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AUTOMATED AIRBORNE LIDAR-BASED ASSESSMENT OF TIMBER MEASUREMENTS FOR FOREST MANAGEMENT

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Abstract
This paper presents processing and analysis techniques to apply LiDAR data to estimate tree diameter at breast height (DBH) – a critical variable applied in a large number of forest management tasks. Our analysis focuses on the estimation of DBH using only LiDAR-derived tree height and tree crown dimensions, i.e., variables accessible from aerial observations. The modeling process was performed using 161 white and red pine trees from four 3850 m^2 plots in the Forêt de l'Aigle located in southwestern Quebec. Segments of the LiDAR data extracted for DBH estimation were obtained using the Individual Tree Crown (ITC) delineation method. Regression models were investigated using height as well as crown dimensions, which increased the precision of the model. This study demonstrates that DBH can be modeled to acceptable accuracy using altimetry data and automated data processing procedures and then be used in high-precision timber volume assessment.

Keywords
forest mensuration, LiDAR, remote sensing,terrain modeling, tree crown, timber volume modeling, white pine.

Introduction

The general trend toward precision and sustainable forestry calls for a transition from mapping relatively homogeneous forest stands and manually interpreting their content to the use of automated, computer-assisted analysis of high-resolution remote sensing data realized on the individual tree crown basis.

The potential of LiDAR (Light Detection And Ranging) technology to provide data applicable to forest management is increasingly well documented [1]. LiDAR can be used to estimate a wide range of forest inventory parameters including individual tree measurements [2] and timber inventory [3] as well as for forest structure analysis [4–6] and stand visualization [7]. Altimetry data collected by LiDAR sensors can complement the multispectral images in obtaining more precise forest inventory information derived from volumetric characteristics [8, 9]. With the rise of the importance of forests as source of biofuel, estimating precisely biomass becomes of strategic importance [10].

One of the most important input variables for forest management decisions is timber volume. Stand timber volume is traditionally estimated by summing the volumes of individual trees within the sample plots. Individual tree volume is in turn estimated by allometric taper equations based on field measurements of diameter and height [11]. These equations are generally species and region specific [12]. A comprehensive set of relationships between field-measured variables used in timber volume estimation is provided in [13]. The most reliable single variable for estimating a large number of forest indices, such as volume and biomass, is the mean diameter at

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breast height (DBH) [14], which can be obtained precisely from field measurements but not directly using remote sensing. Therefore, volume estimation with a sufficient precision of an entire forest tract usually requires considerable field sampling effort and expense. The use of LiDAR-derived canopy height models (CHMs) at the individual tree level paves the way to semi-automated estimation of timber volume.

Indeed, if DBH can be estimated from those forest parameters that can be measured by LiDAR sensors, namely tree height and crown size and shape, other biophysical tree parameters, such as tree volume V can then be estimated from DBH using previously established equations. For example, the relationship between DBH and the crown width in an open stand was studied in [15]. The need for further studies on the issue of the conversion of remote sensing-derived crown size into stem diameter estimation was emphasized in [8].

In this study, we discuss a methodology for the assessment of DBH using exclusively LiDAR data, by determining the relationship between DBH and LiDAR-derived tree height and crown parameters for two large and overtopping tree species, eastern white pine (*Pinus strobus*) and red pine (*Pinus resinosa*). In order to obtain tree crown parameters, individual tree crowns must be identified and delineated. Several methods for automated delineation of tree crowns from high-resolution imagery have been developed for precision forest management. Approaches based on morphological operators [16], Voronoi diagrams [17], local maxima analysis [18] and others have been explored. The Individual Tree Crown (ITC) method [19] was used in our experiments due to the maturity of the technology, the existing software tools, and the repeatability of the results.

This paper is organized as follows. Following the Introduction section, the processing scheme of LiDAR data is presented. The next two sections explain two-stage detection of individual trees – at the stand and the tree-crown level. Then, extraction of tree parameters from LiDAR data is described. The final section discusses the derivation of timber mass models.

Data flow management

The sequence of operations executed on the input data acquired by the airborne laser scanning is shown in Fig. 1. The raw input data are preprocessed in order to obtain precise (x, y, z, intensity) point cloud. Tree stand delineation procedures determine the forest areas within which the assessment of timber volume is performed. The next procedure is the detection of individual tree crowns and the calculation of individual tree parameters required for timber volume models. The results of the assessment can subsequently be used in forest management for such tasks as the calculation of the Annual Allowable Cut (AAC) or silvicultural planning.

