 REVIEW OF GEOMETRIC OPTICAL MODELLING

Geometric optical models provide an opportunity to derive forest structural information from medium spatial resolution (30m) satellite imagery (Li and Strahler 1985; Scarth and Phinn 2000; Peddle 2003). The models determine pixel-level reflectance by deconstructing the forest conditions present that lead to a particular pixel reflectance. Therefore, the signal obtained by the sensor can be modelled as a linear combination of the response from ground scene elements, the shade and sunlit portions of trees, and background that consists of herbaceous vegetation and bare soil (Li and Strahler 1985). The geometric optical model can be run in either forward or inverse mode, where forward mode provides pixel brightness values of given biophysical attributes, whereas the inverse mode computes biophysical attributes from the pixel reflectance. Mathematically, the model inversion is a non-linear minimization problem that can be solved through iterative adjustment of estimated a-priori inputs (Verstraete et al. 1996). Different optimization algorithms are available, based on cost functions to minimize the residuals between forward modelled and measured observations (in this case canopy reflectance). The model by Li and Strahler (1985) estimates reflectance of a pixel based on a small number of structural input parameters: tree height, crown width, crown height, and stand density. The shadow fraction of a given pixel is related to the geometry and density of a simplified canopy surface model, which is illuminated to cast shadows (Li and Strahler 1985; Scarth and Phinn 2000). Using the geometric optical model, crown area can then be used to derive basal area and DBH (Li and Strahler 1985; Scarth and Phinn 2000) and the treeness output has been used as a surrogate for stand density (Li and Strahler 1985; Scarth and Phinn 2000; Peddle et al. 2003).

Geometric optical models have been utilized on large area, medium-spatial resolution, satellite imagery, such as the Landsat Multi-Spectral Scanner (MSS; Li and Strahler 1985) and TM (Scarth and Phinn 2000). Li and Strahler (1985) used Landsat MSS data to estimate crown apex angle, crown height, crown radii, and number of tree crowns of mixed conifer stands with between 64% and 90% accuracy. Scarth and Phinn (2000) used the Li and Strahler geometric optical model on a Landsat TM image of Eucalyptus forests in south east Queensland, Australia to generate estimates of crown cover, canopy size, and stand density. Results agreed well with field survey measurements. Scarth and Phinn (2000) found that crown size and number of tree crowns were the most accurately predicted using the technique with changes in crown height and tree heights more poorly predicted, especially in more uniform forest stands. Peddle et al. (2003) used a multiple forward mode application of geometric optical modelling to produce structural lookup tables for Landsat TM images for pre- and post-harvests in New Brunswick. They used Landsat TM data with the model to estimate stand density, crown radius, and stem counts in pre- and post-harvest stands. Stem counts and stand density from the model were
compared to field data and results indicated a close relationship. Model results were validated for stand density, crown radius, and stem counts, and enabled simple forest structural change detection.

3 REVIEW OF SUSCEPTIBILITY MODELS

Susceptibility indices for mountain pine beetle have been used since the 1970’s (Shore et al. 2000) relying on measurements that can be recorded easily in sample plots or are already included in forest inventory surveys. Several susceptibility models have been developed, in British Columbia, the Shore and Safranyik hazard and risk rating system was adopted in 1995 by the British Columbia Ministry of Forests (British Columbia Ministry of Forests 1995). Shore and Safranyik (1992) define susceptible lodgepole pine stands as having trees with a DBH greater than 15 cm, over 80 years of age, and occurring in a stand density of approximately 1200 trees per hectare, that grow in low elevations at southern latitudes (of British Columbia, where the initial support research took place). The elevation and latitude model parameters act as a surrogate to capture trends related to temperature regimes.

The susceptibility model uses these characteristics to define the likelihood forest stands will be attacked and represents it as a continuous variable (Shore et al. 2000) between 0 (not susceptible) and 1 (highly susceptible) (Shore and Safranyik 1992). The variables in Shore’s susceptibility model are therefore the proportion of pine (P; equation 1), the age of the stand (A) provided by an age factor (Table 1), the stand density (D; Table 2), and a location factor (L). To determine the location, equation 2 is calculated and used in Table 3 to determine the corresponding value for L. The factors are multiplied together to give a total score (equation 3).

\[
P = \frac{\% \text{ basal area pine} \geq 15 \text{ cm}}{\% \text{ basal area all trees} \geq 7.5 \text{ cm}} \times 100
\]

\[
Y = (24.4 \times \text{longitude}) - (121.9 \times \text{latitude}) - (\text{elevation (m)}) + (4545.1)
\]

\[
\text{Susceptibility} = P \times A \times D \times L
\]

Once an area has been evaluated for susceptibility the geographic locations of current mountain pine beetle outbreaks can be overlaid and areas of high susceptibility in close proximity to mountain pine beetle infestations deemed the highest risk of attack (Shore and Safranyik 1992). Evaluation of the susceptibility model has been undertaken. For example, Shore et al. (2000) compared the percent of basal area killed in 41 stands by MPB against the stand susceptibility index and found 40 stands fell within a 95% prediction interval of the model data (Shore et al. 2000). The risk of attack can then be evaluated using Table 4.

