TOWARDS THE ESTIMATION OF TREE STRUCTURAL CLASS IN NORTHWEST COASTAL FORESTS USING LIDAR REMOTE SENSING

C.W. Bater[a,*], N.C. Coops[a], S.E. Gergel[b], N.R. Goodwin[a]

[a]Integrated Remote Sensing Studio, Department of Forest Resources Management
[b] Department of Forest Sciences and Centre for Applied Conservation Research
Faculty of Forestry, University of British Columbia, 2424 Main Mall, Vancouver, British Columbia, V6T 1Z4, Canada
nicholas.coops@ubc.ca, cbater@interchange.ubc.ca, sarah.gergel@ubc.ca, ngoodwin@forestry.ubc.ca

KEY WORDS: Lidar, Forest Structure, Forest Biodiversity, Wildlife Tree Class, Decay Class, Snags

ABSTRACT:

The amount and variability of dead wood in a forest stand is an important indicator of forest biodiversity, and relates to both the structural heterogeneity and the amount of habitat available for biota. In this study, we investigate the capacity of light detection and ranging (lidar) technology to estimate the percentage of dead trees in coastal forests on Vancouver Island, British Columbia, Canada. Twenty-two field plots were established from which the tree structural classes, or wildlife tree (WT) classes, of all stems (DBH > 10 cm) were estimated. For each plot, the frequency distributions of the WT classes were highly skewed, so lognormal distributions were fitted, and the means (μ) and standard deviations (σ) of the log-transformed data were extracted. The relationship between μ and the percentage of dead trees within the plots was highly significant ($r^2 = 0.77$, $p < 0.001$). A variety of metrics were extracted from the lidar vegetation returns and compared against μ, and results indicated that the natural logarithm of the coefficient of variation was the best predictor ($r^2 = 0.75$, $p < 0.001$), followed by the heights of the 20th percentile ($r^2 = 0.69$, $p < 0.001$). In general, results indicated that the lowest lidar height percentiles were more significant predictors of μ, which is likely based on the direct linkage between the number of dead trees in a stand and its canopy architecture.

1. INTRODUCTION

The Canadian province of British Columbia contains approximately half of the country's softwood lumber inventory, and in 2005 the forestry industry was responsible for 45% of the province's manufacturing shipments (BC Stats 2005). While forestry's economic benefits are significant, extraction must be performed in a sustainable manner. In response to this need, the Province of British Columbia has developed a suite of resource values to monitor forest health and sustainability, such as biodiversity, timber, and soil, amongst others.

Each resource value is assessed by monitoring a number of indicators, such as tree height, diameter at breast height (DBH), species richness, and wildlife tree (WT) class (or decay class), which are traditionally measured using field-based approaches in association with aerial photography. Field assessments, however, can be expensive, labour intensive, provide small sample sizes and intensity, and often cover only limited geographic areas, while aerial photography suffers from time and cost issues, is prone to operator bias and subjectivity, and is limited by a shortage of trained interpreters. As a result, there has been increased interest in augmenting ecosystem and timber inventory mapping initiatives using digital remote sensing technologies, including recent research into light detection and ranging (lidar).

Various measures of forest structure and biodiversity have previously been estimated within the context of coastal northwest forests using lidar (e.g. Lefsky et al., 1999; Hudack et al., 2002; Anderson et al., 2005; Lefsky et al., 2005a; Lefsky et al., 2005b; Coops et al., 2007). Seielstad and Queen (2003) discussed the ability of lidar to characterise fuel bed roughness in forests in the western United States, and noted that the direct estimation of coarse woody debris loads may be achievable. One important variable that has not been examined, however, is the decay class or structural life stage of the tree, which captures the growth form of the current individual tree, from young vigorous trees, to older large live trees and veterans, to standing dead snags, to broken stems in various stages of decay. Within British Columbia the form classification is known as the wildlife tree class, which when accumulated over a stand provides an indication of the amount of dead trees and their state of decay. The amount and variability of dead wood is an important indicator of forest biodiversity (Noss, 1999). Snags are a critical component of coastal forests, increasing structural heterogeneity and providing habitat for forest biota (Clayoquot Sound Scientific Panel, 1995). The goal of this paper was to estimate the percentage of dead trees within plots in unmanaged forests by developing statistical relationships between plot-level distributions of WT class and lidar-derived vegetation metrics.

