USING LIDAR AND NORMALIZED DIFFERENCE VEGETATION INDEX TO REMOTELY DETERMINE LAI AND PERCENT CANOPY COVER AT VARYING SCALES

A Thesis

by

ALICIA MARIE RUTLEDGE GRIFFIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2006

Major Subject: Forestry

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Approved by:

Chair of Committee,	Sorin C. Popescu
Committee Members,	Cristine L. S. Morgan
	Ross F. Nelson
	Mark Tjoelker
Head of Department,	Steven Whisenant

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ABSTRACT

Using LiDAR and Normalized Difference Vegetation Index to Remotely Determine LAI and Percent Canopy Cover at Varying Scales. (December 2006)

Alicia Marie Rutledge Griffin, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Sorin C. Popescu

The use of airborne LiDAR (Light Detection and Ranging) as a direct method to evaluate forest canopy parameters is vital in addressing both forest management and ecological concerns. The overall goal of this study was to develop the use of airborne LiDAR in evaluating canopy parameters such as percent canopy cover (PCC) and leaf area index (LAI) for mixed pine and hardwood forests (primarily loblolly pine, *Pinus taeda*, forests) of the southeastern United States. More specific objectives were to: (1) Develop scanning LiDAR and multispectral imagery methods to estimate PCC and LAI over both hardwood and coniferous forests; (2) investigate whether a LiDAR and normalized difference vegetation index (NDVI) data fusion through linear regression improve estimates of these forest canopy characteristics; (3) generate maps of PCC and LAI for the study region, and (4) compare local scale LiDAR-derived PCC and regional scale MODIS-based PCC and investigate the relationship. Scanning LiDAR data was used to derive local scale PCC estimates, and 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 created from the LiDAR dataset and used to determine tree heights per plot. QuickBird multispectral imagery was used to calculate the NDVI for the study area. LiDAR- and NDVI-derived estimates of plot-level PCC and LAI were compared to field observations for 53 plots over 47 square kilometers. Linear regression analysis resulted in models explaining 84% and 78% of the variability associated with PCC and LAI, respectively. For these models to be of use in future studies, LiDAR point density must be 2.5 m. The relationship between regional scale PCC and local scale PCC was investigated by resizing the local scale LiDAR-derived PCC map to lower resolution levels, then determining a regression model relating MODIS data to the local

values of PCC. The results from this comparison showed that MODIS PCC data is not very accurate at local scales. The methods discussed in this paper show great potential for improving the speed and accuracy of ecological studies and forest management.

To my mother and father

ACKNOWLEDGMENTS

I would like to thank my committee chair, Dr. Popescu, and my committee members, Dr. Morgan, Dr. Nelson and Dr. Tjoelker, for their guidance, suggestions, and especially the amount of time they devoted to aiding my research over the past two years.

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Thanks to my friends and family for their support, to my mother for her shining example and to my father for his encouragement. Finally, thanks to my husband Jim for his infinite patience and love.

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CHAPTER I
INTRODUCTION: RELEVANT LITERATURE

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 crowns (Avery and Burkhart, 1994). LAI is especially important to ecological processes such as photosynthesis and net primary production (Nemani et al., 2003; Coops et al., 2004), while PCC, also called canopy cover, is important in assessing canopy structure, particularly gaps. 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., 2002b). Land cover information is an important input for monitoring and modeling ecological and environmental processes at all scales. Determining this information through remote sensing methods is an efficient and effective way to model such processes.

1.1 Local Scale PCC and LAI

Field, or *in situ*, measurements of LAI and canopy cover are necessary to validate remotely sensed values. Various methods, such as measuring reflectance with a hand-held radiometer (Casanova et al., 1998) or using sapwood-LAI allometric equations and optical instruments such as a ceptometer (White et al., 1997) may be employed in the process of determining LAI. 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

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This thesis follows the style of *Remote Sensing of Environment*.

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 (Chen et al., 1997; 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 can be used, either singly or in combination with other indices, to estimate LAI (Curran et al., 1992; White et al., 1997; Casanova et al., 1998; Pocewicz et al., 2004) as can other vegetation indices (Baret and Guyot, 1991). NDVI is included as a parameter in estimating PCC and LAI in this study because of the extensive past use of vegetation indices to successfully predict LAI.

Profiling laser measurements (profiling LiDAR) have been successfully used in canopy closure studies. A profiling laser system gathers ranging, or distance, data along an airplane’s flightline, typically while flying at relatively low altitudes along forested transects. Profiling laser tree height measurements can be linearly related to photointerpreted canopy cover and tree height data, with R^2 values of 0.82 and 0.81 (Nelson et al., 1984). Other studies reinforce this correlation, showing that a laser altimeter can provide canopy cover measurements not significantly different from ground measurements (Weltz et al., 1994), while profiling LiDAR measurements can be directly related to canopy cover (Ritchie et al., 1992). The latter two cases resulted in R^2 values ranging from 0.89 and 0.95 in the first to >0.95 in the second.

LiDAR remote sensing has become more widely used and accepted in ecological and forest inventory studies in recent years (Means et al., 1999; Means et al., 2000; Lefsky et al., 2002; Reutebuch et al., 2005). 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).

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. Another study by 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. This study found that leaf area was consistently underestimated, reflecting the study's underestimation of crown diameter. 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 (Popescu et al., 2002; Popescu and Wynne, 2004; Chen et al., 2006; Koch et al., 2006). Popescu and Wynne's study processed a CHM using the local maximum focal filtering software program TreeVaW, described in greater detail in Chapter II.

This study attempts to relate scanning LiDAR data to *in situ* LAI and PCC values through simple linear regression with NDVI. Theoretically, the combination of LiDAR-estimated canopy characteristics such as height and PCC with vegetation indices rather than a model relying entirely on LiDAR-derived parameters will result in an accurate predictor of LAI and PCC. Ground-reference LAI and PCC values were determined from hemispherical photography.

1.2 Regional Scale PCC and LAI

The National Aeronautics and Space Administration's (NASA's) Moderate Resolution Imaging Spectroradiometer (MODIS), on board the *Terra* spacecraft, provided a major advance in remote sensing of the land when launched in 1999. Whereas before, researchers relied on Advanced Very High Resolution Radiometer (AVHRR) data (with a 1 km spatial resolution) to map global land cover and its changes, the advent of MODIS made available data with greatly improved spectral, spatial, geometric, and radiometric attributes (Friedl et al., 2002; Hansen et al., 2003). One of the annual MODIS standard land cover products is the vegetation continuous fields (VCF) layers, which include 500 m resolution representations of percent bare ground, herbaceous and tree cover at global levels. These layers provide a considerable amount of information about land cover and its change, vital in modeling global biogeochemical and climate cycles (Hansen et al., 2002b).

One study performed by Hansen et al. (2002a) in Western Province, Zambia, attempted to validate the MODIS VCF global tree cover map through a process using field measurements, very high-resolution IKONOS satellite imagery, Landsat Enhanced Thematic Mapper Plus (ETM+) data and ancillary map sources. The study resulted in a root mean square error (RMSE) of 5.2% between a regional ETM+ derived percent canopy cover map and a MODIS tree cover map of the region.

