DIGITAL SURFACE MODEL OF TREE CANOPY STRUCTURE FROM LIDAR DATA THROUGH IMPLICIT SURFACE RECONSTRUCTION

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ABSTRACT

Tree canopy structure is an important factor in forest fire, plant physiology, and tree competition. Quantifying the tree canopy structures is difficult due to the irregular shapes and spacing of the trees. Our method for estimating the canopy structure is based on Light Detection and Ranging (LIDAR) data. LIDAR has three-dimensional point distribution which allows us to ascertain the shape of objects on the ground. Our method consists of three steps. First, we partition the LIDAR points into subsets corresponding to individual trees using level set methods. Second, for each tree we select a subset of points near the crown surface. Finally, we use an isosurface method with radial basis functions to reconstruct the crown surface of each tree from the selected points. The resulting surface provides more precise information about crown base height, which was difficult to measure from discrete points in previous studies. Our approach improves the spatial accuracy of tree level parameters and provides 3D images of crown shapes.

INTRODUCTION

Tree canopy structure is an important factor in forest fire, plant physiology, and tree competition. Quantifying the tree canopy structures is difficult because of their irregular shapes. In previous studies, the explicit equation such as cylinders, paraboloids, cones, ellipsoids, spheroids, and ellipsoids placed on a cylinder has been regressed against field measured tree parameters (Holmgren and *et al*. 2003, 2004b, Nelson, 1997). A relatively recent technology, Light Detection and Ranging (LIDAR) devices determine the physical location of points on three-dimensional objects by measuring the time delay between a transmission of a laser pulse directed towards the object and the detection of the reflected signal. There are mainly two kinds of returns: the last return and the other returns (first returns). Most of the first returns are reflected from tree canopy, while the last return is reflected from the ground. The last return is used to make Digital Terrain Models (DTMs) and first returns have a good potential to measure the shape of tree canopy structure.

LIDAR footprint size influences the reflected area of the object on the ground (Goodwin and *et al.* 2006). Smaller footprint size is more suitable for tree level measurement than large-footprint size. The point density range on the ground can be up to 20 points per square meter with current technology (Ackerman, 1999). Conventionally, plot level tree parameters have been assessed by LIDAR derived tree parameters, which are reviewed in the next section. Techniques developed for plot level are, however, not good enough to use higher density LIDAR data to measure canopy structure and we can use advanced techniques to get precise measurement for canopy structure.

Small-footprint LIDAR data has been used for estimating fuel parameters (Anderson and *et al.* 2005, Morsdorf and *et al.* 2004, Riaño and *et al.* 2003, 2004), inventory (Goodwin and *et al.* 2006, Holmgren, 2003, 2004a, 2004b, Hyyppä and *et al*, 2001, Leckie *et al.* 2003, Magnussen and *et al*, 1998, 1999, Means and *et al*. 2000, Nelson and *et al.* 1997, Næsset and *et al.* 1997, 2001, 2002a, Persson and *et al.*, 2002, and Popescu and *et al.* 2003, 2004), biophysical properties of forest stands (Brandberg and *et al*. 2003, 2007, Næsset and *et al.* 2002b, 2005a, 2005b, Popescu and *et al.* 2004, Bortolot and *et al*. 2005), and ecosystem parameters (Bortolot and *et al.* 2005, Lim and *et al.* 2004, Zimble and *et al*, 2003). LIDAR has been widely used for forestry and ecosystem studies. The tree parameter estimation in previous research is mainly categorized into two levels: plot and tree level.

