Using LIDAR and Normalized Difference Vegetation Index to remotely determine LAI and percent canopy cover

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Abstract

The goal of this study was to use airborne LIDAR (Light Detection and Ranging) to evaluate percent canopy cover (PCC) and leaf area index (LAI) in loblolly pine forests of the southeastern United States, in order to address forest management and ecological concerns. More specific objectives were to: (1) Develop scanning LIDAR methods to estimate PCC and LAI over primarily coniferous forests; and (2) investigate whether a LIDAR and normalized difference vegetation index (NDVI) data fusion through linear regression improve estimates of these forest canopy characteristics. Scanning LIDAR data was used to derive local scale PCC estimates through use of the height bin method; then TreeVaW, a LIDAR software application, was used to locate individual trees to derive an estimate of plot-level PCC. A canopy height model (CHM) was used to determine tree heights per plot. QuickBird multispectral imagery was used to calculate NDVI. LIDAR- and NDVI-derived estimates of plot-level PCC and LAI were compared to field observations for 43 plots over 47 km^2. Linear regression analysis resulted in LIDAR-only models explaining 84% and 78% of the variability associated with PCC and LAI, respectively; it is concluded that LIDAR alone can be used to estimate these canopy parameters.

Keywords: LIDAR, leaf area index, percent canopy cover, forest inventory

1. Introduction

Leaf area index (LAI) and percent canopy cover (PCC) are important biophysical and ecophysical factors in addressing forest management issues such as fuel models and forest inventory, and ecological concerns including carbon sequestration and climate change. LAI is defined as one-sided leaf area per unit ground surface area (Chapin *et al.* 2002), while PCC is defined as the percent of a forest area occupied by the vertical projections of tree leaves (Avery and Burkhart 1994). LAI is especially important to ecological processes such as photosynthesis and net primary production (Coops *et al.* 2004), while PCC, also called canopy cover, is important in assessing canopy structure. PCC has grown in importance as a result of the needs to quantify the global woody biomass, quantify global carbon stocks and globally assess the condition of ecosystems (Hansen *et al.* 2002). Determining this information through remote sensing methods is an efficient and effective way to model such processes.

Field, or *in situ*, measurements of LAI and canopy cover are necessary to validate remotely sensed values. Direct methods of estimating LAI include destructive sampling of the forest canopy, leaf litterfall collection and vertical point-quadrant sampling (Duranton *et al.* 2001). Indirect methods, less time-consuming than direct methods, range from employing a spherical densiometer, which is dependent on human intuition and level of experience (Englund *et al.* 2000), to plant canopy analyzers such as the Li-COR LAI-2000, to hemispherical photography (Riaño *et al.* 2004). This study employs hemispherical photography analysis because it is a precise and less time-consuming data collection process; however, it has been shown to underestimate field values of LAI (Mussche *et al.* 2001; Merilo *et al.* 2004; Jonckheere *et al.* 2005).

Previous studies have related multispectral imagery to forest canopy characteristics. Landsat ETM+ satellite data can be used to accurately predict LAI for coniferous forests by direct plot-level correlation and geostatistical analysis (Berterretche *et al.* 2005). Another study (Schlerf and Atzberger 2006) examined the use of hyperspectral remote sensing data to predict LAI, with an R^2 value of 0.73 relative to ground measurements. The normalized difference vegetation index (NDVI) calculated from Landsat TM data has been used, either singly or in combination with other indices, to estimate LAI (Curran *et al.* 1992; Pocewicz *et al.* 2004) as can other vegetation indices (Baret and Guyot 1991).

LIDAR remote sensing has become more widely used and accepted in ecological and forest inventory studies in recent years (Nelson *et al.* 1984; Means *et al.* 2000; Lefsky *et al.* 2002; Reutebuch *et al.* 2005). Small-footprint laser scanners have been successfully used to predict mean tree height, with one regression explaining 83% of the variability in ground-truth mean tree height (Naesset and Bjerknes 2001; Naesset 2004). Waveform LIDAR has been shown to predict 75% of the variability in LAI in Douglas-fir and western hemlock forests (Lefsky *et al.* 1999). Airborne scanning LIDAR has also been shown to be accurate in estimating biophysical parameters of forest stands (Popescu *et al.* 2004), and to be an excellent predictor of hemispherical photography-estimated LAI and PCC (Riaño *et al.* 2004). Scanning LIDAR was also found to have a strong correlation with hemispherical photo-estimated LAI (Lovell *et al.* 2003). Most recently, Morsdorf *et al.* (2006) used small-footprint airborne laser scanning data to predict fractional canopy cover and LAI, with R^2 values of 0.73 and 0.69, respectively.