[Insert Table 1 near here]

[Insert Table 2 near here]

[Insert Table 3 near here]

[Insert Table 4 near here]
MATERIAL AND METHODS

4.1 Study area

The research area is situated on the border of British Columbia and Alberta and is representative of the pine-dominated forest stands that are under increasing infestation pressure and are co-located with private and public managed forest lands as well as parks and protected areas (Figure 1). The topography consists of high-elevation (1800 m) mountainous regions, mid-elevation forests (1200 m), and some low-elevation prairie land (900 m). The forested areas are dominated by mature lodgepole pine occasionally mixed with black spruce (*Picea mariana* (Mill.) BSP) which grow on valley sides. Subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.), western larch (*Larix occidentalis* Nutt.), and a large proportion of black spruce grow in flat areas, around swamps and on river banks.

Lodgepole pine naturally regenerated following fires in the early part of the 20th century, which resulted in even-aged, pine dominated stands that grow to uniform dimensions (Moir 1965). In western Canada, historical information suggests that prior to more recent suppression activities, fires were the dominant natural disturbance in the region resulting in large burned areas that were naturally repopulated with lodgepole pine (Logan and Powell 2001).

The forest in the study area is considered to be susceptible to mountain pine beetles as the majority of stands in this area are densely stocked with trees larger than 15 cm DBH, and are generally over 80 years old. Furthermore, these stands are in close proximity to the infestation spreading north and east across British Columbia and are experiencing increasing levels of infestation (Safranyik et al. 2010). Aerial overview survey data collected of the study area indicates a low level of infestation at the lower elevations. Mountain pine beetle infestations are historically uncommon in this area however stand susceptibility assessment of the current forest resources is needed to understand where infestations may occur in the future.

4.2 Data

In order to complete the data analysis a flow diagram was developed that outlines the required processing steps (Figure 2). A Landsat-5 TM image was acquired on the 31st August 2009 (path: 47, row: 22) with a sun azimuth of 149.84°, and a solar zenith of 50.59 m. A top of atmosphere correction was completed for all six optical channels using the QUick Atmospheric Correction (QUAC) model to remove the atmospheric distortions from the image (Bernstein et al. 2005).

Earth Observation for Sustainable Development of forests (EOSD) data, which identifies 23 land cover classes from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) imagery representing circa year 2000 conditions (Wulder et al. 2008) was used to create a forest mask to remove no forested areas from the image. A 30 m digital elevation model of the area was also obtained, from the ASTER sensor aboard the Terra satellite (ASTER GDEM Validation Team 2009) and used to provide elevation data.
In areas where forest inventory data existed we extracted either the Vegetation Resource Inventory (VRI) data from British Columbia and Alberta Vegetation Inventory (AVI) data from Alberta both of which were compiled using similar two-phase forest inventory approaches, where in phase one aerial photographs are used to delineate polygons representing vegetation type, and interpretation is performed to derive stand conditions. In the second phase, ground data are used to calibrate and validate these estimates. Both datasets were available in digital format and were incorporated into a GIS. Two variables in the forest inventory provided validation data for the geometric optical technique: crown closure estimates which were available at 10% classified intervals, and stand density.

4.3 Application of the geometric optical model

To apply the geometric optical modelling approach, we identified spectral endmembers within the image based on linear unmixing (Scarth and Phinn 2000). Various algorithms are available to estimate endmembers which essentially rotate a point cloud until the apices can be identified and points at these locations selected to derive three endmembers (sunlit canopy, sunlit background, and shadow). Sunlit background consists of elements such as bare soil, duff, branch matter, and herbaceous ground layers that are present in canopy gaps. Once computed, the shaded canopy and shaded background were merged to create a shadow image (Figure 3). In this study we used the sequential maximum angle convex cone (SMACC) model (Gruninger et al., 2004). The endmembers must satisfy a positivity constraint so none of them contain values less than zero (Gruninger et al. 2004). The model defines spectral endmembers as vectors within a data set that cannot be represented by a positive linear combination of other vectors. Once the end members were defined the Li Strahler model was inverted using the trust-region reflective algorithm based on the interior-reflective Newton method of Coleman and Li (1996, 1999; Coleman et al. 2002) to best match the spectral signatures of the endmembers derived from spectral mixture analysis. The trust-region reflective algorithm iteratively computes the geometric model varying the a-priori model inputs until the reflectance predicted by the model best match the reflectance observed by the Landsat imagery.