2. METHODS

2.1 Area of Investigation

Our investigation focused on the Kennedy Flats, Clayoquot Sound, Vancouver Island, British Columbia, Canada, (49°0'35" N, 125°37'21" W). Clayoquot Sound includes both mature first and second growth forest. The area is classified as Coastal Western Hemlock (CWH) zone, based on the Biogeoclimatic Ecosystem Classification (BEC) system (Meidinger and Pojar 1991), and has been mapped using the province's Terrestrial Ecosystem Mapping (TEM) classification system, which is derived from 1:20,000 to 1:50,000 aerial photography (Mitchell

[*] Corresponding author

et al., 1989; Demarchi et al., 1990). Based on the TEM classification system, the area encompasses the full range of forest structural stages from shrub and herb (14% of total area), pole and sapling (32%), young forest (4%), and old forest (46%).

2.2 Field Data Collection

Field data were collected in 2005 and 2006 from 22 forest plots ranging from pole/sapling to old forest based on the TEM classification (Table 1). Five of the old forest plots were located in variable retention harvest blocks. Data were collected from 625 m^2 or greater rectangular plots, with plot centres and corners mapped at a horizontal accuracy of approximately 1-5 m using a post-processed differentially corrected GPS (Trimble GeoXT). For each stem with a DBH > 10 cm, distance and bearing from plot centre, tree height, DBH, and species were recorded, with crown dimensions measured for every fifth tree. For conifers, the WT class was estimated using a field sheet showing growth and decay stages ranked 1 through 9: classes 1-2 were living trees; 3-5 were dead trees with hard wood; 6 represented dead trees with broken tops and spongy wood; 7 and 8 were dead trees with broken tops and soft wood; and class 9 represented dead and fallen trees.

Variable	Pole/Sapling n = 5 (mean/range)	Young Forest n = 3 (mean/range)	Old Forest n = 12 (mean/range)
Stems ha^{-1}	1491 / 1544	1147 / 816	957 / 1391
Basal Area (m^2 ha^{-1})	144.9 / 127.3	84.1 / 36.8	142.3 / 372.6
Mean Height (m)	19.3 / 5.3	18.3 / 3.9	12.6 / 12.6
Standard Deviation of Height (m)	6.1 / 2.0	5.1 / 1.3	6.33 / 12.1
Maximum Height (m)	32.5 / 18.0	25.8 / 4.7	27.0 / 30.4
Mean DBH (cm)	27.8 / 12.8	25.6 / 5.5	31.3 / 37.2
Maximum DBH (cm)	107.6 / 106.8	125.7 / 98.9	170.5 / 343.2
Standard Deviation of DBH (cm)	17.2 / 13.7	15.8 / 5.4	29.4 / 63.4
Dead Trees (WT Class 3+) (%)	12.0 / 18.1	13.1 / 9.0	19.6 / 12.1

Table 1. Summary statistics for sample plots by age class for stems with a DBH > 10 cm. Two outliers were excluded from this summary and all subsequent analyses.

Initial examination of the field data indicated that two plots were outliers and excluded from analysis. The first was composed of extremely dense overstocked conifer and contained no lidar ground returns; the second was located in a stand which had experienced significant disturbance, possibly from insect infestation, resulting in a stand structure not replicated in the dataset.

2.3 Fitting Lognormal Probability Density Functions to WT Class Data

For all plots, the majority of the trees were living (WT classes 1 and 2), with the small remainder being dead and in various stages of decay (WT classes 3-9), resulting in skewed distributions. Lognormal distributions may be fitted to data that are highly skewed, which is a common problem across the biological sciences (Limpert et al., 2001). A random variable (x) has a lognormal distribution if log(x), usually the natural logarithm, is normally distributed. For each plot, lognormal probability density functions (PDFs) were then fit to the frequency distributions of WT classes using the following equation:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} * \exp\left(-\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right) \quad (1)$$

where $f(x)$ = the lognormally distributed variable
μ = mean of x or scale parameter
σ = standard deviation of x or shape parameter

The μ and σ parameters are related to the frequency distribution of WT class of a given plot in similar ways. Stands containing large numbers of healthy living trees (e.g. WT class 1) tend to have small values for μ and σ. Increases in the percentages of dead trees, however, particularly in the more advanced stages of decay, will cause increases in both parameters (Figure 1).

