INVENTORY FROM ABOVE: AUTOMATED LIDAR ASSESSMENT OF FOREST CANOPY PARAMETERS

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ABSTRACT
The use of airborne Light Detection and Ranging (LiDAR) to evaluate forest canopy parameters is vital in order to properly address both ecological concerns and forest management. This study was conducted in the Piney Woods region near Huntsville, Texas. The overall goal of this paper is to develop the use of airborne laser methods in evaluating various canopy parameters such as percent canopy cover (PCC) and leaf area index (LAI). Both these parameters are of interest in determining biomass and fuel loads as well as carbon models. A model is being developed through linear regression for estimating LAI and canopy cover from scanning LiDAR and QuickBird imagery. For accuracy purposes, the parameters of interest are assessed by both airborne and ground-based methods. This study attempts to meet the following goals: to develop automated LiDAR processing methods to estimate LAI and canopy cover over both coniferous and hardwood forests; to develop a frame to fuse scanning LiDAR data with multispectral imagery, such as MODIS, and improve estimates over large areas from local to regional scales; and to generate maps of percent canopy cover and LAI for the study region. The methods discussed in this paper show great potential for improving the speed and accuracy of forest inventory.

INTRODUCTION
This project attempts to determine the percent canopy cover (PCC) and leaf area index (LAI) of a region through use of LiDAR. PCC, also known as canopy closure, is defined as the percent of a forest area occupied by the vertical projection of tree crowns. LAI is defined as the one sided green leaf area per unit ground area. These parameters are especially important in estimating carbon models and biomass, but are also useful in studying carbon sequestration. PCC and LAI are also helpful in examining global climate change, fuel models, and fire risk, as well as aiding in forest inventory and management. The use of airborne LiDAR to evaluate forest canopy parameters is vital in order to properly address both forest management and ecological concerns in a timely and cost-effective manner.

Objectives
This project attempts to meet the following goals:
1) to develop scanning LiDAR methods to estimate LAI and PCC over both coniferous and hardwood forests;
2) to investigate whether a LiDAR and NDVI data fusion through linear regression improve estimates of these forest canopy characteristics; and
3) to generate maps of PCC and LAI for the study region.

Study Area
The region to be studied is the Piney Woods near Huntsville, Texas. LiDAR data of the region was collected and in situ data is used for accuracy assessment purposes. This data is from sixty-two plots in the study area, taken between May and July, 2004. These sixty-two plots were inventoried and their canopies photographed using a hemispherical lens.
METHODS

Various methods used in this study are detailed in Figure 1. LiDAR data is used to generate both a canopy height model (CHM) and two different estimates of LiDAR-derived PCC. The CHM, useful in itself, is also processed using TreeVaW software to determine local (plot-level) PCC. Airborne LiDAR has been shown to be accurate in estimating biophysical parameters of forest stands (Popescu et al, 2004). The normalized difference vegetation index (NDVI) calculated from QuickBird multispectral imagery can be used to estimate LAI (Curren et al, 1992; White et al, 1997). Statistical measures (mean, standard deviation, maximum) are extracted from all five of these parameters and are used to formulate a regression model based on ground reference data calculated using the hemispherical photos. This model is then entered into ENVI image processing software by means of Band Math and used to generate regional maps of PCC and LAI.

Figure 1. Methodology used in this study.
Height Bins

The height bin method is used in this project. The term “height bin” refers to a subdivision of LIDAR height returns. In the case of this project, the LIDAR returns are sectioned as follows:

- Bin 1: 0-0.5ft
- Bin 2: 0.5-1.0ft
- Bin 3: 1.0-1.5ft
- Bin 4: 1.5-2.0ft
- Bin 5: 2.0-5.0ft
- Bin 6: 5.0-10.0ft
- Bin 7: 10.0-15.0ft
- Bin 8: 15.0-20.0ft
- Bin 9: 20.0-25.0ft
- Bin 10: 25.0-30.0ft
- Bin 11: >30.0ft

![Figure 2. Height bin divisions, LiDAR point cloud.](image)

Figure 2 illustrates the height bins method over a cross-section of the LiDAR point cloud. The lower four height bins correspond to field data (in half-meter increments) while the upper bins are spaced in five-meter increments. The entire LiDAR point cloud is broken down into small segments to be analyzed in this manner. The first height-bin driven method sums the upper seven height bins to estimate PCC. The second method uses the single lowest height bin to estimate PCC. The formulas used to estimate the respective LiDAR-derived PCC are:

\[ PCC_{lidar,5-11} = \text{SUM}(\text{Height Bin 5-Height Bin 11}) \]

\[ PCC_{lidar,1} = 1 - \text{Height Bin 1} \]

These LiDAR-derived PCC are used in conjunction with other parameters to successfully formulate linear models of PCC and LAI.