In order to allow faster processing of the imagery, a lookup table of forest stand structural information based on field collected data was produced in advance. This table contains a list of ranges of spectral endmember for all possible combinations of input parameters within a given range and precision. The lookup table was then searched using a k-means nearest neighbour algorithm for each iteration of the trust-region algorithm in order to improve the model outputs until a least squares fit was found. As with Scarth and Phinn (2000) we focused our analysis and model performance on the estimation of two of the geometric optical model outputs; crown radius and stand density.

Once the model had run, pixels were averaged within the forestry inventory polygons (Wulder and Franklin 2001) and the mean, maximum, minimum, and range were calculated for each polygon. Initial values and ranges of the structural parameters required by the inversion algorithm were obtained from previous field studies undertaken in the area (Coggins et al 2008a).
4.4 Model performance assessment

To assess the accuracy of the model, the outputs were compared to existing forest inventory data which was available over portions of the Landsat scene. The forest inventory provides information on the managed forest stands in the study area. The forest inventory contains attributes of forest structure on a polygon basis that are produced from manual interpretation of aerial photos and calibrated for quality using field visits. The forest inventory data is used to calibrate the geometric optical model, utilizing independent samples of conditions collected from locations within the boundary of the Landsat image to represent a range of forest structural conditions. Furthermore, the forest inventory data enables direct comparison between model output and inventory data as attributes are complementary.

To do so we first compared stand density estimates between the model and the forest inventory. As the interpreted stand density estimates from the aerial photography within the forest inventory were not truly continuous we grouped the stand density into four remaining density classes. In absence of crown radius estimates in the forest inventory data the modelled crown radius was compared to inventory crown closure estimates which were available at 10% classified intervals.

The inventory and model output were compared using a Kruskal-Wallis ANOVA by ranks, a non-parametric statistical test that compares sample medians, whereas a parametric ANOVA compares means (Stat Soft 2005). The Kruskal-Wallis test calculates a Chi-square value (an H statistic) based on the number of classes and the number of observations in the data set which is presented as (number of classes -1, and the number of observations) = H statistic, significance. Bonferroni tests were then used to assess differences between classes of data. Once confidence in the geometric optical model outputs was achieved, we applied the susceptibility model as described below.

4.5 Susceptibility model development

Tree diameter required by the susceptibility model was approximated using the crown radius predicted by the geometric optical model in two steps: 1) the crown area was computed from the crown radius assuming a circular shape; and 2) a relationship between field measured DBH and crown area was created from the field data (Coggins et al. 2008a) and used to determine mean DBH as follows:

$$\text{Mean DBH} = 9.0902 \times \log(\text{crown area}) + 12.869$$

A mask was then created to remove all pixels with a DBH less than 15 cm. Basal area per pixel was then calculated using the mean DBH and the proportion of pine derived from forest inventory data. The height predicted from the geometric optical model was converted to stand age using standard lodgepole pine inventory tables (Thrower 1994). The stand density layer (D) was taken directly from the model output of \( m \), and reclassified to reflect stand density factors given by the susceptibility model. A location factor was determined for each pixel, with elevation extracted from the digital elevation model, and the latitude and longitude determined for each pixel in a GIS.
Finally, the four layers were multiplied together to determine the susceptibility of each pixel to attack, with values in the final layer between 0 and 1. The layer was classified to four categories using four evenly spaced breaks to determine the estimated susceptibility to mountain pine beetle attack giving categories that ranged from 0 to 0.249, 0.25 to 0.499, 0.50 to 0.749, and 0.75 to 100. These categories were assigned labels to indicate different levels of susceptibility (low, medium, high and very high). Lastly, to provide a further comparison, in areas of the Landsat scene where the forest inventory data was available, the susceptibility of each forest inventory polygon was calculated using the approach of Wulder et al. (2004) who used standard forest inventory polygon data and simple look up tables based on the Shore and Safranyik model parameters.

5 RESULTS

Output from the geometric optical model consisted of four layers, each of which described biophysical attributes, treeness \((m)\), crown radius \((r)\), crown height \((b)\), and tree height \((h)\), of the trees within each pixel (Figure 4).