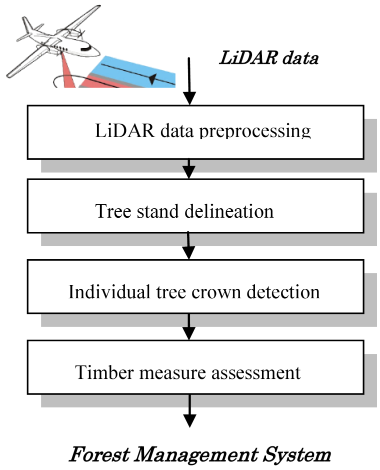

Fig. 1. Data flow diagram.

The laser scanning data used to develop model presented in this paper were acquired by LaserMap Image Plus Inc. in August and November, 2005 for an approximately 75 km^2 study area, and delivered in 1 km^2 tiles. The acquisition resulted in the point footprint of 25 cm and the pulse density of 2 pulses/m^2. Data were pre-processed using Optech's REALM software and delivered by the data provider as raw points and as raster layers. In order to produce fine-grained raster models of known derivation using data combined from the two acquisitions, raw point data were re-processed in-house.

Plots were located in fire-originated eastern white pine and red pine stands on sandy fluviatile deposits along the Eagle River lowlands in the Forêt de l'Aigle, southwestern Quebec. We used four existing plots of 35 m radius, previously established to study white pine response to thinning. Although thinned in 1998 (38% basal area removed), they have all over 30 m^2/ha in basal area and DBH of over 19 cm (Table 1). DBH and species were recorded for all trees with DBH $>$ 9.1 cm in 2004. DBH was measured at standard height (1.3 m above ground) using a caliper (1 mm precision). Tree crown position was classified as dominant, co-dominant, intermediate, or oppressed. The precise position of the center of each tree (at breast height) to the center of the plot was described by polar coordinate with distance (obtained with a rangefinder/hypsometer (Haglof Vertex 3) and angle (with a compass). Additional field work was done in 2006 to determine the absolute

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location of the center of two plots using high precision GPS (5700/Trimble R7 and 5800/Trimble R8) with station-based correction. These were precisely co-registered (< 0.5 m) to the LiDAR models (described below) using visual analysis of relative tree locations. The two remaining plots were registered to the LiDAR models using approximate GPS coordinates and visual analysis.

Table 1
Structural and compositional characteristics of sample plots. Trees targeted for DBH estimation are dominant and co-dominant pines.

Plot number		**1**	**2**	**3**	**4**
Latitude		46.24°N	46.22°N	46.22°N	46.21°N
Longitude		76.34°W	76.34°W	76.33°W	76.32°W
Number of trees	All trees	169	243	336	255
	Dominant trees	54	47	73	68
	Targets correctly delineated	34	29	47	51
DBH (cm)	Mean	26.7	21.4	19.1	22.5
	StdDev	15.5	12.8	11.3	14.4
Basal area (m^2/ha)	White pine	29.9	21.0	25.6	31.5
	Other coniferous	1.9	3.3	6.8	4.9
	Hardwood	0.9	6.4	1.4	0.7
	Total	32.7	30.7	33.7	37.0

Tree stands extraction using LiDAR data

Automated extraction of the forest zones was performed using the Canopy Height Model (CHM). This approach allows for the application of exclusively LiDAR data, and limiting manual delineation from forest inventory maps. The delineated tree stands were obtained through scale dependent [20] thresholding of CHM.

CHM is generated as the difference between the top of the vegetation model (Digital Surface Model, DSM) and a model of the bare-earth surface (Digital Elevation Model, DEM). For each tile, points classified by the data provider as "ground" were extracted using a Perl script and imported into ESRI ArcGIS to construct the DEM. Points were converted first to a Triangulated Irregular Network (TIN), resulting in linear interpolations between neighboring points, and then to a raster of 0.5 m resolution.

To produce the DSM, the points representing the top of the vegetation canopy must be selected from the point cloud. The selection procedure consisted in selecting the locally highest points while excluding outliers, as identified by the data provider. Dedicated shell and Perl scripts were produced to extract surface points from the raw ASCII files, which were then converted to TINs and rasters using the same procedure as for the DEM. The DEM and DSM layers were then subtracted to generate the CHM. Finished tiles were mosaicked in PCI's OrthoEngine to generate seamless digital models. Sample digital models for a part of the Forêt de l'Aigle area are illustrated in Fig. 2.