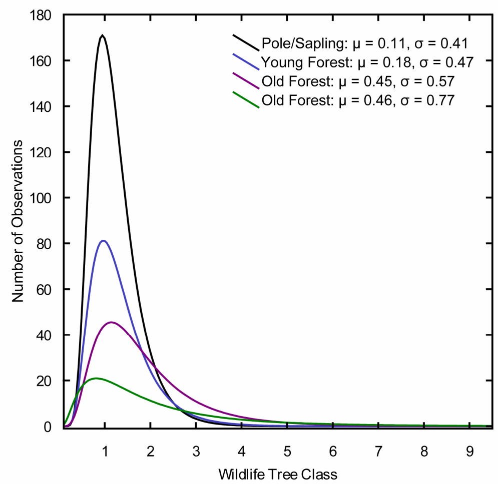

Figure 1. Examples of lognormal distributions fit to WT class frequencies in one pole/sapling, one young forest, and two old forest plots. Note increases μ and σ as stand age increases.

The lognormal μ and σ parameters were compared to the percentages of dead trees (WT classes 3-9) within each plot using linear regression techniques. These parameters were then used as proxies to represent the percentage of dead trees within each plot.

2.4 Lidar Data Collection and Variable Extraction

Small footprint laser data were collected during July 2005 by Terra Remote Sensing (Sidney, British Columbia), using a TRSI Mark II two-return sensor onboard a fixed-wing platform. Flying at a mean height of 800 m above ground level, the survey was optimized to achieve a nominal point spacing of one laser pulse return every 1.5 m^2 (Table 2). Ground and non-ground returns were separated using Terrascan v 4.006 (Terrasolid, Helsinki, Finland).

Sensor and Survey Parameters	Value
Sensor Type	TRSI Mark II discrete return sensor
Number of Returns	Two, first and last
Beam Divergence Angle (mrad)	0.5
Wavelength (nm)	1064
Mean Flying Height Above Ground (m)	800
Pulse Frequency (kHz)	50
Mirror Scan Rate (Hz)	30
Scan Angle (degrees)	±23
Mean Footprint Diameter (m)	0.4

Table 2. Lidar sensor and survey parameters.

A 0.5 m spatial resolution digital elevation model (DEM) was created by applying a natural neighbour interpolation algorithm to the ground returns (Sibson, 1981; Sambridge et al., 1995). The heights of the vegetation returns above the ground were then computed by subtracting the DEM heights from the vegetation return heights. A large number of variables were extracted from the lidar vegetation data based on Gobakken and Næsset (2005), and Næsset (2002; 2004), but without removing returns below a height threshold. These variables attempt to capture vertical structure by classifying hits into percentiles based on their height distribution through the forest canopy, and included the 5, 10, 15… 95 percentiles, in addition to the means, maximums, standard deviations, and coefficients of variation of vegetation return heights within each plot. The natural logarithms of the cases of each variable were also computed.

2.5 Data Analysis

The lidar-derived variables were compared to the lognormal parameters for the WT class distributions using both correlation analyses and simple regression approaches to test the significance of these relationships.

3. RESULTS

3.1 Predicting the Percentages of Dead Trees with Lidar-Derived Variables.

The best lidar-derived variables for directly predicting the percentages of dead trees in the plots (where 0% indicates a stand contains no dead trees, and 100% is indicative of a stand where all trees are dead and showing some sign of decay) were the natural logarithm of the coefficients of variation (r^2 = 0.42, r = 0.64, RMSE = 4.4%, p = 0.0021) and the heights of the 20th percentiles (r^2 = 0.39, r = 0.62, RMSE = 4.5%, p = 0.0033).

3.2 Lognormal Distribution Parameters and Percentages of Dead Trees

Using the plot-based field observations, the relationship between the percentage of dead trees and the parameters derived from the fitted logarithmic distributions (i.e. μ and σ) were explored. Results indicated that μ (mean of the lognormally distributed variable, or scale) was the best predictor of the percentage of dead trees (Figure 2).