A separate study was performed in the southwestern United States (White et al., 2005) to investigate the accuracy of the VCF tree cover product. The results of this study show that the MODIS vegetation continuous field tree cover product has an overall RMSE between 24 and 31% for the southwestern USA. Another study attempted to calibrate the global model against regional training data in the European Alps (Schwarz & Zimmermann, 2005) using generalized linear models (GLM). This study concluded that GLMs are appropriate for deriving continuous fields of fractional tree cover for complex topography at regional scales; MODIS data was successfully calibrated for use in the context of the European Alps. More work is necessary to determine whether the MODIS VCF percent tree cover map can be calibrated for use in other regions of the

USA, in particular the southeastern states. This study attempts to calibrate MODIS data with locally estimated PCC and LAI maps in order to generate accurate regional estimates of both characteristics.

1.3 Objectives

The overall goal of this study was to develop a use of LiDAR in evaluating canopy parameters of percent canopy cover and leaf area index for 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;

(2) use multiple linear regressions to predict PCC and LAI using LiDAR and NDVI;

(3) generate local scale maps of PCC and LAI for the study region; and

(4) investigate the relationship between LiDAR-derived and MODIS-based PCC.

CHAPTER II
LOCAL SCALE PCC AND LAI: LIDAR AND NDVI

2.1 Introduction

Leaf area index and percent canopy cover are vital biophysical and ecophysical factors in addressing forest management issues such as fuel models and forest inventory, and ecological concerns including carbon sequestration and global warming. 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 crowns (Avery and Burkhart, 1994).

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2.1.1 Objectives

The overall 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;

(2) use multiple linear regressions to predict PCC and LAI using LiDAR and NDVI; and

(3) generate local scale maps of PCC and LAI for the study region.

2.2 Materials and Methods

2.2.1 Study Area

The study area is located in the southern United States (30° 42' N, 95° 23' W), in the Piney Woods region of East Texas (Figure 2.1). It includes a portion of the Sam Houston

National Forest, characterized by deciduous and pine stands with an urban interface and an area of 47.45 km^2. The study area is composed of 28.08 km^2 (59.17%) of pine forest, 10.84 km^2 (22.84%) of deciduous forest, and 8.54 km^2 (17.99%) of non-forested areas including urban areas, agricultural fields, etc. A mean elevation of 85 m, with a minimum of 62 m and a maximum of 105 m, and gentle slopes characterize the topography of the study area.

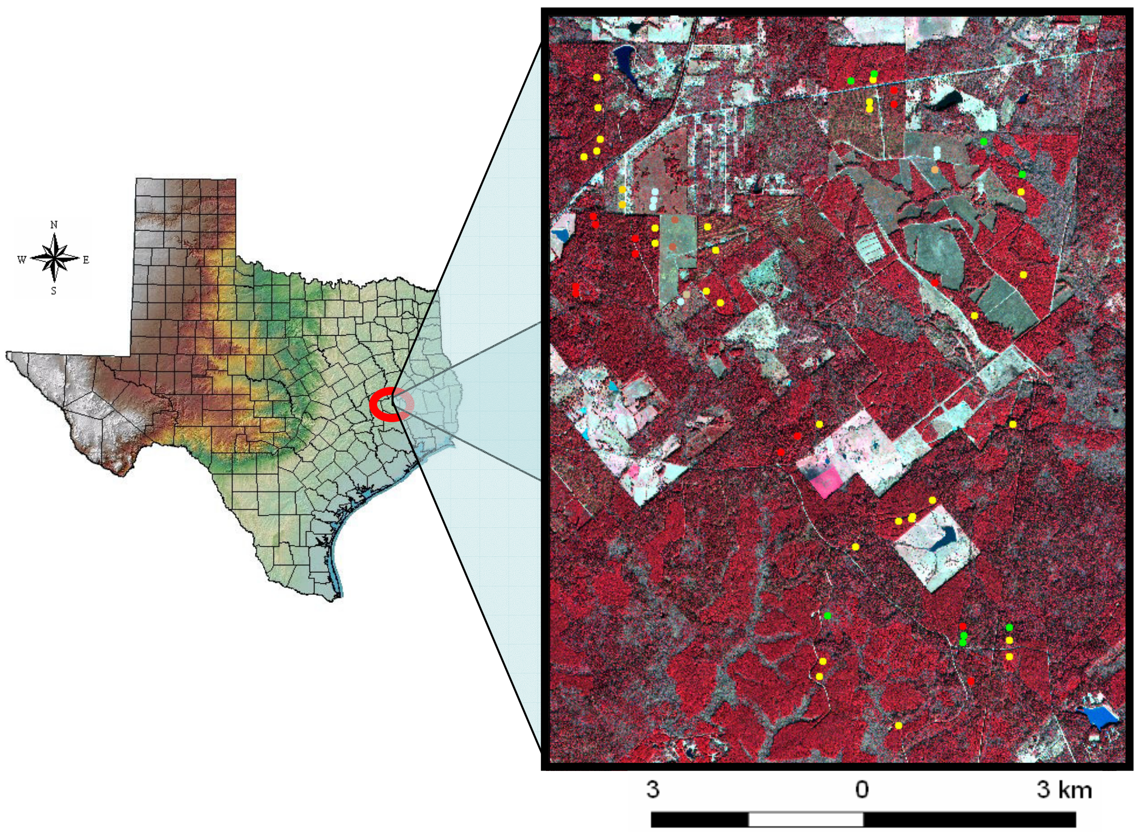

Fig. 2.1. A QuickBird image of the study area with plot locations superimposed. Resolution is 2.5 m.

2.2.2 Field Measurements

The ground reference data were collected between May 2004 to July 2004 by photographing canopy characteristics on 53 circular plots (locations shown in Figure

2.1), of which 35 covered 404.7 km^2 (1/10 acres) and 18 covered 40.47 km^2 (1/100 acres). The 18 smaller plots were used 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 (described in section 2.2.4), and each plot was mapped by recording GPS coordinates for the plot center. Plots were evenly distributed over the study area, coinciding with a separate dataset of profiling laser measurements collected at the time of this study.

2.2.3 LiDAR Data and Multispectral Imagery

LiDAR data for the study area was collected in March 2004, during the leaf-off season, 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 20-30 cm and 15 cm, respectively, and a point density of 2.6 points/m^2. The average swath width was 350m, with 19 north-south flight lines and 28 east-west flight lines (see Figure 2.2). LiDAR point elevations were interpolated to form a digital surface model with a spatial resolution of 0.5 m, with only the highest laser hits per 0.5 m x 0.5 m 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 0.5 m, was created by subtracting ground elevation from the digital surface model. The CHM was interpolated to a cell size of 2.5 m prior to any calculations.