Plot Level LIDAR Estimation

The plot level tree parameters derived from LIDAR points have been correlated with plot level field measurement and in order to model tree parameters at the plot level. Quantile regression has been applied in previous studies (Lim and *et al.* 2004, Means *et. al.* 2000, Næsset and *et al.* 1997, 2001, 2002a, 2002b, 2005a, 2005b). As reported, the number of plots is increased in the field, the sampling error is decreased and then the precision of the difference between field and LIDAR measurement is increased (Magnussen and *et al*, 1998, Næsset and *et al.* 2001). The precision also depends on the size of plots and LIDAR point density (Zimble and *et al*, 2003) and moreover plot level parameters derived from LIDAR are influenced and underestimated by returns coming from non-forested area or ground (Bortolot and *et al*. 2005). The stand vertical structure within a plot is highly related with plot level estimation. Even though LIDAR points for a single tree are extracted from a group of points, tree level parameters are averaged and the mean value is assigned to the size of an entire plot. For plot level tree parameters in the field, Lorey's mean height, which is a mean height weighed by basal area, is used as a plot level mean tree height and the other tree parameters are simply averaged.

Tree Level LIDAR Estimation

While plot level parameters were mainly estimated based on regression analysis, the tree level parameters were given based on the segmentation of trees from a group of LIDAR points. Two different segmentation techniques for LIDAR data have been developed: one uses only LIDAR data (Hyyppä *et. al.* 2001; Persson *et. al.* 2002; Brandtberg *et. al.* 2003; Holmgren *et. al.* 2003, 2004; Riaño *et. al.* 2003, 2004; Morsdorf *et. al.* 2004; Chen *et. al.* 2006) and the other uses a fusion of LIDAR and high resolution spectral imagery (Leckie *et al.* 2003; Popescu *et al.* 2003, 2004).

Segmentation techniques developed using LIDAR data only are the K-means method (Riaño *et. al.* 2003, 2004; Morsdorf *et al.* 2004) and watershed segmentation (Sollie 2003; Chen *et. al.* 2006). Especially, a marker-controlled method improves the absolute accuracy of the result (Chen *et. al.* 2006). In this study, a marker-controlled segmentation is used.

Better methods, which generate an initial surface from discrete LIDAR points, are required to identify treetops as markers for the segmentation. The accuracy of the resulting smooth surface depends on the shape and size of the filter when the height surface is generated from discrete points. Popescu and co-authors found that the circular window filter is better for maintaining the actual tree shape (Popescu *et al.* 2003, 2004). The window size was determined by the linear regression with a quadratic model between field measured tree height and crown width. (Popescu *et al.* 2004). Since tree height and crown width haven't been measured in the field for this research, the following approach is taken.

As another segmentation approach, Hyyppä and co-authors used the combination of a Gaussian filter over local maxima of laser returns and an image labeling technique for the surface derived from LIDAR data (Hyyppä *et. al.*

2001). This technique used local maxima as the marker points to segment the surface. We improved this approach by automatically setting all local peaks of the surface as marker points with level set method.

Several tree parameters at tree level have been observed from segmented LIDAR points. Tree heights are highly correlated with field measured tree height (Morsdorf *et. al.* 2004). Persson and co-authors reported an R^2 value of 0.76 for their measurement of crown diameter by using active counter technique for the cross section LIDAR distribution (Persson *et. al.* 2002). Holmgren and co-authors defined the crown base height as the height at which point density is less than 1% of the total vertical LIDAR point distribution and reported an R^2 value of 0.84 between crown base height in the field and those determined by LIDAR (Holmgren *et. al.* 2004). While tree height and crown diameter derived from LIDAR are highly correlated with field measurement, it is still difficult to obtain crown base height from discrete LIDAR points, because the crown base height could not be clearly defined for irregularly scattered LIDAR points. In this study, we take a graphical approach to measure the crown base height from a wrapped surface reconstructed from discrete LIDAR points. With the wrapped surface, it is possible to measure the various crown base height for a tree, because the continuous surface is created and covered the bottom of discrete LIDAR points.

Surface Reconstruction

There have been several ways to reconstruct surfaces from laser ranging data. In general, subdivision surface (Bloomenthal *et al*, 1997) and Non-Uniform Rational B-Spline (NURB) surface (Shirley *et al.* 2005) are utilized. Both of these methods, however, require optimized initial meshes (Hoppe, 1994). The common characteristics of these methods are that the resulting surfaces don't interpolate initial points exactly.