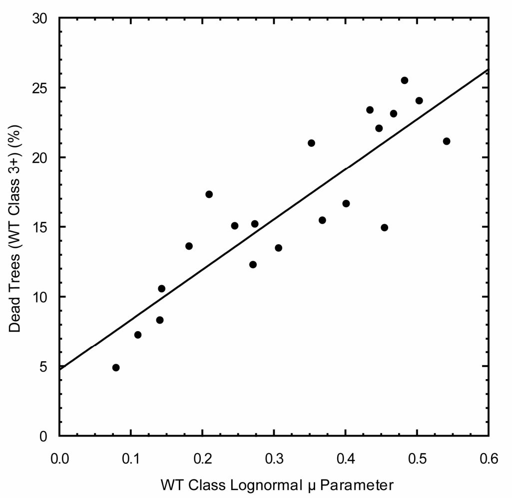

Figure 2. The best predictor of the percentage of dead trees in each plot was the lognormal μ parameter. Model: r^2 = 0.77, r = 0.88, RMSE = 2.8%, p = <0.001; y = 4.73+35.96*x

3.3 Predicting the Lognormal μ Parameter with Lidar-Derived Variables

The best predictors of the WT class lognormal μ parameter were the natural logarithm of the coefficients of variation (Figure 3) and heights of the 20th percentiles (Figure 4) The lowest height percentiles, from the 5th to the 35th, were each capable of explaining 60%-70% of the variance in μ, and all were negatively correlated with the parameter. This capacity diminished with increases in the percentiles (Figure 5).

Figure 6 shows the height of the 20th percentile and the percentage of dead trees by structural class. As forest stands increase in age, the percentage of dead trees and the number of canopy gaps increase, allowing lidar pulse returns to penetrate deeper through the forest canopy. The trend of the mean vegetation return height varies closely with that of the 20th

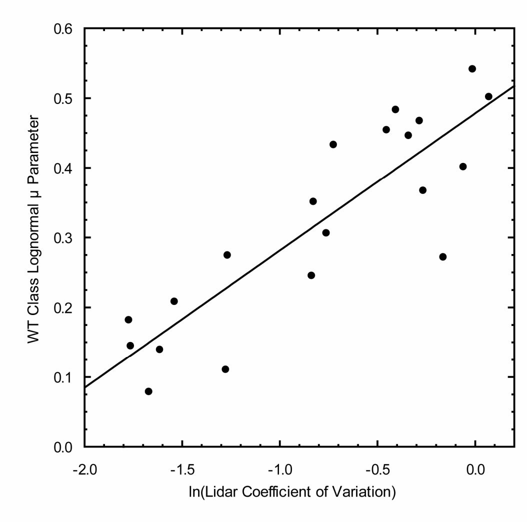

Figure 3. The best predictor of the WT class lognormal μ parameter was the natural logarithm of the lidar coefficient of variation. Model: $r^2 = 0.75$, $r = 0.87$, RMSE = 0.070, $p < 0.001$; $y = 0.48+0.20*x$

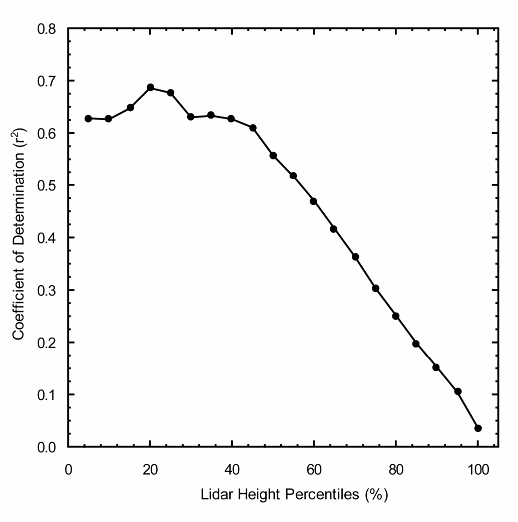

Figure 5. The lidar height percentiles, plotted against the coefficients of determination between the lognormal μ parameter and the heights of the percentiles. It is the lowest percentiles that account for most of the variance in μ. Note that all Pearson correlation coefficients were negative, indicating an inverse relationship between μ and the heights of the percentiles.

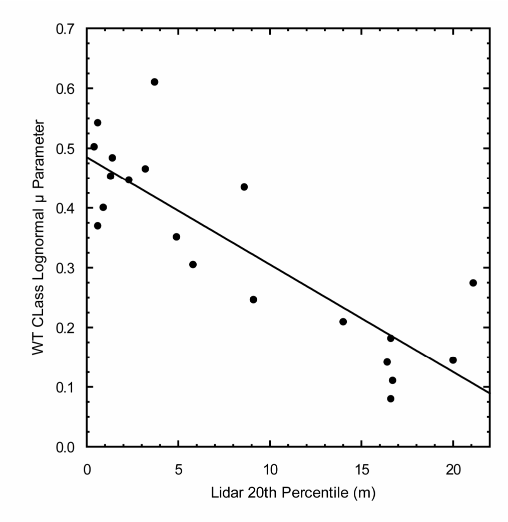

Figure 4. The WT class lognormal μ parameter estimated using the lidar 20^{th} percentile. Model: $r^2 = 0.69$, $r = -0.83$, RMSE = 0.079, $p < 0.001$; $y = 0.45-0.16*x$