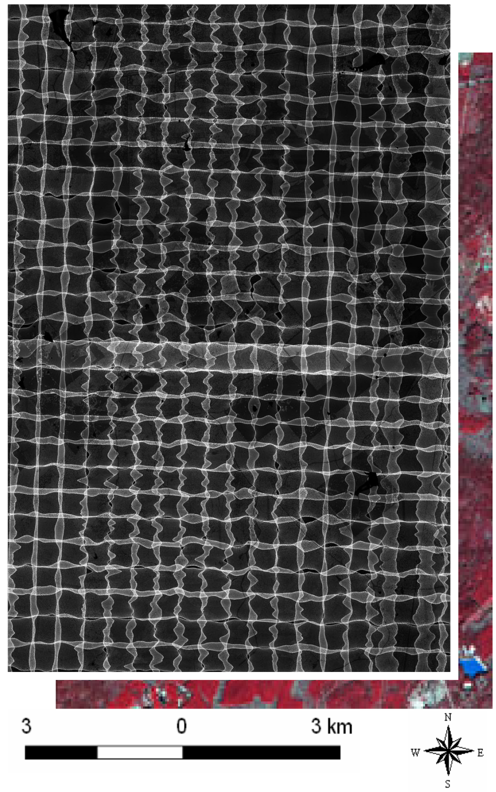

Fig. 2.2. LiDAR collection swath locations overlaid with a QuickBird image of the study area.

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, personal conversation).

Multispectral QuickBird imagery (DigitalGlobe. Longmont, CO, USA) was available for the study area as well (Figure 2.1), with a resolution of 2.5 m. These data were used to calculate NDVI as defined by Baret and Guyot (1991):

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{2.1}$$

where *NIR* is the near-infrared reflectance value and *R* the red reflectance value for a given pixel. The Band Math function of ENVI software (ITT Industries Inc., Boulder, CO, USA) was used to calculate NDVI.

2.2.4 Hemispherical Photography

Plot-level ground reference values of PCC and LAI were quantified using hemispherical photography. An example of one such canopy photograph is shown in Figure 2.3. Photographs were taken at 1.5 m above ground level using a horizontally-leveled CoolPix 8700 digital camera (Nikon) with an FC-E9 fisheye lens converter (Nikon). Photograph quality was set to 3264 × 2448 pixels. Photographs were analyzed for plot-level PCC and LAI using HemiView Canopy Analysis Software (Delta-T Devices Ltd., Cambridge, UK). Photo analysis involved a user-defined threshold intensity for each photo that determines whether pixels are classified as open (sky) or obscured (canopy). Photographs were taken under available light conditions, both overcast and sunny, which resulted in several plot photographs containing sun glare and other non-uniformities. HemiView algorithms are designed for uniform canopies and light conditions, with major non-uniformities causing fairly large errors. Thus, photographs containing canopy edges (i.e. plots near clearings or roads) and several plot photographs containing sun glare were removed from regression analysis. In total, ten plots were removed from the data set. 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. With that in mind, the results of this study will be most applicable to loblolly pine forest.

Fig. 2.3. Hemispherical photograph of a field plot.

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 is based on Beer's Law:

$$G(\theta) = e^{(-K(\theta) \times LAI_{obs})} \tag{2.2}$$

where *G* is gap fraction and *K(θ)* 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 and includes sky obstruction by branches or stems, thereby possibly underestimating actual LAI. Hereafter, this estimate observed LAI will be referred to as LAI_{obs}.

In HemiView, PCC (referred to in the software literature as CoverGnd) was 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:

$$PCC_{obs} = \left[1 - e^{(-K(x,0)\times LAI_{obs})}\right]\times 100 \tag{2.3}$$

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. An ellipsoidal leaf angle distribution parameter greater than 1 represents a canopy where the elements are predominantly horizontal, and less than 1 represents a canopy where the elements are predominantly vertical (HemiView User Manual, 1999). The extinction coefficient itself can vary between 0.28 and 0.50 for coniferous stands and between 0.28 and 0.58 for deciduous stands (Bréda, 2003).

2.2.5 LiDAR-derived Percent Canopy Cover

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. All three methods are described in detail in the following section.

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, in review). Height bins are created by subdividing normalized laser point returns into bins 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. The percentage of laser canopy hits is 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 (in review), with height ranges defined in Figure 2.4.

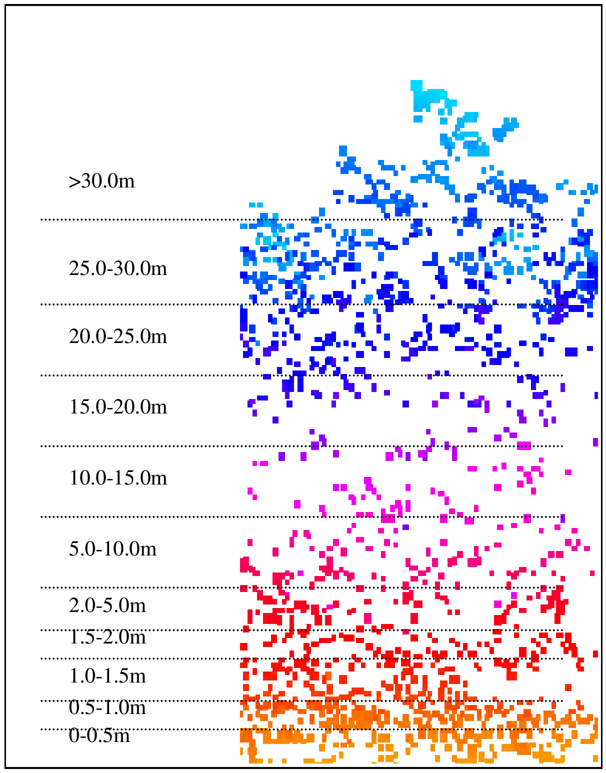

Fig. 2.4. Height bin method shown on a sample LiDAR point cloud cross-section.

These height bins were generated as a multiband image of these predefined height intervals and 2.5 m × 2.5 m pixel dimensions (Figure 2.5). Each volumetric unit can be seen as a 2.5 m × 2.5 m × (varying) m voxel, a three-dimensional volume element corresponding to a pixel, also described by Popescu and Zhao (in review).