Predicted crown radius was compared to the 10% interval crown closure classes from the forest inventory data. Results confirmed that as crown radius decreased, crown closure increased with open forest stands having wider crowns, with more closed canopies being associated with smaller, narrow, crowns (Figure 5). The modelled crown radius ranged from of 1.8 to 2.7 m, which is consistent with field measurements (Coggins et al 2008a).

The standard error around the mean in each crown closure class yielded distinct, statistically significant differences between model estimates and equivalent data from forest inventory confirmed by the Kruskal-Wallis ANOVA, where \(H(6, N = 439) = 256, p < 0.001\). A post-hoc, Bonferroni test confirmed however, that class 1 is different from all classes (except 7), class 2 is different from all classes except 3 and 7, class 4, 5, and 6 are different from class 1 and 2. Class 7 is not significantly different from all other classes because of a single observation in this class. A simple logarithmic trend line through the means of the classes confirmed the strong trend between the inventory and the modelled data \((r^2 = 0.9, p < 0.001)\).

The relationship between the geometric optical modelled treeness \((m)\) and stand density as provided by the inventory is shown in Figure 6 and demonstrated an increasing trend. A Kruskal-Wallis test indicates that the predicted treeness model output is statistically significant when compared to forest inventory information, where \(H(3, N = 480) = 26.6096, p < 0.001\). However, a post-hoc Bonferroni test indicates class 1 was over predicted by the model (Figure 6) and overall some confusion exists between the first three classes, while class 4 was significantly different from all other classes \((p < 0.001)\).

With confidence in the predictions we computed the final location variable required by the infestation model \((L)\) using equation 2, thus enabling calculation of susceptibility over the study area (Figure 7).

| Insert Figure 4 near here |
| Insert Figure 5 near here |
| Insert Figure 6 near here |
| Insert Figure 7 near here |

Table 5 shows a comparison between the forest susceptibility derived from the inventory and our approach. The geometric optical model output estimated more forest with low
susceptibility, but indicates decreases in both the medium and high susceptibility classes, while more area is estimated to be very highly susceptible.

[Insert Table 5 near here]

5 DISCUSSION

In this research we described the inversion of a geometric optical model to obtain pine beetle susceptibility maps. In order to successfully apply the geometric optical model, spectral unmixing was undertaken resulting in images of sunlit canopy, sunlit background, and shadow. Low levels of sunlit background occurred in shaded areas, such as protected mountain slopes and within forests in valley bottoms. High values in the sunlit canopy image occurred in forests that were not shaded by mountains, such as those in flat regions. Results indicate that pixels containing elements of sunlit canopy and shadow are generally less pure than the pixels selected for sunlit background. Shadows are generally much lower on snow covered mountain tops and in clear cuts.

Both stand density and crown radius were compared to forest inventory variables. While estimates of forest height were generated by the model, generally height and thus age varied only slightly across the study area and therefore, did not strongly influence the susceptibility predictions as much as stand density and crown radius. In addition there was no estimate of age available in the inventory data making a comparison with inventory data difficult. Overall, results indicate a positive relationship between observed and predicted stand density, although there is room for significant improvement. In this study, despite significant results with the Kruskal-Wallis tests, subsequent post-hoc Bonferroni tests indicated some differences between classes of data, but this was not consistent throughout. Where modelled stand density was high, forest inventory stand density was also high, with the Kruskal-Wallis test confirming classes were significantly different from each other. However subsequent Bonferroni tests indicated that low stand densities were less distinct and in general, low density was over predicted by the geometric optical model. A possible cause for this confusion could be due to the detection of ground vegetation, which is spectrally similar to tree crowns, and thus included in estimates of the treeness parameter. When these layers were entered into the susceptibility model, it is apparent that forests most susceptible to mountain pine beetle occur on the valley bottoms, with susceptibility decreasing at higher elevations as previously reported in the study area, which reflects findings from other studies performed in the area (Fall et al. 2006).