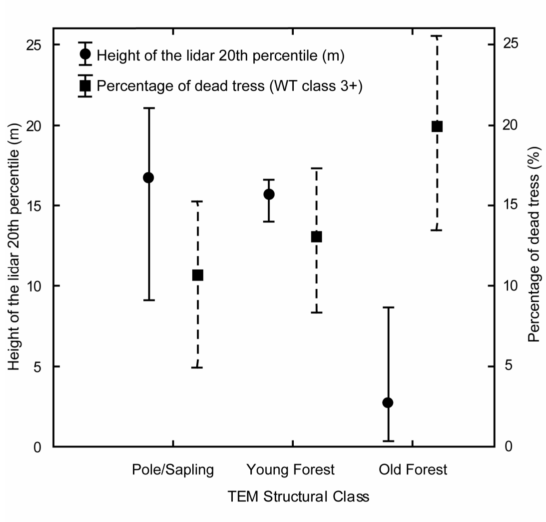

Figure 6. Means and ranges of (1) lidar-derived heights of the 20^{th} percentile, and (2) the percentage of dead trees, grouped by TEM structural class.

percentile (r = 0.88). The standard deviation of the vegetation return heights, however, were relatively stable across the age classes, resulting in an increase in the coefficient of variation from approximately 0.15 to 0.3 for pole sapling and young forest, to 0.4-1.2 for old forest.

4. DISCUSSION

The distribution of WT classes, or tree structural classes, within a plot is an important variable to consider when developing an understanding of the current structure of a forest stand, as well as for managing the stand for wildlife and biodiversity values. Whilst the range of wildlife tree classes from 1 to 9 within a plot is highly variable, fitting distributions to the observed frequency of WT classes and correlating these parameters with a simplified index of the proportions of live and dead stems is, we believe, an important result. Once we have developed confidence in our capacity to understand how the distribution parameters vary over the landscape as a function of stand form, we then look to lidar technology to extrapolate over large areas.

The results presented here indicate the capacity of lidar to estimate lognormal parameters describing the percentage of dead trees within plots in unmanaged forests. The method was superior to simply attempting to predict the percentage of dead trees directly using lidar-derived variables. The natural logarithm of the coefficient of variation was the best predictor of μ, however, generally all of the lower percentiles were also strongly and negatively correlated with the parameter. We believe this is a result of the direct linkage noted by Clark et al. (2004) between tree mortality and overall stand structure.

Clayoquot Sound's old forests are characterized by heterogeneous canopies and patchy understories, with gaps where old trees have died and young ones are regenerating (Clayoquot Sound Scientific Panel, 1995). These gaps, at least partly the result of the presence of defoliated, often limbless snags with very different structures than living trees, increased the mean penetration depth of lidar returns into the forest canopy, and decreased the heights of the lower height percentiles. Critically, non-ground returns were not removed below a given height threshold, and though many may have actually intercepted the understorey, coarse woody debris, large stones, or the ground, their inclusion was nonetheless an important contribution to the analyses.

Increasing the number of plots across the full range of tree structural class distributions is a necessary next step to both adequately capture the heterogeneity within and between the structural classes (especially old forests) found in the study area. Additional field data will also enable the application of multivariate statistical techniques, where more than a single predictor variable can be employed. Furthermore, additional research is required to determine if these techniques can be extended to managed forests. We believe that distribution parameters can be robust proxies for plot-based indicators of forest structure and biodiversity, and can be useful to ecologists and forest managers interested in augmenting their current mapping initiatives using lidar remote sensing.

5. REFERENCES

Anderson, H.A., McGaughey, R.J., and Reutebuch, S.E., 2005. Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment*, 94, 441-449.