For the reconstruction from LIDAR data points, a fabric draping technique (Yusuf, 2003) was developed but it does not wrap the lower part of the canopy. Another method, voxel-based reconstruction (Phattaralerphong *et al.* 2005), uses a photo interpretation technique and ray-box intersection to reconstruct voxels for a crown shape from eight directional perspective views for one tree. A drawback to this voxel-based method is the fact that it is rare to get eight directional view images for one tree and the total crown volume is calculated by the sum of the voxels. So the volume depends on the size of the voxel. Since not all approaches are suitable for irregularly scattered LIDAR points, implicit surface reconstruction is employed to reconstruct the tree shape in this study.

Implicit surface reconstruction is widely used in computer graphics to construct 3D models of physical objects from noisy scanned laser points (Bloomenthal *et al*, 1997). The approach developed in this research uses radial basis functions (RBFs) (Carr *et. al.* 1997, 2001, 2003, Bishop 2005, Wendland *et. al.* 2005) to obtain an interpolated surface that effectively "wraps" the tree crown.

Objectives

The objectives of this study are to:

1) Introduce a proposed way to wrap LIDAR points through implicit surface reconstruction.
2) Provide a continuous surface to measure crown height and crown base height from the wrapped surface.
3) Create two dimensional quantile surface over discrete LIDAR points with 1m pixel resolution.
4) Identify significant percentile of crown height and crown base height with various types of treatment plot.

DATA

Research Site

The research site is in the Mission Creek area, located in the Wenatchee National Forest in Eastern Washington State. The main species are Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*). Summers are dry and hot, and natural disturbance regime is characterized by frequent low intensity forest fires (Agee 1993, Hessburg *et al*. 2005)

Field Data

In Mission Creek, a total of 12 study units were established for fire and fire surrogates studies involving treatment plots of control, burn only, thin/burn, and thin only, with three replications per treatment, were randomly assigned (Agee *et. al*. 2001). Each plot is 50 m x 50 m square. The stem locations of all the trees within the plots were collected using a differential GPS receiver (Trimble, Santa Clara, California) and an Impulse laser rangefinder with a Mapstar compass (Lasertech, Inc., Englewood, Colorado) in Summer 2003 and 2004.

For the purpose of analyzing the vertical structure of the trees in the plots, tree species and crown position (dominant, co-dominant, intermediate, and suppressed) were recorded for all trees > 5 cm diameter in the plots.

LIDAR Data

Small footprint LIDAR data were acquired by Optec Airborne Laser Terrain Mapper (ALTM) 30/70 LIDAR system. The coordinates of the LIDAR points are UTM zone 10 and NAD83. The pulse of the LIDAR dataset is 70 kHz, which means the mean density of points is 6.5 points m^{-2}. The vendor selected last returns based on filtering algorithm. The last returns were only used to create DTM. For this analysis, the DTM values were subtracted from the ground elevation of all LIDAR points to make Digital Canopy Height Model (DCHM) and remove any slope effect. Table 1 shows the system settings of this sensor. Each one of treatment units was randomly chosen to see the influence of vertical stand structure for LIDAR returns. The characteristics of the plots, which are used in this study, are shown in table 2.

Table 1. LIDAR sensor system settings

Date of survey	August 30th 2004
Laser sensor	Optec's ALTM 30/70
Flying height	1,000 m
Impulse frequency	70,000 Hz
Scan angle from nadir	25 degrees
Laser pulse density	6.5 pulses m^{-2}
Approximate Z accuracy	27 cm

Table 2. The characteristics of the plots used in this study.