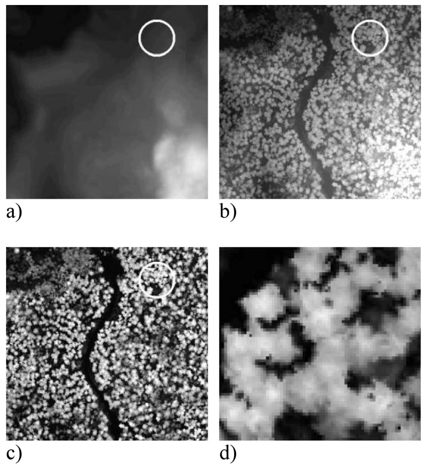

Fig. 2. Examples of digital terrain models: a) DEM, b) DSM and c) CHM d) a sub-area of c) showing individual tree crowns. The circle indicates one of the study plots.

The Canopy Hight Model, obtained by subtracting data shown in Fig. 2b from the data in Fig. 2a, is depicted in Fig. 2c. The encircled portion of the image indicates the location of Plot 1.

Individual tree crown delineation

The ITC method was originally developed to delineate tree crowns from high-resolution aerial imagery. First, it identifies locally dark pixels, and uses these as starting points for a region-growing algorithm to detect valleys of shadow between tree crowns. These valleys are then connected to produce a bitmap outlining individual crown candidates. Then, the other step is the crown delineation in the spaces between the shadow valleys. The maximum jump distance that can be used to split an isol is 4 pixels. With a resolution of 60 cm ITC can split a crown that is 2.4 m wide. ITC Suite is available as an add-on tool to PCI Geomatica.

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By using ITC on the CHM rather than imagery, layover and illumination effects were avoided. A modification of the valley-following technique using the water-flow accumulation algorithms in ArcDesktop produced somewhat smaller crowns with more realistic crown shapes (Fig. 3).

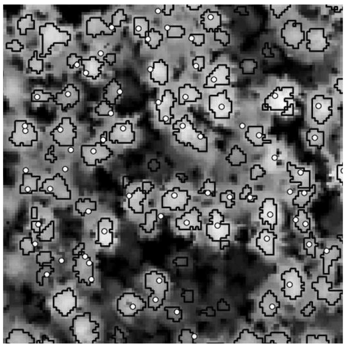

Fig. 3. Results of tree crown delineation. White dots indicate the stem position of dominant and co-dominant field-mapped trees.

Extraction of tree parameters

Tree height and crown dimensions were estimated for individual field-measured dominant or co-dominant pines based on the CHM. In cases where a crown included more than one stem, we used data from the larger tree.

Tree height

The height H of individual trees was determined using LiDAR points classified as canopy or ground points (Fig. 4a). The points involved in the calculations were located inside volumes bounded by the ITC-delineated crowns (Fig. 4b). Height was defined (Fig. 4c) as the difference between the elevations of the highest canopy point and the mean ground height.

Crown dimensions

The feasibility of calculating mean tree crown diameter at the plot level from LiDAR-derived tree parameters was demonstrated in [21]. Two crown dimension variables: length (L) and width (D) were defined as the measure of the crown size and shape. The crown length is the distance between the two most distant cells in the raster polygon forming the isol. It corresponds roughly to the diameter of a circle circumscribed on the delineated raster shape of the tree crown. The crown width is calculated by drawing a line perpendicular to the line of the length (L) at its center. The width is the distance between the first and the last intersection with the isol. Examples of tree crowns and their dimensions L and D are illustrated in Fig. 5.

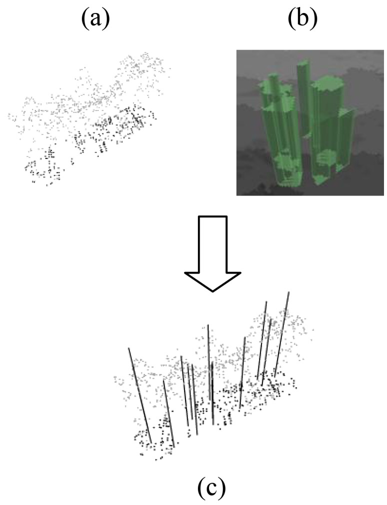

Fig. 4. Schematic illustration of the procedure for calculating tree heights.

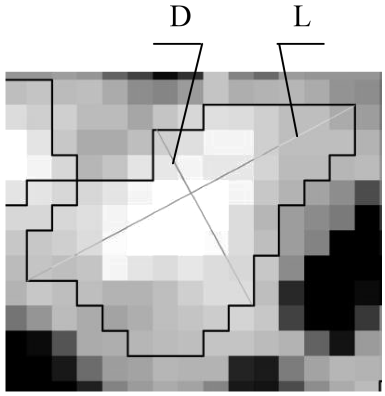

Fig. 5. Illustration of crown length L and width D.