Hemispherical Photography

Hemispherical photography of the forest canopy from the ground is an accurate method of evaluating PCC and LAI (Riaño et al, 2004). These photographs are analyzed using HemiView, a Delta-T Devices software application, in order to determine local PCC values \((PCC_{GR})\) and LAI values \((LAI_{GR})\) (Hemiview, 2005). An example is shown in Figure 3.

![Figure 3. Hemi. photo.](image)

TreeVaW Processing

Local values of PCC can be determined by using TreeVaW, an IDL executable program that uses a continuously varying filter window to detect tree locations and crown radii. These tree crowns are superimposed on our plot locations and sizes to determine the percentage of crown area overlaying the plot area of 380m². An example of local PCC is shown in Figure 4.
These plot-level estimates are then used along with previously discussed parameters to formulate a linear model.

**Linear Regression**
Linear regressions are performed using SAS software in order to relate various statistical properties of the LiDAR-derived estimates and multispectral-derived parameter to *in situ* data. The following parameters are used in the regression equations:

- $x_{PCC\text{lidar},5-11}$ = mean, LIDAR-derived canopy cover, upper height bins
- $\sigma_{PCC\text{lidar},5-11}$ = standard deviation, LIDAR-derived canopy cover, upper height bins
- $x_{PCC\text{lidar},1}$ = mean, LIDAR-derived canopy cover, lowest height bin
- $\sigma_{PCC\text{lidar},1}$ = standard deviation, LIDAR-derived canopy cover, lowest height bin
- $x_{\text{ndvi}}$ = mean, NDVI
- $\sigma_{\text{ndvi}}$ = standard deviation, NDVI
- $X_{\text{chm}}$ = maximum value, CHM
- $x_{\text{chm}}$ = mean, CHM
- $\sigma_{\text{chm}}$ = standard deviation, CHM
- $PCC_{\text{TreeVaW}}$ = TreeVaW-derived canopy cover
- $PCC_{\text{GR}}$ = percent canopy cover, ground-reference
- $LAI_{\text{GR}}$ = leaf area index, ground-reference

**Figure 4.** TreeVaW-derived PCC. Plot shown in yellow, trees in black. (Superimposed on CHM.)
RESULTS

Various regressions are performed for both observed (in situ) PCC and LAI. These regressions are performed once using only LiDAR-based variables, then once more using all available parameters. Several statistical outliers were removed from the dataset during the regression process. The models with the greatest accuracy are as follows:

**Model 1:** PCC using all available variables

\[
PCC_{\text{pred}} = 0.14 + 1.06 \times PCC_{\text{lidar,5-11}} - 0.37 \times \text{ndvi} + 0.01 \times \text{chm} - 0.01 \times \text{chm}, \quad R^2 = 0.86
\]

**Model 2:** LAI using all available variables

\[
LAI_{\text{pred}} = 0.05 + 3.47 \times PCC_{\text{lidar,5-11}}, \quad R^2 = 0.78
\]

All variables left in the models are significant at the 0.15 level. Significant variables included statistics from NDVI, indicating that the vegetation index as well as LiDAR is important in predicting PCC. LAI predictions were unchanged by the addition of NDVI-based variables. TreeVaW-derived PCC and LiDAR-estimated (Height Bin 1) PCC were not found to be significant in the regressions models. LiDAR-derived PCC and TreeVaW-derived PCC are compared to observed values of canopy cover in Figures 5 and 6.

![Figure 5. Observed PCC vs. predicted PCC](image1)

![Figure 6. Observed LAI vs. predicted LAI](image2)

The correlation coefficient for the PCC regression using both LiDAR and NDVI statistics (Model 1) is approximately 0.86 and the correlation coefficient for the LAI regression (Model 2) is approximately 0.78. Thus Models 1 and 2 were used to generate regional maps of PCC and LAI, subsets of which are shown in Figure 7.
DISCUSSION AND CONCLUSIONS

As one can see from the correlation coefficients, the predicted regression values for PCC ($PCC_{pred}$) LAI ($LAI_{pred}$) are highly correlated with the ground reference values. These results strongly suggest that the height bin method shows potential for being a future standard method of LIDAR analysis in determining PCC and LAI. This method could one day be used in analysis packages as it allows one to depict the vertical distribution of a forest canopy.

REFERENCES