Percent canopy cover can be found at the plot or stand level by examining tree locations and crown dimensions. Crown radius models have been used to accurately estimate non-overlapping canopy cover. Gill *et al.* (2000) used ordinary least-squares linear regression equations to calibrate canopy cover values derived from forest inventory data; their model had an R^2 value of 0.67. Roberts *et al.* (2005) estimated individual tree leaf area through linear regression between ground data and LIDAR-derived estimates of tree height and crown dimensions, finding that leaf area was consistently underestimated. A LIDAR-derived canopy height model (CHM) can be processed to accurately identify individual trees and their heights in forest or rangeland, as shown in studies, some using the local maximum focal filtering software program TreeVaW (Popescu *et al.* 2002; Popescu and Wynne 2004; Koch *et al.* 2006).

This study attempts to relate scanning LIDAR data to *in situ* LAI and PCC values through simple linear regression with NDVI. LIDAR height bins, the products of a LIDAR processing technique that breaks the vertical forest structure into viewable "slices," are utilized as an innovative method of calculating PCC and LAI (Popescu and Zhao 2008). Theoretically, the combination of LIDAR-estimated canopy characteristics such as height and PCC with vegetation indices will result in an accurate predictor of LAI and PCC.

The goal of this study was to develop a use of LIDAR in evaluating percent canopy cover and leaf area index of primarily pine and mixed pine-hardwood forests typical of the southeastern United States. Specific objectives were to:

(1) Develop scanning LIDAR methods to estimate PCC and LAI over primarily pine forests in East Texas; and
(2) use multiple linear regressions to predict PCC and LAI using LIDAR and NDVI.

2. Study Site and Data Collection

2.1 Study Area

The study area is located in the southern United States (30°42'N, 95°23'W), in East Texas. It includes a portion of the Sam Houston National Forest, characterized by deciduous and pine stands with an urban interface and an area of 47.45km^2. The study area is composed of 28.08km^2 (59.17%) of pine forest (primarily loblolly pine, *Pinus taeda*), 10.84km^2 (22.84%) of deciduous forest, and 8.54km^2 (17.99%) of non-forested areas including urban areas, agricultural fields, etc. The average diameter at breast height (DBH) is 31cm, average tree height is 20m, average crown diameter is 5.9m and the average height to crown base is 11.8m. A mean elevation of 85m, with a minimum of 62m and a maximum of 105m, and gentle slopes characterize the topography of the study area.

The ground reference data were collected between May 2004 to July 2004 by photographing canopy characteristics on 53 evenly distributed circular plots of which 35 covered 404.7m^2 (0.1 acre) and 18 covered 40.5m^2 (0.01 acre). The 18 smaller plots were in areas of young pine plantations, with little variation of tree height or crown width. A hemispherical photograph of the forest canopy was taken from the center of each plot and each plot was mapped by recording GPS coordinates for the plot center.

2.2 Hemispherical Photographs for Ground Reference Data

A hemispherical photograph of the forest canopy was taken from the center of each plot at 1.5m above ground level (resolution of 3264×2448 pixels) using a horizontally-leveled Nikon CoolPix 8700 digital camera and a FC-E9 fisheye lens. Ten plot photographs contained sun glare and other non-uniformities due to various light conditions at the photograph cell and proximity of clearings to the plots, and were removed from the analysis. Of the remaining 43 plots, 35 plots were in loblolly pine forest, 5 plots were in hardwood stands, and 4 plots were in mixed forest. Thus the results of this study will be most applicable to loblolly pine forest. The photographs were analyzed for plot-level PCC and LAI using HemiView Canopy Analysis Software (©Delta-T Devices Ltd., UK).