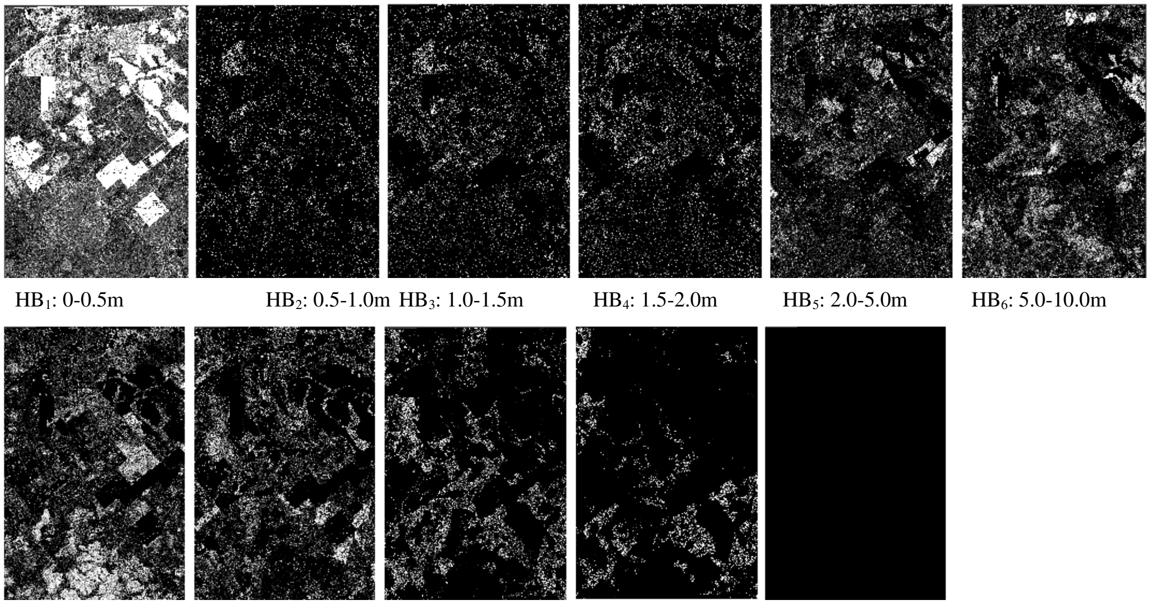

Fig. 2.5. Multiband image of the eleven height bins used in this study, showing the study area. Resolution is 2.5 m.

Two estimates of plot-level 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 and thus a sum of the seven highest height bins (HB_5 through HB_{11}) is used to model plot-level PCC:

$$PCC_{lidar,5-11} = \sum_{5}^{11} HB_n \tag{2.4}$$

where HB_n is a height bin image of number n (see Figure 2.5 for numbering).

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 this second plot-level PCC is as follows:

$$PCC_{lidar,1} = 1.0 - HB_1 \tag{2.5}$$

where notation is the same as in Equation 2.4.

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. ITT Industries Inc., Boulder, CO, 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 also operates on an assumed relationship between tree height and crown radius (derived from field inventory data), with tall trees being identified with large filter windows and shorter trees being identified with smaller filter windows. A past study, Popescu et al. (2003), showed that TreeVaW explained 62 - 63% of the variance for both pine and deciduous tree crown size. These variance values are lower than expected, but can be explained by the fact that TreeVaW software is designed to measure the non-overlapping crown diameter but field measurements were taken of each tree's crown in full, thus including overlapping crown diameters.

TreeVaW was used to identify individual tree locations and crown size for each field plot. Non-overlapping projected tree crown area was then plotted with plot area against the CHM (Figure 2.6) and total projected crown area (A_{crown}) calculated. Figure 1.5 shows the plot boundary in cyan, projected tree area boundaries in magenta and the LiDAR-derived CHM as the grayscale background.

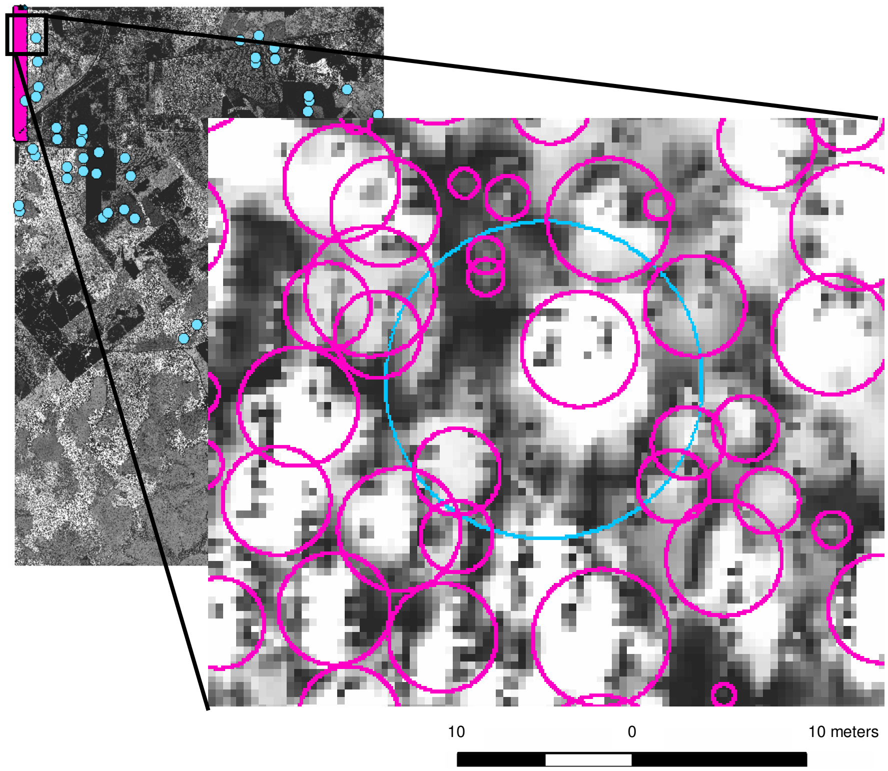

Fig. 2.6. TreeVaW processing of the canopy height model (CHM). The plot outline is shown in blue and tree crown projections are shown in magenta.

Then, plot-level TreeVaW-derived PCC can be determined:

$$PCC_{trvw} = \frac{A_{crown}}{A_{plot}} \tag{2.6}$$

where A_{plot} is the total plot area. The described methods and further analysis are detailed in Figure 2.7.