ID	Category	Dominant	Co-dominant	Intermediate	Suppressed	Dead +Snag	Total
Plot 1	*C	38	93	39	38	21	229
Plot 2	*B	17	29	12	20	32	124
Plot 3	*T	9	14	6	3	1	33
Plot 4	*TB	11	4	4	4	47	70

* B: burned treatment plot, C: control treatment plot, T: thinned treatment plot, TB: thinned and treatment plot

METHOD

Small footprint LIDAR points represent surface returns, with potential to represent the tree canopy structure. The points are distributed irregularly in three dimensional space. To identify the top of a single tree from the group of points, a smooth surface is created utilizing the discrete point crowd. In order to create the surface, a Gaussian spatial filter is convoluted for the local top points obtained within the cell of a regular square grid area (Hyyppä and *et al*, 2001). In this research LIDAR point density is 6.5 points per square meter and the size of the grid is set to 1 m^2 to get the height of local maximum points.

A level set method (the plane slice method for a smooth three-dimensional surface) is utilized for the identification of local peaks, and the gradient flow is then taken to classify all the pixels on the surface image into each segment representing a tree. As a result, the tree level LIDAR points are extracted automatically based on the segmentation image.

To verify the segmentation results, the shortest path algorithm called Dijkstra's algorithm (Goodrich and *et al.*, 2006) is used as a link between the local peak points identified from the LIDAR points and stem locations collected by fieldwork. From the segmented group of points representing a tree, the points on the surface of crown are only selected by piecewise convex hull in terms of LIDAR height distribution. The points on the surface are only used for the wrapping procedure.

Significant percentile heights of canopy height are identified using quantile regression for crown height and crown base height derived from the wrapped surface.

These quantile analyses are mainly conducted using R package for statistical analysis (The R project for statistical computing) and the graphics of the results are created with Matlab software (The MathWorks)

Level Set Method

We use a level set method to identify the local peaks of the smooth surface. In this approach, the surface is sliced at a certain height and continues progressively through the surface at height interval 0.1 m recursively from the bottom to the top of the smooth surface. For each sliced plane, a value of 0 is assigned for pixels whose height is less than the height of the level set plane and 1 for all others to create a binary image. Based on this binary image, a connected component labeling is implemented to label and classify the pixels. In order to identify the peaks, one sliced image at a certain height is compared with the other image of the next height to see the difference between them. If the total number of labels is decreased from one image to the other, the marching sliced plane passes some local peaks of the surface and the locations of the missed local peaks are collected at that height.

After identifying the local peaks of the surface, a gradient flow analysis in eight neighboring pixels is used to determine which peak the surrounding pixels belonged to. All pixels are classified based on an identifying number given to each local peak. From the classified image, all discrete LIDAR points are assigned to point clusters, representing individual trees.

Verification of the Segmentation Results

We use Dijkstra's algorithm, which is one of the shortest path algorithms (Goodrich *et. al.* 2006) to connect between the identified local peaks and stem locations. After identifying the local peaks from the segmentation method, the location of trees was verified by linking the identified peaks with stem locations given by the field data.

For Dijkstra's algorithm, all points belonging to an individual point cloud are sorted and connected to the adjacent points to create edges. Dijkstra's algorithm is used to find the tracking path from the local peak identified by the level set method to the GPS stem location. If a peak and stem locations match on each other, the segmentation result is considered as positive and if not, negative.

Even though the GPS stem location and the treetop derived from LIDAR are linked by the shortest algorithm, not all trees are identified by the segmentation method. The segmentation method used in this study mainly identifies dominant and co-dominant trees. The basal area of the segmented tree contains multiple stem GPS locations, which are classified as suppressed or intermediate trees. If the basal area derived by the segmentation method contains multiple stem GPS points, the area has a vertically overlapped structure. In other words, if the basal area contains only one stem GPS point, the area only has one tree and it is a perfect match.

LIDAR Point Selection

Clusters of LIDAR points representing individual trees are given from the previous section. These points cover not only the surface of tree crowns, but also are taken from the interior of the tree crown. In order to remove the points inside the crown, a two-dimensional convex hull algorithm is used at selected height locations to remove interior points. The crown base height is also required to know the bottom of the crown in order to remove unnecessary points for the wrapping step. The technique developed by Holmgren *et al.* (2004) is used to calculate the crown base height. They defined the crown base height for LIDAR points by using a median filter for a vertical height profile of LIDAR points after labeling the binary indicator based on vertical point density. Although the convex hull gets most of the points that outlined the crown shape, outlier points still remain. To remove the outliers, a cylinder, which has a radius defined by the mean and one standard deviation of the distance from x and y coordinates of the local peak, is applied.