LAI was estimated by HemiView algorithms to be half of the total leaf area per unit ground surface area, based on the ellipsoidal leaf angle distribution. The HemiView calculation of LAI (LAI_{obs}) is based on Beer's Law:

$$G(\theta) = e^{(-K(\theta)\times LAI_{obs})} \tag{1}$$

where G is gap fraction and $K(\theta)$ is the extinction coefficient at zenith angle θ (range computed for the canopy during processing). HemiView measures gap fraction values directly from the hemispherical photo, then finds the values for the extinction coefficient and LAI that best fit for an ellipsoidally distributed theoretical canopy, then applies those values in subsequent calculations. HemiView-calculated LAI is termed "effective LAI" as it does not account for non-random distribution of foliage, possibly underestimating actual LAI.

In HemiView, PCC is defined as the vertically projected canopy area per unit ground area. It is calculated as follows assuming the canopy has an ellipsoidal leaf angle distribution:

$$PCC_{obs} = \left[1 - e^{(-K(x,0)\times LAI_{obs})}\right]\times 100 \tag{2}$$

where $K(x,0)$ is the extinction coefficient for a zenith angle of zero and x is the ellipsoidal leaf angle distribution parameter, defined as the ratio between the semihorizontal and semivertical axes of an ideal ellipsoid.

2.3 LIDAR Data

LIDAR data for the study area was collected in March 2004, during the leaf-off season, from an average of 1000m above ground level by M7 Visual Intelligence of Houston, Texas. The LIDAR system (Leica ALS40 Airborne Laser Scanner. Atlanta, GA, USA) records first and last returns per laser pulse and has horizontal and vertical accuracies of 20-30cm and 15cm, respectively. The LIDAR system provided a 10° swath from nadir for a total scan angle of 20°, resulting in a point density of 2.6 points/m^2 (distance between laser points is thus 0.62m). The average swath width was 350m, with 19 north-south flight lines and 28 east-west flight lines. LIDAR point elevations were interpolated to form a digital surface model with a spatial resolution of 0.5m, with only the highest laser hits per 0.5m x 0.5m cells being used in the interpolation to better characterize the top canopy surface using techniques described by Popescu and Wynne (2004). The CHM, a three-dimensional model of vegetation height with a resolution of 0.5m, was created by subtracting ground elevation from the digital surface model. The CHM was interpolated to a cell size of 2.5m prior to any calculations.

Though the LIDAR data was collected during the leaf-off season, this was not expected to adversely impact the PCC and LAI estimates. The majority of the study area plots (34) were pine stands, thus retaining foliage during the leaf-off season. However, scanning LIDAR pulses would still be returned from large and small branches on hardwood and mixed stands during the leaf-off season; the pulses "lost" due to the lack of leaves would be negligible (Nelson 2006).

2.4 NDVI Values from a QuickBird Image

Multispectral, orthorectified QuickBird imagery (leaf-off, 2004; DigitalGlobe. Longmont, CO, USA) was available for the study area as well with a resolution of 2.5m. These data were used to calculate NDVI as defined by Baret and Guyot (1991):

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{3}$$

where *NIR* is the near-infrared reflectance value and *R* the red reflectance value for a given pixel.

3. Methods

3.1 Percent Canopy Cover Estimates from LIDAR Data

Three distinct methods were employed to derive PCC from LIDAR data: two involving the use of height bins and one that determines tree locations from the CHM. Height bins are the products of an original LIDAR processing technique that breaks the vertical forest structure into viewable "slices;" this technique is an emerging method of using LIDAR data in forest inventory (Popescu and Zhao 2008). Height bins are created by subdividing normalized laser point returns into intervals defined by a range of heights. Laser points in each height interval are normalized to percentages by the total number of points above the projected ground area of each pixel. Percentages of laser canopy hits are considered to be especially appropriate for LIDAR estimation of canopy properties (Riaño *et al.* 2004). For this study, eleven height bins were generated through software developments described by Popescu and Zhao (2008), with height ranges of 0-0.5m, 0.5-1.0m, 1.0-1.5m, 1.5-2.0m, 2.0-5.0m, 5.0-10m, 10-15m, 15-20m, 20-25m, 25-30m, and >30m. These height bins were generated as a multiband image of the predefined height intervals and 2.5m × 2.5m pixel dimensions.

Two estimates of PCC were derived from the bins. The first method assumes that the crowns of interest belong to trees with a height of over 2.0m; a sum of the seven uppermost height bins (HB_5 through HB_{11}) is used to model PCC:

$$PCC_{lidar,5-11} = \sum_{5}^{11} HB_n \tag{4}$$

where HB_n is a height bin image band of number n.