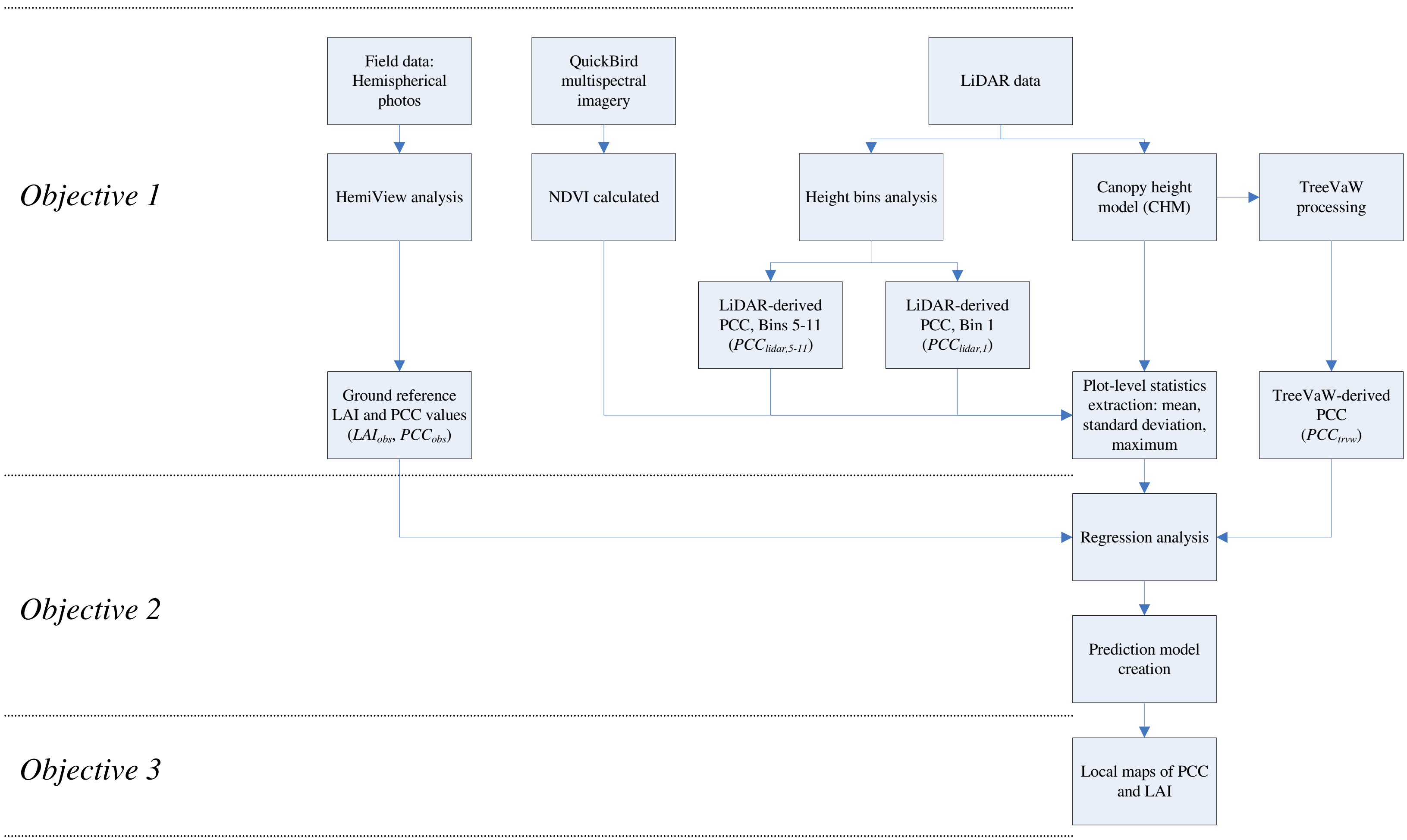

Fig. 2.7. An overview of the data and methods used in this study, as they relate to the stated objectives.

2.2.6 Regression Analysis

SAS software (SAS Institute, Inc., Cary, NC, USA) was used to relate the various LiDAR-derived variables and NDVI variables to plot-level observed values of PCC and LAI. The independent and dependent variables used in this series of stepwise linear regressions are defined in Table 2.1.

Table 2.1
Stepwise linear regression variable definitions

Independent variable		**Property (Plot-Level)**
(1)	$x_{PCClidar,5\text{-}11}$	Mean, LiDAR-derived PCC, Height Bins 5-11
	$\sigma_{PCClidar,5\text{-}11}$	Standard deviation, LiDAR-derived PCC, Height Bins 5-11
(2)	$x_{PCClidar,1}$	Mean, LiDAR-derived PCC, Height Bin 1
	$\sigma_{PCClidar,1}$	Standard deviation, LiDAR-derived PCC, Height Bin 1
(3)	PCC_{trvw}	Mean, TreeVaW-derived PCC
(4)	x_{chm}	Mean, Canopy Height Model
	σ_{chm}	Standard deviation, Canopy Height Model
	X_{chm}	Maximum, Canopy Height Model
(5)	x_{ndvi}	Mean, Normalized Difference Vegetation Index
	σ_{ndvi}	Standard deviation, Normalized Difference Vegetation Index

Dependent variable	**Property (Plot-Level)**
PCC_{obs}	Observed PCC (HemiView)
LAI_{obs}	Observed LAI (HemiView)

The PROC REG procedure of SAS was used to fit least-squares estimates of PCC and LAI to linear regression models for eight different datasets, including varying combinations of the independent variables. These combinations are listed in Table 2.2. Stepwise selection was employed in each regression to determine the variables remaining in each model. Variables retained in each regression were significant at the 0.15 level. Each model was checked for collinearity; variance inflation factor values for retained variables were well below 10, thus there was no concern about collinearity.

Table 2.2
Variables included in stepwise linear regressions

	Independent variables included (listed by number, Table 2.1)	
Regression #	**PCC**	**LAI**
1	(1), (4)	(1), (4)
2	(2), (4)	(2), (4)
3	(3), (4)	(3), (4)
4	(1), (2), (3), (4)	(1), (2), (3), (4)
5	(1), (4), (5)	(1), (4), (5)
6	(2), (4), (5)	(2), (4), (5)
7	(3), (4), (5)	(3), (4), (5)
8	(1), (2), (3), (4), (5)	(1), (2), (3), (4), (5)

Next, 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 ($x_{PCClidar,5\text{-}11}$). These regressions were performed using Microsoft Excel software (Microsoft Corporation, Redmond, WA, USA). These linear regressions were pursued to determine how well a single LiDAR-derived parameter could predict both PCC and LAI.

2.3 Results and Discussion

2.3.1 Results

Regression data properties such as mean average, maximum and minimum are reported in Table 2.3. All variables had a fairly normal distribution.

Table 2.3
Summary statistics of data used in linear regression analysis

Values/Units	Mean	Maximum	Minimum	Range	n (# observations)
PCC_{obs} (%)	53.16	86.8	0	86.8	43
LAI_{obs}	1.95	3.52	0.08	3.44	43
$x_{PCC,lidar5\text{-}11}$ (%)	54.49	79.88	0	79.88	43
$\sigma_{PCC,lidar5\text{-}11}$ (%)	19.76	33.87	0	33.87	43
$x_{PCC,lidar1}$ (%)	59.25	83.39	0.1	83.29	43
$\sigma_{PCC,lidar1}$ (%)	19.38	34.69	0.86	33.83	43
PCC_{trvw} (%)	40.05	79.28	0	79.28	43
X_{chm} (m)	20.56	37.07	0.38	36.69	43
x_{chm} (m)	8.25	20.74	0.07	20.67	43
σ_{chm} (m)	7.74	24.75	0.03	24.72	43
x_{ndvi}	0.51	0.65	0.29	0.36	43
σ_{ndvi}	0.08	0.12	0.03	0.09	43

Models resulting from the linear regressions for predicting plot-level PCC and LAI using LiDAR-derived variables are shown in Table 2.4. Models including LiDAR-derived variables and NDVI variables in the regressions are shown in Table 2.5.