Wrapping Surface

A nonparametric interpolating surface through the surface points of each individual tree is constructed from RBFs. As a first step toward creating a wrapped surface, the Euclidean distance, which is defined as the distance between any arbitrary points in the space and the closest point on the surface, is calculated by RBFs. After calculating Euclidean distance for all the points in the space, an isosurface is used to display closed and wrapped surfaces created for nonparametric tree shapes in zero level set surfaces (Kato *et. al,* 2006)

Quantile surface

Quantile regression can yield more information from the statistical data than classical linear regression (Koenker, 2004). Generally, the 99th quantile height represents the tree height and the 1st quantile height represents the ground surface for local LIDAR points (Riaño *et. al.* 2003, 2004). Quantile regression is categorized into two main approaches, linear and non-linear models. The linear quantile regression describes the general tendency, which is based on the conditional mean of each quantile group. However, irregularly scattered data like LIDAR points are not fitted to a linear regression model well. Therefore, nonparametric quantile regression is introduced and used for the irregularly distributed LIDAR data in this study.

Nonparametric quantile regression uses piecewise linear within the given intervals and weights are provided by kernel density to fit a smooth quantile surface over the data. The general formula for two dimensional quantile plane is described below (Koenker, 2004).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i$$

where x_{1i} is the point spacing for x1 axis and x_{2i} is for x2 axis
τ th conditional quantile function for the quantile regression plane is:

$$Q_y(\tau | x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + E_u^{-1}(\tau) \cdot$$

where $x = [x_1, x_2]$, E(u) is the error function at the τ th quantile.
The loss function of nonparametric quantile regression is:

$$\min_{\beta \in R^2} \sum_{i=1}^{n} \sum_{j=1}^{m} w_{i,j}(x_1, x_2) \rho_\tau (y_{i,j} - \beta_0 - \beta_1 (x_{1i} - x_1) - \beta_2 (x_{2j} - x_2))$$

where $w_{i,j}(x_1, x_2) = K((x_1 - x_{1i}, x_2 - x_{2j})/h)/h$, K is kernel function with bandwidth(*h*), Gaussian kernel density is used for K(u).

In nonparametric regression, higher order polynomials can be used to estimate a fitted curve for irregularly distributed points. But as the order of polynomials used to fit the data get higher, the resulting curves become overfitted to the data. It is difficult to determine the appropriate order to fit the entire data, because the density of irregular points is diverse across the area. Instead of using polynomial regression, piecewise linear quantile regression is applied for each interval. To utilize piecewise linear quantile regression, the basis function ($(x_i - x)$ terms in the formula above) is used and local linear quantile regression is weighed by the kernel density ($w_i(x)$ term in the formula).

The bandwidth (parameter variable: *h*) of kernel density is related with the shape of the curve. The parameter *h* is determined by the number of sampling points to smooth the curve with weights. The larger the bandwidth is, the more neighboring points are included to smooth the curve with Gaussian weight.

The basis function is obtained from the distance between one regular sample point and all the other sample points. The regular points are initially generated as the sample points. The regular spacing of the generated points decided how well the resulting curves fit on the actual data. If finer spacing is taken, finer linear lines are fitted in the intervals and the curves get spiky.

Two axes are engaged for the fitted curve in two dimensions to make the quantile surface for each plot. In order to create a surface, 1m sampling grid points and 2m by 2m kernel window are taken in this study to smooth the surface. 2m by 2m window of the kernel is used based on the criteria that the number of first returns is more than ten.