The second method assumes that any laser point that is returned from on or near the ground, i.e. HB_1, was from a pulse that did not encounter a canopy obstruction. Therefore, the equation used to derive PCC is as follows:

$$PCC_{lidar,1} = 1.0 - HB_1 \tag{5}$$

where notation is the same as in Equation 4.

The third method of deriving PCC from LIDAR data was performed at the plot level only. Individual trees were located and their crowns measured on the LIDAR-derived CHM through automated processing with TreeVaW software. TreeVaW is an IDL-executable program (Interactive Data Language, ©2006, ITT Industries Inc., USA) that uses a continuously varying filter window to detect tree locations, tree heights and crown radii, with algorithms described in Popescu and Wynne (2004) and Popescu *et al.* (2004). In summary, TreeVaW software identifies single trees using an adaptive technique for local maximum focal filtering, operating on the assumption that laser values of high elevation in a spatial neighborhood represent the highest part of a tree crown.

TreeVaW was used to identify individual tree locations and crown size for each field plot. The total projected crown area for each plot is (A_{crown}) calculated; TreeVaW-derived PCC is:

$$PCC_{trvw} = \frac{A_{crown}}{A_{plot}} \tag{6}$$

where A_{plot} is the total plot area.

3.2 Statistical Analysis of Predictions

SAS software (SAS Institute, Inc., Cary, NC, USA) was used to relate various LIDAR-derived variables and NDVI variables to plot-level observed values of PCC and LAI. Least-squares estimates of PCC and LAI were fitted to linear regression models for eight different datasets, including varying combinations of the independent variables. Stepwise selection was employed in each regression to determine the variables remaining in each model. Variables retained in each regression were significant at the 0.05 level.

Finally, two simple linear regressions were performed to directly compare observed PCC and LAI (PCC_{obs} and LAI_{obs}) with LIDAR-derived PCC using Height Bins 5-11 ($x_{PCClidar,5-11}$). These regressions were performed using Microsoft Excel software (Microsoft Corporation, Redmond, WA, USA), in order to determine how well a single LIDAR-derived parameter could predict both PCC and LAI.

4. Results and Discussion

4.1 Results

LIDAR-estimated PCC variables using Height Bins 5-11 are present in the models with the greater coefficients of determination, while the models incorporating TreeVaW-derived PCC values have the lowest coefficients of determination. The model with the highest R^2 value for PCC used LIDAR-estimated PCC (Height Bins 5-11), NDVI variables and CHM variables; this model had an R^2 value of 0.86 as well as a low RMSE value (9%). However, a PCC model using only LIDAR-derived variables had an R^2 value of 0.84 and an identical RMSE value. It can be concluded that the NDVI variables are relatively unimportant in predicting PCC when compared to LIDAR-derived variables. The model selected to predict PCC is thus:

$$PCC_{pred} = 0.01 + 0.93x_{PCClidar,5-11} + 0.01X_{chm} - 0.01x_{chm}\,. \tag{7}$$

Where PCC_{pred} is the predicted value of PCC, $x_{PCClidar,5-11}$ is the mean of LIDAR-derived PCC using Height Bins 5-11, X_{chm} is the maximum value of the CHM and x_{chm} is the mean value of the CHM.

The strongest LAI model was found using the first regression method with LIDAR-derived (Height Bins 5-11) variables only; this model has an R^2 value of 0.78 and a comparatively low RMSE value. The prediction models incorporating both LIDAR and NDVI variables in general have higher coefficients of determination than those using only LIDAR-derived values, but by such as small range as to be negligible. Thus, LIDAR variables can be used without NDVI information to predict PCC and LAI. The model selected to predict LAI is:

$$LAI_{pred} = 0.05 + 3.47x_{PCClidar,5-11} \tag{8}$$

Where LAI_{pred} is the predicted value of LAI and $x_{PCClidar,5-11}$ is the mean of LIDAR-derived PCC using Height Bins 5-11.

When plotting LAI_{pred} against observed values of LAI (LAI_{obs}), a square root transformation was applied to LAI_{obs} to compensate for a slightly curvilinear relationship (Figure 1a); the transformation found a linear relationship with a high coefficient of determination (R^2 = 0.85). The coefficient of determination for the untransformed variable (LAI_{obs}) was calculated as well and found to be 0.75. The regression results for PCC_{pred} and LAI_{pred} compare well to other studies. Riaño *et al.* (2004) attained coefficients of determination of approximately 0.75 for PCC and approximately 0.90 for LAI and concluded that LIDAR was an excellent measure of both. Scanning LIDAR was found to have a strong correlation with hemispherical photo-estimated LAI in the study of Lovell *et al.* (2003), returning R^2 values between 0.77 and 0.98.