Table 2.4
Results for estimating PCC and LAI using LiDAR-derived variables only, n=43

R^2	RMSE	Model*
Independent variables included: (1), (4)		
0.84	0.09	$PCC_{pred}=-0.01+0.93x_{PCClidar,5\text{-}11}+0.01X_{chm}-0.01x_{chm}$
0.78	0.38	$LAI_{pred}=0.05+3.47x_{PCClidar,5\text{-}11}$
Independent variables included: (2), (4)		
0.76	0.11	$PCC_{pred}=-0.02+0.88x_{PCClidar,1}+0.01X_{chm}-0.01x_{chm}$
0.72	0.43	$LAI_{pred}=-0.02+3.31x_{PCClidar,1}$
Independent variables included: (3), (4)		
0.43	0.17	$PCC_{pred}=0.17+0.01\sigma_{chm}+0.63PCC_{trvw}$
0.42	0.62	$LAI_{pred}=0.62+0.04\sigma_{chm}+2.46PCC_{trvw}$
Independent variables included: (1), (2), (3), (4)		
0.84	0.09	$PCC_{pred}=-0.01+0.93x_{PCClidar,5\text{-}11}+0.01X_{chm}-0.01x_{chm}$
0.78	0.38	$LAI_{pred}=0.05+3.47x_{PCClidar,5\text{-}11}$

*where variables and property identifying numbers are defined in Table 2.1

Table 2.5
Results for estimating PCC and LAI using both LiDAR-derived and NDVI variables, n=43

R^2	RMSE	Model*
Independent variables included: (1), (4), (5)		
0.86	0.09	$PCC_{pred}=0.14+1.06x_{PCClidar,5\text{-}11}-0.37x_{ndvi}+0.01X_{chm}-0.01x_{chm}$
0.78	0.38	$LAI_{pred}=0.05+3.47x_{PCClidar,5\text{-}11}$
Independent variables included: (2), (4), (5)		
0.78	0.11	$PCC_{pred}=0.26+1.18x_{PCClidar,1}-0.70x_{ndvi}-0.01x_{chm}$
0.72	0.43	$LAI_{pred}=-0.02+3.31x_{PCClidar,1}$
Independent variables included: (3), (4), (5)		
0.46	0.16	$PCC_{pred}=-0.03+0.50x_{ndvi}+0.01\sigma_{chm}+0.50PCC_{trvw}$
0.52	0.57	$LAI_{pred}=-1.05+3.58x_{ndvi}+0.03X_{chm}+1.43PCC_{trvw}$
Independent variables included: (1), (2), (3), (4), (5)		
0.86	0.09	$PCC_{pred}=0.14+1.06x_{PCClidar,5\text{-}11}-0.37x_{ndvi}+0.01X_{chm}-0.01x_{chm}$
0.78	0.38	$LAI_{pred}=0.05+3.47x_{PCClidar,5\text{-}11}$

*where variables and property identifying numbers are defined in Table 2.1

As can be observed, 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 (Table 2.5). However, a PCC model using only LiDAR-derived variables had an R^2 value of 0.84 and an identical RMSE value (Table 2.4, equation boxed in red). One can see that the NDVI variables are relatively unimportant in predicting PCC when compared to LiDAR-derived variables. The model selected to predict PCC is:

$$PCC_{pred} = 0.01 + 0.93x_{PCClidar,5-11} + 0.01X_{chm} - 0.01x_{chm}. \qquad (2.7)$$

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 (Table 2.4, also boxed in red). One can easily observe that the prediction models incorporating both LiDAR and NDVI variables (Table 2.5) in general have higher coefficients of determination than those using only LiDAR-derived values (Table 2.4), 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:

$$LAI_{pred} = 0.05 + 3.47x_{PCClidar,5-11} \tag{2.8}$$

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; 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.

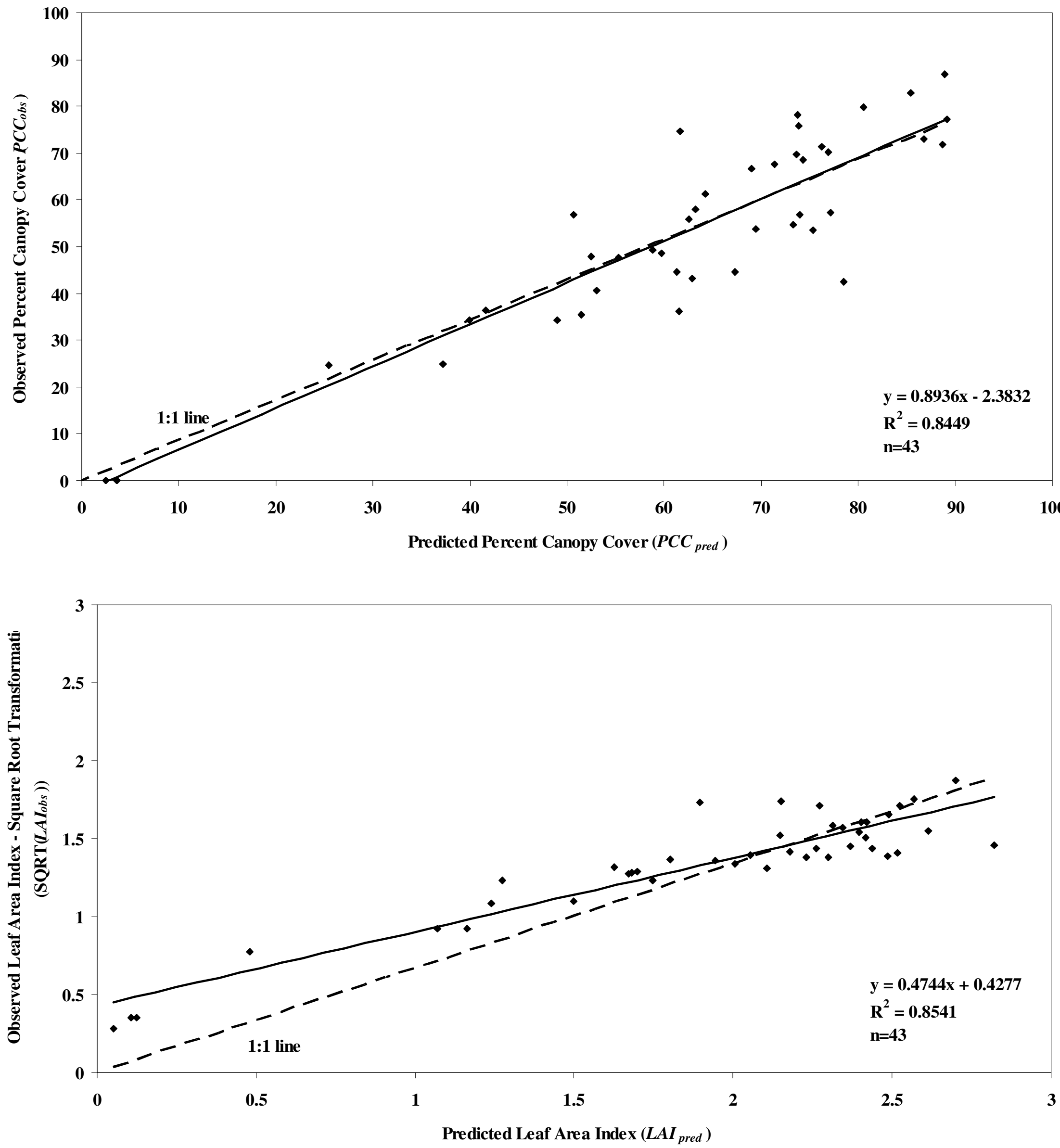

Fig. 2.8. Observed percent canopy cover (PCC) and leaf area index (LAI) compared to predicted PCC and LAI. Predicted values were taken from linear regression models. A square root transformation was applied to the observed LAI values in order to find a linear relationship.