Timber Measure Modeling

Data Analysis

A total of 161 tree crowns were correctly delineated: 145 were white pines and 16 red. Summary statistics for these trees are in Table 2.

Table 2
Summary statistics for trees used in the analysis.

	Tree DBH [mm]	Tree Height [m]	Crown Diameter [m]	Crown Length [m]
Min.	23.10	19.75	2.68	1.34
Mean	44.00	28.89	5.87	3.78
Median	43.35	28.98	5.91	3.75
Max.	65.30	34.68	10.48	6.32
Std. Dev.	9.55	2.62	1.33	0.97

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Box plots of the trees in each plot (Fig. 6) show that the distribution of DBH in plots P1, P2 and P4 are similar. The tree stem diameters in Plot 3 are somewhat smaller.

A test of the normality of data distribution was performed and assessed using the Q-Q (quantile-quantile) plot shown in Fig. 7. Expected normal values (Y-axis) were calculated using Blom's proportional estimation formula. The X-axis represents the normalized distribution of DBH, with zero mean and unity variance. The form of the plot is an indication that the data from all the plots can be clustered and used together for the model development.

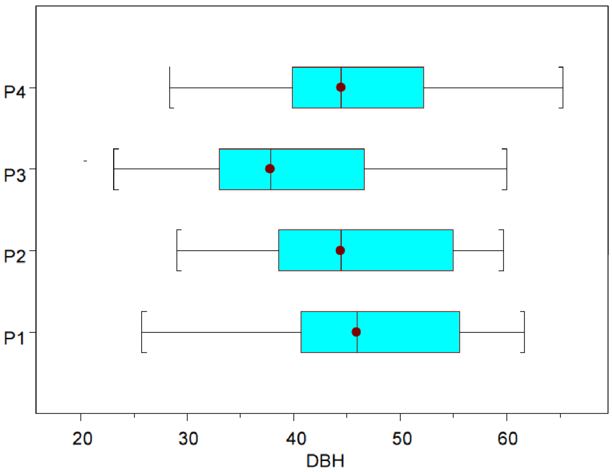

Fig. 6. Box plots of the tree DBH distribution for the four sample plots.

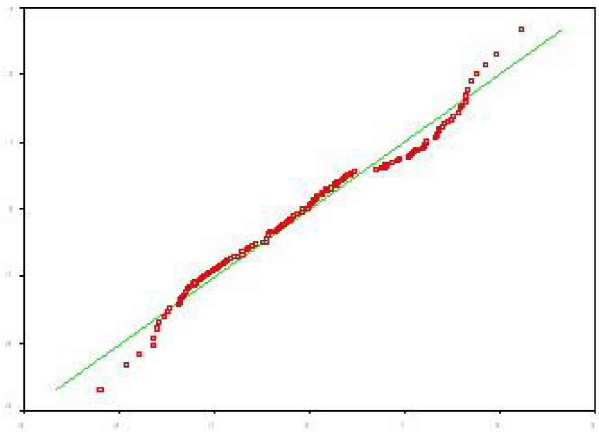

Fig. 7. Q-Q plot for trees in four sample plots.

Model Development

The relationship between H and DBH over the full range of H usually takes form of a sigmoid curve. This relationship is best approximated by a non-linear function. Sigmoidal growth equations such as the Chapman-Richards, Weibull – type, and Schnute equations provide the most satisfactory results [22]. Polynomial-type height-diameter models have to be treated with caution, since their extrapolation may often lead to unrealistic height predictions [23]. Development and evaluation of relative performance of several nonlinear tree-height models based on diameter measurements for 9 boreal forest tree species in Ontario was reported in [24].