When comparing observed field values to the selected model-predicted values (Figure 1a), it is seen that LIDAR-derived estimates slightly overestimate both PCC and LAI. This is consistent with the aforementioned studies and is possibly influenced by the small number of plots with low LAI values. Another possible source of error is that LIDAR data was collected during the leaf-off season while ground-reference data was collected during the leaf-on season. The majority of ground plots, 34 plots out of the total 43, were in pine plantations or pine stands and thus the majority of trees would have retained their needles for both the LIDAR and field data collections.

The simple linear regression results between observed PCC and LAI (PCC_{obs} and LAI_{obs}) and

LIDAR-derived PCC using Height Bins 5-11 ($x_{PCClidar,5-11}$) are promising, with r^2 values of 0.80 and 0.85 and RMSE values of 9.29% and 7.86% for PCC_{obs} and SQRT(LAI_{obs}), respectively. A square root transformation was again used to correct a curvilinear LAI_{obs} relationship to a linear relationship with LIDAR-derived PCC values (Figure 1b). The equations describing these LIDAR-predicted canopy characteristics (PCC_{pred_lidar} and LAI_{pred_lidar}) are:

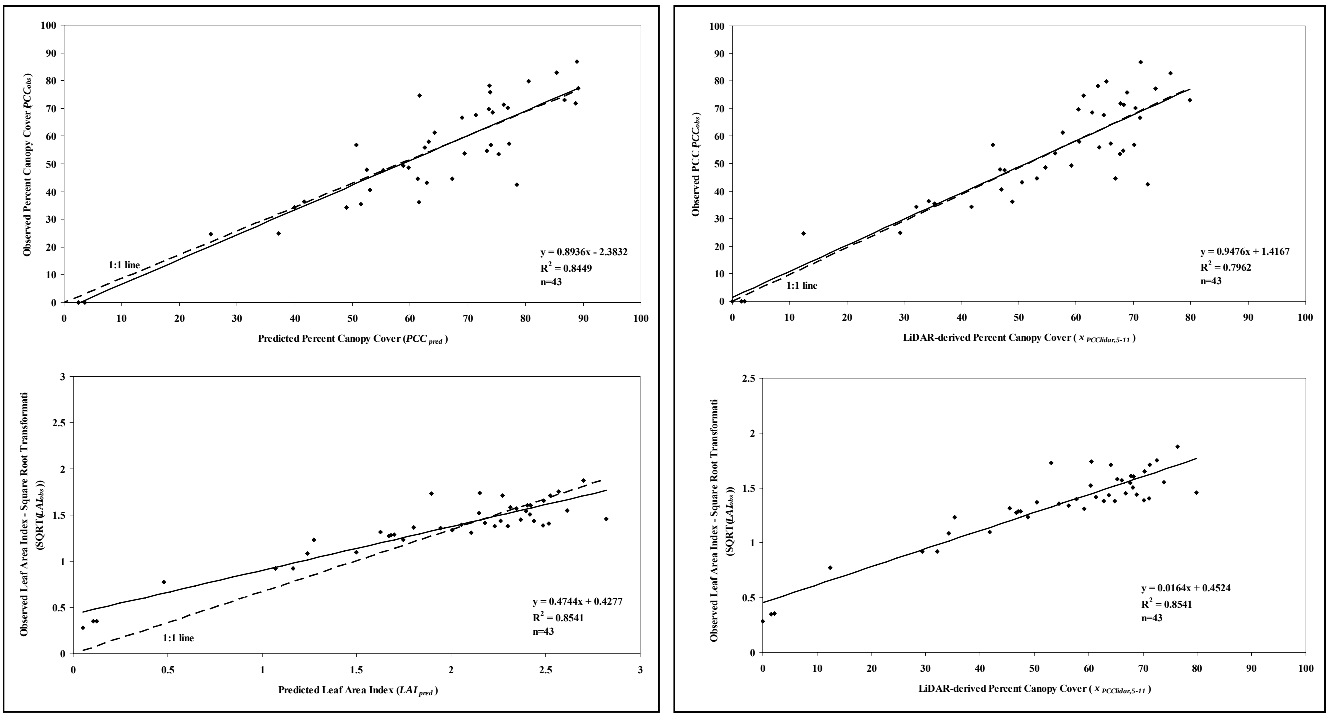
$$PCC_{pred\_lidar} = 0.95x_{PCClidar,5-11} + 1.42 \tag{9}$$