When comparing observed field values (determined through HemiView processing) to the selected model-predicted (linear regression) values (Figure 2.8), it can be seen that

LiDAR-derived estimates slightly overestimate both PCC and LAI. This is consistent with the aforementioned studies and coincides with the tendency of HemiView software to underestimate canopy parameters, such as returning “effective LAI” rather than true 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. This discrepancy should affect the PCC and LAI values for predominantly hardwood plots. However, the majority of ground plots, 34 plots out of the total 43, were in pine plantations or pine stands in the Sam Houston National Forest and surrounding private land. Thus, the majority of plots would have retained their needles for both the LiDAR and field data collections.

Simple linear regression results between observed PCC and LAI (PCC_{obs} and LAI_{obs}) and LiDAR-derived PCC using Height Bins 5-11 ($x_{PCClidar,5\text{-}11}$) 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. Plots of these linear relationships are shown in Figure 2.9. The equations describing these LiDAR-predicted canopy characteristics (PCC_{pred_lidar} and LAI_{pred_lidar}) are thus

$$PCC_{pred\_lidar} = 0.95 x_{PCClidar,5-11} + 1.42 \tag{2.9}$$

and

$$LAI_{pred\_lidar} = \left[0.02 x_{PCClidar,5-11} + 0.45\right]^2 . \tag{2.10}$$

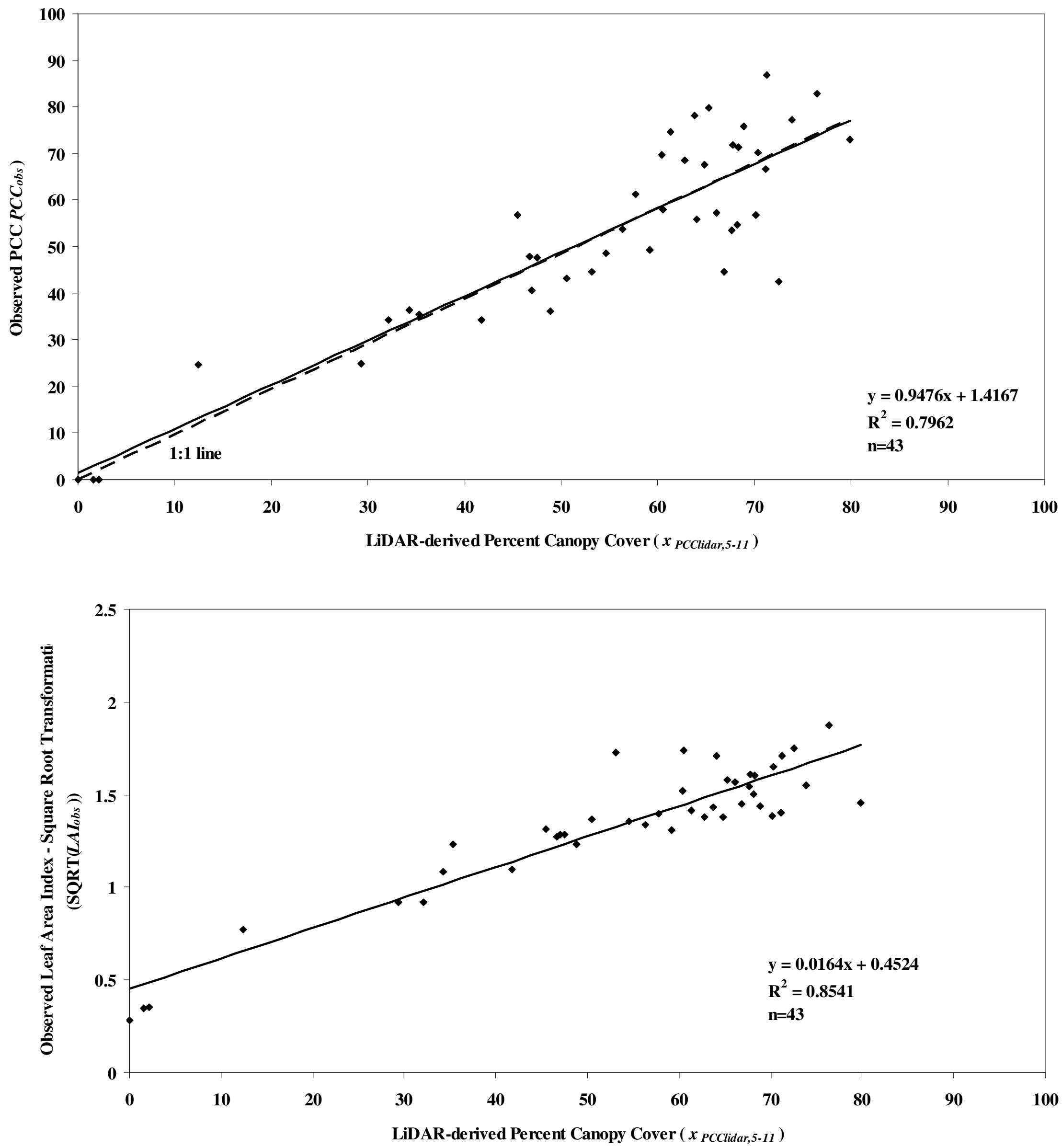

Fig. 2.9. Observed percent canopy cover (PCC) and leaf area index (LAI) compared to LiDAR-derived PCC. A square root transformation was applied to the observed LAI values in order to find a linear relationship.

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. The previously selected PCC_{pred} and LAI_{pred} models were used to produce high-resolution maps of PCC and LAI for the study area forests. Figure 2.10 shows subsets of these maps (with 2.5 m resolution) for a mixed forest (upper) and young pine forest (lower). Differences in forest type and canopy characteristics are readily apparent through visual inspection.