BC Stats, 2005. Fact sheet released by the British Columbia Ministry of Labour and Citizen's Services, "Quick facts about British Columbia," Victoria, Canada. http://www.bcstats.gov.bc.ca/data/qf.pdf (accessed 12 October 2006)

Clark, D.B., Castro, C.S., Alvarado, L.D.A., and Read, J.M., 2004. Quantifying mortality of tropical rain forest trees using high-spatial-resolution satellite data. *Ecology Letters*, 7, 52-59. DOI: 10.1046/j.1461-0248.2003.00547.x

Clayoquot Sound Scientific Panel, 1995. Sustainable Ecosystem Management in Clayoquot Sound. Report 5, Halfmoon Bay, British Columbia, Canada.

Coops, N.C., Hilker, T., Wulder, M.A., St-Onge, B., Newnham, G., Siggins, A., and Troymow, J.A., 2007. Estimating canopy structure of Douglas-fir forest stands from discrete-return LiDAR. *Trees*. DOI:10.1007/s00468-006-0119-6

Demarchi, D. A., Marsh, R. D., Harcombe, A. P. and Lea, E. C., 1990. The Environment (of British Columbia). In: R.W. Campbell, N.K. Dawe, I. McTaggart-Cowan, J. M. Cooper, G. W. Kaiser, and M. C. E. McNall (Eds.). *The Birds of British Columbia*. Royal British Columbia Museum, Environment Canada, and Canadian Wildlife Service, Victoria, British Columbia, Canada Victoria, pp. 55-142.

Gobakken, T., and Næsset, E., 2005. Weibull and percentile models for lidar-based estimation of basal area distribution. *Scandinavian Journal of Forest Research*, 20, 490-502.

Hudack, A.T., Lefsky, M.A., Cohen, W.B., Berterretche, M., 2002. Integration of lidar and Landsat ETM+ data for estimating and mapping forest canopy height. *Remote Sensing of Environment*, 82, 397-416.

Lefsky, M.A., Cohen, W.B., Acker, S.A., Parker, G.G., Spies, T.A. and Harding, D, 1999. LiDAR remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests. *Remote Sensing of Environment*, 70, 339-361.

Lefsky, M.A., Hudack, A.T., Cohen, W., and Acker, S.A., 2005a. Geographic variability in lidar predictions of forest stand structure in the Pacific Northwest. *Remote Sensing of Environment*, 95, 532-548.

Lefsky, M.A., Turner, D.P., Guzy, M., and Cohen, W.B., 2005b. Combining lidar estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modeled forest productivity. *Remote Sensing of Environment*, 95, 549-558.

Limpert, E., Stahel, W.A., Abbt, M., 2001. Log-normal distributions across the sciences: keys and clues. *BioScience*, 51(5), 341-352.

Meidinger, D. and Pojar, J., 1991. *Ecosystems of British Columbia*. BC Special Report Series No. 6. BC Ministry of Forests, Victoria, British Columbia, Canada.

Mitchell, W.R., Green, R.N., Hope, F.D. and Klinka, K., 1989. *Methods for Biogeoclimatic Ecosystem Mapping*. Rep.

RR89002-KL. BC Ministry of Forest Resources, Victoria, British Columbia, Canada.

Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, 80, 88-99.

Næsset, E., 2004. Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. *Scandinavian Journal of Forest Research*, 19, 164-179.

Noss, R.F., 1999. Assessing and monitoring forest biodiversity: a suggested framework and indicators. *Forest Ecology and Management*, 115, 135-146.

Sambridge, M., Braun, J., and McQueen, H., 1995. Geophysical parameterisation and interpolation of irregular data using natural neighbours. *Geophysical Journal International*, 122, 837-857.

Seielstad, C,A, and Queen, L.P, 2003. Using airborne laser altimetry to determine fuel models for estimating fire behaviour. *Journal of Forestry*, 101(4), 10-15.

Sibson, R., 1981. A brief description of natural neighbour interpolation. In V. Barnett (Ed.), *Interpreting Multivariate Data*. Wiley, Chichester, pp. 21-36.

6. ACKNOWLEDGEMENTS

This research is partly support by the British Columbia Forest Science Program (Y07-1024), NSERC grants to Bater and Coops, and funds from the BC Ministry of Forests and Range. Dr. Denis Collins (BCMF&R) provided valuable discussion on methods and results. We thank Parks Canada and Interfor for providing access to the study area, and Clayoquot Biosphere Trust for the use of a field office in 2005. Yulia Stange, Kate Kirby, Andy Ackland, Yanny Barney, Selina Agbayani, Sam Coggins, Jessica Currie, Jamie Pascoe, Shanley Thompson, and Trevor (TG) Jones provided significant help with the field program.