The most frequently used Chapman-Richards function can be expressed as:

$$H = 1.3 + a(1 - e^{-bDBH})^c \tag{1}$$

where H is total tree height in meters, DBH is outside bark tree diameter at breast height (1.3 m) in centimeters, a, b, and c are asymptote, scale and shape parameters, respectively. In this study, we search for an inverse equation, the general form of which is

$$DBH = f(\ln H) \tag{2}$$

Different criteria can be used in order to determine the best regression model, including maximizing the coefficient of determination R^2, minimizing the root mean square error RMSE, forward selection, and backward elimination. Using information criteria for multivariate model selection [25] has been shown to be superior to heuristic methods, such as stepwise regression. In the process of optimal model selection the Akaike Information Criterion (AIC) was used [26]. AIC is a function of the number of observations n, the residual sum of squares (RSS) from the estimated model, and the number of parameters p, as shown in Eq. (3).

$$AIC = n \ln\left(\frac{RSS}{n}\right) + 2p \tag{3}$$

The first term in Eq. (3) is a measure of the model lack of fit while the second term is a penalty term for additional parameters in the model. The preferred model is the one with the lowest AIC value. Different model variants of Eq. (2) were investigated using the three LIDAR-derived parameters (H, L, D) within our model selection procedure. A summary of twelve different models is given in Table 3.

The model with both the lowest AIC value (AIC = 521.2) and the highest value of R^2 ($R^2 = 0.732$) is the model of the form

$$DBH = a_0 + a_1 H + a_3 \log D + a_4 \log L \tag{4}$$

where

$$a_0 = 330, \quad a_1 = 7.8, \quad a_2 = -366,$$
$$a_3 = 25.9, \quad \text{and} \quad a_4 = 11.2.$$

The graph of the measured DBH values versus the values from the fitted model as in Eq. (4) is shown in Fig. 7.

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Table 3
Summary of models with the height and crown size terms.

No	Terms	R^2	AIC
1	H, D	0.709	530.3
2	H, L	0.660	555.4
3	logH, D	0.697	536.8
4	H, logH, D	0.722	524.6
5	H, logH, L, D	0.729	523.1
6	H, logDlogH	0.716	526.4
7	H, logH, logDlogL	0.728	521.4
8	H^2, logH, logDlogL	0.727	522.2
9	H, sqrtH, logDlogL	0.728	521.7
10	H, logH, sqrtH, logDlogL	0.728	523.4
11	H, logH, logD, logL	0.732	521.2
12	H, logH, logD	0.725	523.1

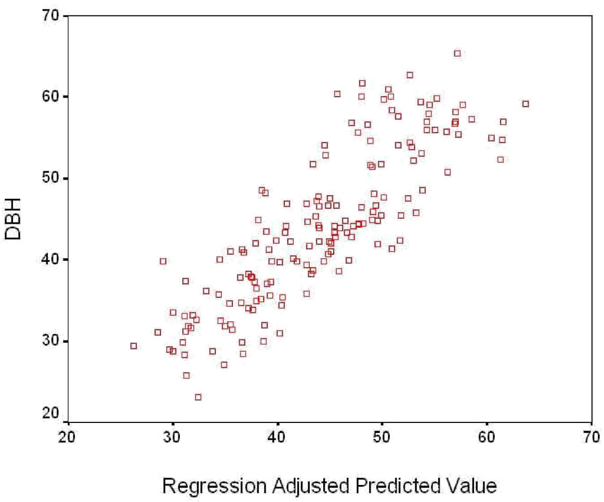

Fig. 8. Measured versus fitted DBH for model (4).

It can be noticed from Table 3 that the impact of the crown width D on the model precision is more significant than that of the crown length L. This can be interpreted as the importance of the level of development of the crown in both perpendicular directions. Indeed, white pine, the dominant tree species in our sample, can exhibit very asymmetrical star-shaped crown, as one can see in Fig. 2d.

Conclusions

The goal of this study was to develop a methodology for the assessment of timber volume from remote sensing laser scan data. A relationship between DBH and LiDAR-derived tree height and tree crown parameters was successfully established, allowing for the use of standard tree volume allometric equations for forest management tasks. The models investigated here were limited to even-aged pine stand (mostly white pine), where tree crowns are large and mostly well individualized. Additional field samples are needed to assess performance in other stand types.

The introduction of tree crown parameters, crown length and crown width, significantly enhanced the precision of the assessment of DBH. This demonstrates the importance of efficient crown detection and delineation algorithms using LiDAR data. The ITC method applied in this work, although mature and well-studied, was designed primarily for panchromatic and multi-spectral imagery. Correct segmentation of tree crowns remains a challenging scientific task.

The work presented in the paper focused on the assessment of individual tree parameters indispensable to implement precision forest inventory. Plot-level parameters, important for forest management practices, can be obtained through regression analysis and cross-validation with plot-level field-measured parameters. It should also be noted that the height-DBH relationships are known to be affected by local environmental conditions and often vary within a geographic region. Further development of individual-tree height–diameter models specific for different ecoregions is of critical importance for forest management [27].

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