$$LAI_{pred\_lidar} = \left[0.02x_{PCClidar,5-11} + 0.45\right]^2 \tag{10}$$

4.2 Discussion

LIDAR-predicted PCC and LAI are comparable in accuracy to the selected regression models. These models are even preferable in the long term because of their simplicity. It is interesting to note that the TreeVaW-derived PCC was removed through stepwise selection and thus not present in the final regression model, though TreeVaW software has performed well in related studies (Popescu and Wynne 2004; Popescu and Zhao 2008). One possible explanation for TreeVaW's lack of performance in the current study is that its continuously varying filter window identifies only dominant and co-dominant trees, while hemispherical photography captures understory vegetation in addition to the taller tree crowns. TreeVaW processing of a LIDAR-derived CHM, while an effective way to locate individual trees and determine tree crown dimensions, was not an accurate method of determining plot-level PCC.

Estimation of forest structural attributes is one of the more thoroughly pursued applications of LIDAR remote sensing (Lefsky et al. 2002; Riaño et al., 2004). One goal of this study was to develop a linear regression relating LIDAR data and multispectral imagery to ground-reference values of PCC and LAI for hardwood and pine forests. Linear regression analysis of LIDAR variables explains 84% of the variance associated with plot-level PCC and 78% of the variance for plot-level LAI. A second objective was to evaluate whether LIDAR and NDVI data fusion would improve estimates of PCC and LAI. While data fusion did improve PCC model coefficients of determination by 2%, this was not a great enough improvement to justify retaining NDVI variables in the final PCC prediction model. LAI regression models were unaffected by the inclusion of NDVI variables; LIDAR-derived parameters alone were a good predictor of plot-level LAI. In the process of investigating linear regression analysis, it was found that LIDAR-derived PCC had an excellent relationship to field values of PCC and LAI. Simple linear regressions related LIDAR-derived PCC to field values of PCC and LAI, an exciting development for future ecological studies in primarily loblolly pine forests. Using LIDAR to directly determine these canopy properties would make the process accurate and efficient. Finally, the overall objective of this study was to develop a use of LIDAR in evaluating forest canopy parameters such as PCC and LAI. Results clearly show that scanning LIDAR data can be used to accurately estimate PCC and LAI.



(a) (b)

Figure 1: (a) Observed percent canopy cover (PCC) and leaf area index (LAI) compared to predicted PCC and LAI.
(b) Observed percent canopy cover (PCC) and leaf area index (LAI) compared to LIDAR-derived PCC.

LIDAR data processing by the height bin method, as used in this study, has the potential to become a standardized method of large-scale LIDAR forestry data processing. This approach was shown to be effective and accurate in predicting PCC and LAI in this study and has also been used in a study concerning mapping surface forest fuels (Mutlu *et al.* 2008). The height bin method has also been used in conjunction with TreeVaW processing to estimate biophysical parameters of individual trees, such as total tree height, crown width, and height to crown base (Popescu and Zhao 2008).

Determining ground reference values of LAI using hemispherical photography immediately introduced the possibility of underestimating these values (Merilo *et al.* 2004), although other indirect methods of measuring LAI tend to underestimate it as well (Mussche *et al.* 2001; Bréda 2003). In the future it may be helpful to determine a scale for LAI values, to calibrate them with direct measurements and compensate for clumping factors (Bréda 2003; Coops *et al.* 2004). Doing so may increase the agreement between the estimated LAI and ground reference values.

5 Conclusions

Our approach is unique in that it combines LIDAR estimates of PCC derived from height bins with a LIDAR-based CHM to estimate forest canopy characteristics through regression analysis. This method proved to be an accurate estimate of plot-level PCC and LAI, allowing us to predict these values at a local scale. PCC and LAI are important biophysical parameters in carbon sequestration and climate studies. Since LIDAR data can be acquired fairly quickly compared to ground-level forest inventory, our method could allow for fast, accurate, more effective ecological research as well as forest management.

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