The susceptibility derived from geometric optical modelling showed differences when compared to the forest inventory data estimates. These differences are likely to be principally due to the date of data acquisition. The Landsat imagery was acquired in 2009, while the majority of the stand information in the forest inventory data had not been updated since 1991. Additionally, the Landsat imagery is consistent across the scene, whereas inventory data is an assemblage of information collected over long periods of time. Therefore, remotely sensed data potentially produces estimates that reflect current stand conditions by accounting for the current density and DBH measurements which will increase susceptibility ratings. Likewise forest disturbances such as, recent harvesting, damage by fire or insect attack will decrease susceptibility ratings. Both harvesting and fires have occurred regularly throughout the study area since
1991 and would account for the increase in area considered least likely to be attacked. As such, cohorts of trees which have been harvested from the high susceptibility stand classes from 1991 to 2009 will result in differences in the two methods and could account for disparity between the forest inventory data and the layer predicted by the geometric optical model. Indeed, the Alberta and British Columbia governments have completed aggressive mitigation programs throughout the study area, within this time period. Geometric optical modelling used in conjunction with medium spatial resolution satellite imagery produces data that can potentially map the susceptibility of forests over large areas. Landsat imagery has increased spatial accuracy over other data sources and is able to provide estimates of biophysical attributes of forest stands on a per pixel basis. For Landsat TM data, attributes are given in a 30 x 30 m pixel, whereas inventory data sources are polygon-based, covering (in some cases) several hectares. Therefore, data supplied by geometric optical modelling approaches can potentially more accurately reproduce the variability of forest stands rather than average values over a large polygon. Also, given the opportunity to collect data every 16 days, forest attributes could be recalculated regularly, without the need for extensive field work to validate output. Therefore, it is relatively simple to map areas that have undergone forest operations or areas affected by natural disturbance. Attacked forest can be delineated on remotely sensed imagery, where the biophysical attributes of attacked stands (DBH, stand density) can be used to stratify the area and augment forest inventory to aid with management and mitigation of insect infestations.

Besides providing strata for further investigation, geometric optical modelling has potential operational advantages. It is possible to run the model to define susceptibility over large areas, by using contiguous (i.e., composited) Landsat scenes acquired during the same month, representing the same year. For instance, the modelling approach could potentially be applied to the pine forests with non-existent or dated inventory data, to prioritise management in areas in close proximity to the current infestation or where infestation appears possible. By using a similar approach as applied in this communication, EOSD data can be used to define forested areas, and then the model run on these areas to produce reasonable outputs. Application of a geometric optical model requires time to produce inputs (i.e., fraction images) that will provide realistic output. With the model already constructed and applied for this study it would be possible to provide code to users, with this reported application offering guidance. Another possible concern is the computing power required by complex models, our runs were completed in over evening on a computer that is readily available from most retailers. After processing is complete, the output can be manipulated in a GIS, which is accessible to most natural resource companies, and the susceptibility layer computed.
CONCLUSION

Geometric optical models can be applied to produce frequent updates to maintain currency of information on forest resources and provide data equivalent to forest inventory attributes, reducing the need for plot data collection or interpretation and attribution of air photos. Susceptibility models that use the data output from the model also provide an opportunity to locate highly susceptible forest stands and either position high-spatial resolution remotely sensed imagery in areas that were previously inaccessible or locations to deploy ground crews to perform field surveys in specific areas. While this study used a mountain pine beetle disturbed site, the approach should be applicable also to susceptibility models of other disturbance factors, providing variables can be linked to vegetation structural information.

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Table 2. Density factor for the mountain pine beetle susceptibility model.

Table 3. Location factor for the mountain pine beetle susceptibility model.

Table 4. Estimate of risk of attack using the proximity of mountain pine beetle attacked stands to susceptible stands.

Table 5. Comparison of susceptibility estimated by forest inventory data and by geometric optical models given as the percent of the forest land base.

Table 1

<table>
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<th>Age</th>
<th>Factor</th>
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<tr>
<td>(\leq 60) years</td>
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<td>61 – 80</td>
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<td>(\geq 81)</td>
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*adapted from Shore and Safranyik (1992).

Table 2

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<th>Density</th>
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<td>(\leq 250) sph</td>
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<td>251 - 750</td>
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<tr>
<td>751 – 1500</td>
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<tr>
<td>2001 - 2500</td>
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<tr>
<td>(\geq 2501)</td>
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*adapted from Shore and Safranyik (1992).

Table 3

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<tr>
<td>0 to -500</td>
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<tr>
<td>&lt; -500</td>
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*adapted from Shore and Safranyik (1992).

Table 4

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<td>Low (&gt;1 km to MPB)</td>
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<tr>
<td>Moderate (&lt;1 km to MPB)</td>
<td>Moderate</td>
</tr>
<tr>
<td>High (within MPB attack)</td>
<td>High</td>
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</tbody>
</table>

*adapted from Shore and Safranyik (1992).
Table 5

<table>
<thead>
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<th>Susceptibility rating</th>
<th>Forest inventory data %</th>
<th>Geometric optical model data %</th>
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<tr>
<td>Low</td>
<td>39%</td>
<td>58%</td>
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<tr>
<td>Medium</td>
<td>31%</td>
<td>8%</td>
</tr>
<tr>
<td>High</td>
<td>28%</td>
<td>7%</td>
</tr>
<tr>
<td>Very high</td>
<td>2%</td>
<td>27%</td>
</tr>
</tbody>
</table>

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