Regression analysis

Points are regularly generated with 1m spacing over the plot. The dependent variables of regression are the height of 10 percent increment percentiles of first returns (10P, 20P, 30P, 40P, 50P, 60P, 70P, 80P, and 90P) and maximum and minimum height (Max, Min) of first returns within 1m by 1m grid of the surfaces. The independent variables are tree level crown height (CH) and crown base height (CBH) obtained by the wrapped surface.

$$
\begin{aligned}
\ln h = \ln\beta_0 + \beta_1\ln h_{10} + \beta_2 \ln h_{20} + \beta_3 \ln h_{30} + \beta_4 \ln h_{40} + \beta_5 \ln h_{50} \\
+\beta_6 \ln h_{60} + \beta_7 \ln h_{70} + \beta_8 \ln h_{80} + \beta_9 \ln h_{90} + \beta_{10} \ln h_{Max} + \beta_{11} \ln h_{Min}
\end{aligned}
$$

where: h is tree level crown height or crown base height obtained by wrapped surface. h_{10}, h_{20}, h_{30}, h_{40}, h_{50}, h_{60}, h_{70}, $h_{80,}$ and h_{90} are the heights of 10 percent increment percentiles. h_{Max} and h_{Min} are the maximum and minimum height of first returns. β*'s* values are the coefficients and β_0 is residual.

CONCLUSIONS AND DISCUSSIONS

Segmentation Result and Wrapped Surface

The result of level set method is shown with DCHM in Figure 1. Segmentation of all LIDAR points of a plot is shown on the right of Figure 1. Each segment is colored differently.

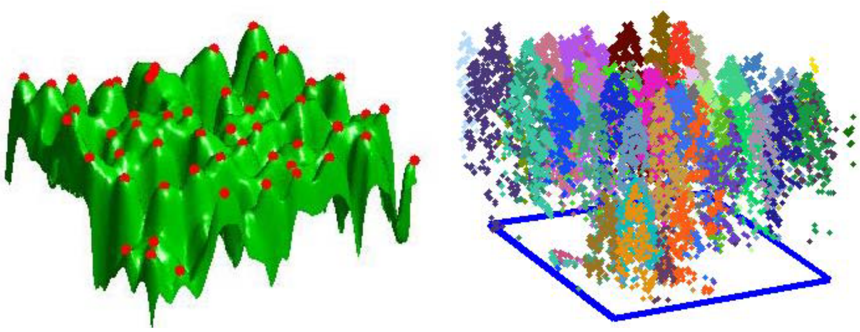

Figure 1. Segmentation result. On the left, red points are the identified local peaks by level set method. On the right, segmented trees for plot 2 are represented by points with different colors.

Table 3 shows the result based on vertical stand structure. The accuracy depends on the shape of smoothed maximum height surface. It is also related with vertical stand structure. If a co-dominant tree stands close to a dominant tree, the co-dominant tree is obscured or merged into one segment, which is identified as dominant.

Table 3. Number of tree tops identified by level set method from the smoothed surface is compared with the number of GPS points shown by vertical stand structure.

ID	Category	*D	Result	*CD	Result	D+CD	Result	*I	Result	*S	Result	Sn&De	Total	Result
Plot 1	**C	38	14 (37)	93	17(18)	131	31(24)	39	9(23)	38	8(21)	21	229	48(21)
Plot 2	**B	17	8(47)	29	13(45)	46	21(46)	12	2(17)	20	4(20)	8	86	41(48)
Plot 3	**T	9	8(89)	14	9(64)	23	17(74)	6	3(50)	3	0(0)	1	32	22(69)
Plot 4	**TB	11	8(73)	4	3(75)	15	11(73)	4	3(75)	4	2(50)	47	70	36(51)

* D: dominant, CD: co-dominant, I: intermediate, S: suppressed, Sn&De: Snag, De: Dead.
** B: burned treatment plot, C: control, T: thinned treatment plot, TB: thinned and burn treatment plot.
( ) indicates percentage of the accuracy.

The number of stems influences the accuracy of segmentation result. As the number of stems was increased, that of identified treetops was decreased. Since the treetops were identified from DCHM created from local maximum points, the accuracy to find dominant trees was higher than the others. Plot 1 (control plot) had the lowest accuracy (38 %) identifying dominant trees by Dijkstra algorithm. Dijikstra's algorithm always searched the shortest path from a treetop to stem location. The shortest path, however, did not always give correct link between them especially when many suppressed trees existed under a dominant tree. In the case of the plot which has vertically overlapped stands, the shortest pass connected between a treetop and a stem location of a suppressed or co-dominant tree instead of a dominant tree.

Thinned and thinned/burned plots were more accurate because they were less influenced by understory vegetation than other plots. Plot 3 had more identified trees than plot 4, because it had less number of dead trees and snags. If the treetops were not identified accurately, one wrapped surface was created and covered multiple stands.

Wrapped surface created by RBFs and isosurface is shown in Figure 2.

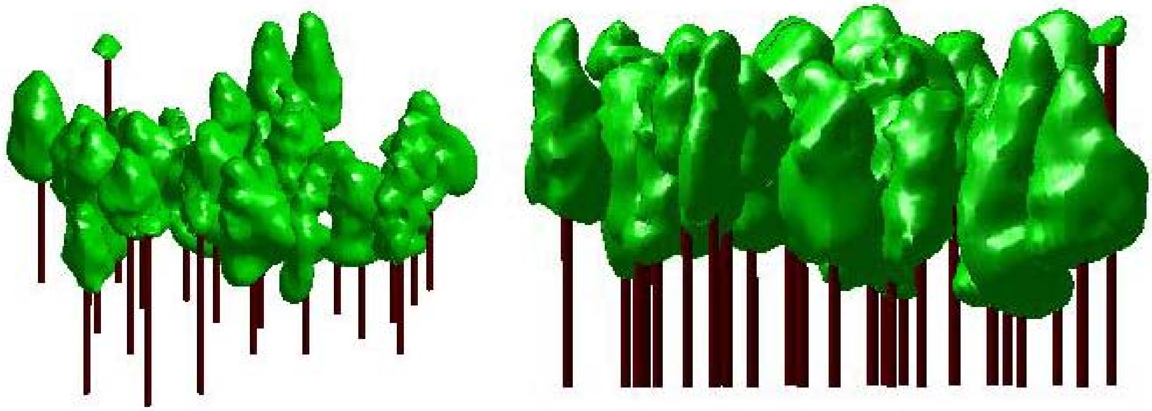

Figure 2. The wrapped surface is shown for plot 2 (The left image is shown by slant top view and the right image is shown by side view).

Quantile Surface

Two-dimensional quantile surface was created with 1m pixel resolution. 90, 50, and 20 percentile surface of canopy height are displayed (Figure 3). The values on these percentile canopy surfaces were used for dependent variables of regression analysis in the next session.

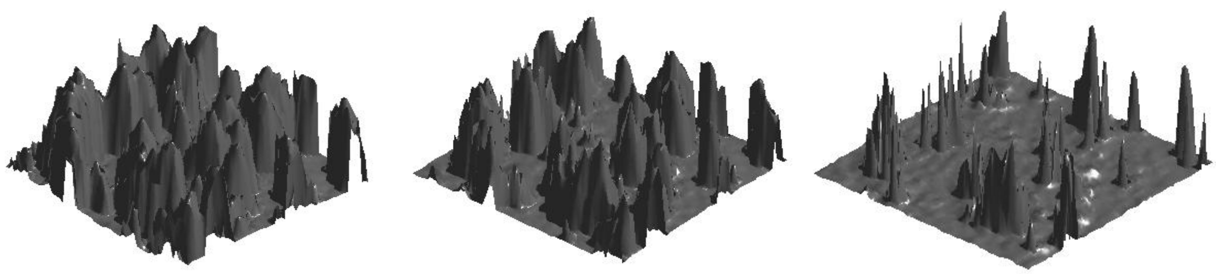

Figure 3. Quantile surface is displayed for plot 4. The left image is 90% canopy height surface, the middle image is 50% canopy height surface, and the right image is 20% canopy height surface.

Regression Analysis

Crown height and crown base height obtained from wrapped surface were regressed against dependent variables from 10 percent increment percentiles of canopy height within 1m by 1m pixels. Significant percentile of canopy height for the crown height and the crown base height was assessed and the result is shown in Table 4.

Table 4 The result of regression analysis for tree level estimation.

	Plot 1 (C)		**Plot 2 (B)**		**Plot 3 (T)**		**Plot 4 (TB)**	
	ln (cbh)	**ln** (ch)	**ln** (cbh)	**ln** (ch)	**Ln** (cbh)	**ln** (ch)	**Ln** (cbh)	**ln** (ch)
ln (Min)	***	NS	**	*	·	NS	***	*
ln (10P)	NS	NS	NS	NS	NS	NS	***	NS
ln (20P)	*	NS	NS	*	***	NS	NS	NS
ln (30P)	NS	NS	·	NS	NS	NS	NS	NS
ln (40P)	NS	NS	NS	NS	NS	NS	NS	NS
ln (50P)	·	*	NS	NS	NS	NS	NS	**
ln (60P)	NS	NS	NS	NS	*	NS	NS	NS
ln (70P)	NS	NS	*	NS	NS	NS	NS	NS
ln (80P)	NS	NS	NS	NS	NS	NS	NS	NS
ln (90P)	NS	NS	NS	***	NS	·	NS	NS
ln(Max)	***	***	***	***	***	***	***	***

B: burned treatment plot, C: control, T: thinned treatment plot, TB: thinned and burn treatment plot.
ch: crown height derived by the wrapped surface, cbh: crown base height derived by the wrapped surface.
Significance codes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, · : $p < 0.1$, NS : not significant.

Significant percentiles of crown base height for plot 2 (burned plot) were higher than those for plot 3 (thinned) and plot 4 (thinned/burned plot). There was correlation between the number of stems and the height of significant percentile. As the number of stems was increased, significant percentile of crown base height was getting higher. Significant percentile of crown base height for plot 1 (control plot) was, however, lower than that for plot 2 (burned plot), because plot 1 had more dead trees and snag in understory, while they were removed by prescribed burning treatment in plot 2.

The number of stems is highly related with LIDAR vertical point distribution and point density (Næsset and *et al*. 2002). Crown height was always highly correlated with the maximum height. Therefore, crown height can be estimated from maximum height of LIDAR points. However, small footprint LIDAR returns tend to be reflected from a part of canopy surface and not entire canopy (Lefsky, 1999). One side of canopy surface which faces towards the laser sensor reflect more returns than the other side of canopy. At the other side or the bottom part of canopy, LIDAR points were sparser. It depends on the amount of biomass (leaves and branches), which intercepts the laser. Therefore, the crown base height given by the wrapped surface can be higher than the field measured values.

Næsset and co-authors (2002) concluded that plot-level estimation was more accurate than tree level estimation with poor laser sampling density, which had the average resolution of 0.94m. Maximum height of first return and 25 percentiles height of all returns were the most significant for individual tree height and crown base height, respectively in their research. In this study, LIDAR with higher point density, 6.5 per square meter, was used. The density is six times higher than that of their data and the precision of tree level estimation is increased. It is possible to make a model and provide various tree parameters within the basal area of one tree by using stepwise quantile regression. The size of pixel to create quantile surface depends on LIDAR point density.

Since crown shape derived from wrapped surface has not been verified by field measurement in this study, more fieldwork is required. Wrapped surface has good advantage to provide various values of crown base height. In addition, any tree parameters identified from the wrapped surface can be regressed against and are modeled through stepwise quantile regression within a pixel of a given size. This analysis was aimed to bridge between graphical approach and statistical interpretation for crown parameters derived from LIDAR in fine resolution.

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