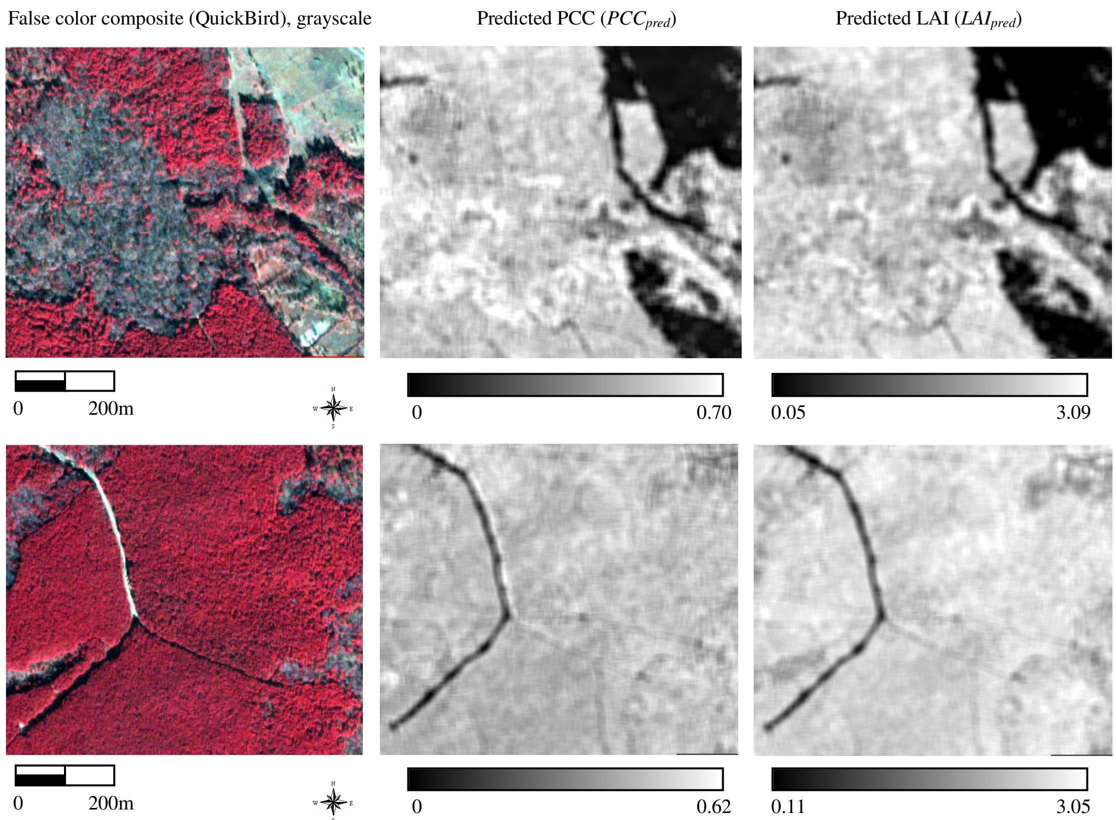

Fig. 2.10. Maps of predicted percent canopy cover (PCC) and leaf area index (LAI), generated by predictive equations from linear regression. Resolution is 2.5 m.

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, in review). For a study performed in the Piedmont region of Virginia, U.S.A., Popescu and Wynne found that LiDAR measurements explained 97% of the variance of pine plot mean height and 79% of the variance for deciduous plot mean height. 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. A possible source of error in deriving TreeVaW-estimated PCC was the assumption that most tree crowns are circular. It is possible that this assumption skewed plot-level modeling of individual crown dimensions and thus the overall projected crown area. 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.

2.3.2 Conclusions

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, in fact, 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.

A third objective was to generate PCC and LAI maps of the study area. Maps were produced using the prediction models in Equations 2.7 and 2.8. These maps could have been produced from LiDAR-derived PCC with similar accuracy levels. Finally, the overall objective of the first part of this study (Chapter II) 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 and generate high-resolution maps of these characteristics at a local scale, using multiple regression.

A series of linear regressions incorporating independent variables from two LiDAR-derived canopy cover estimates, a LiDAR-derived CHM, TreeVaW-derived PCC values and NDVI was generated. Results indicate a strong relationship between LiDAR variables and observed PCC values, with the most predictive regression model having an R^2 value of 0.84. The best model prediction of LAI, also using only LiDAR variables, is nearly as strong with an R^2 value of 0.78. Simple linear regression results between observed PCC and LAI and LiDAR-derived PCC using Height Bins 5-11 are very 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.

This correlation is in keeping with the observed trend of previously cited studies, which also found a strong correlation between LiDAR-estimated canopy characteristics and observed LAI or PCC. The PCC estimation in particular was a good use of LiDAR because the coefficient of determination was near those of previous studies (Lovell et al., 2003; Popescu et al., 2004; Riaño et al., 2004).

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 and crown fuels (Mutlu, in review). The height bin methods 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, in review).

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, N.J.J., 2003; Coops et al., 2004). Doing so may have increased the agreement between the estimated LAI and ground reference values in this study.

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. This method could allow for fast, accurate, more effective ecological research as well as forest management.

CHAPTER III
REGIONAL SCALE PCC: MODIS COMPARISON

3.1 Introduction

Percent canopy cover (PCC) is a vital biophysical and ecophysical property for the monitoring and modeling of environmental and ecological processes at regional to global scales. Maps of this property are welcome aids to researchers in climate change, ecosystem and biogeochemical studies. PCC has also taken on increased importance in the political and ecological arenas for quantifying global carbon stocks.

The National Aeronautics and Space Administration's (NASA's) Moderate Resolution Imaging Spectroradiometer (MODIS), on board the *Terra* spacecraft, provided a major advance in remote sensing of the land when launched in 1999. Whereas before, researchers relied on Advanced Very High Resolution Radiometer (AVHRR) data (with a 1 km spatial resolution) to map global land cover and its changes, the advent of MODIS made available data with greatly improved spectral, spatial, geometric, and radiometric attributes (Friedl et al., 2002; Hansen et al., 2003). One of the annual MODIS standard land cover products is the vegetation continuous fields (VCF) layers, which include 500 m resolution representations of percent bare ground, herbaceous and tree cover at global levels. These layers provide a considerable amount of information about land cover and land cover change, which is vital in modeling global biogeochemical and climate cycles (Hansen et al., 2002b).

One study performed by Hansen et al. (2002a) in Western Province, Zambia, attempted to validate the MODIS VCF global tree cover map at a regional scale through a process using field measurements, very high-resolution IKONOS satellite imagery, Landsat Enhanced Thematic Mapper Plus (ETM+) data and ancillary map sources. The study resulted in a root mean square error (RMSE) of 5.2% between a regional ETM+ derived percent canopy cover map and a MODIS tree cover map of the region.

A separate study was performed in the southwestern United States (White et al., 2005) to investigate the accuracy of the VCF tree cover product. The results of this study show that the MODIS VCF tree cover product has an overall RMSE between 24 and 31% for the southwestern USA. Schwarz & Zimmermann (2005) attempted to calibrate the global MODIS tree cover model against regional training data in the European Alps using generalized linear models. This study concluded that generalized linear models are appropriate for deriving continuous fields of fractional tree cover for complex topography at regional scales; MODIS data was successfully calibrated for use at regional scales in the context of the European Alps. More work is necessary to determine whether the MODIS VCF percent tree cover map can be calibrated for use in other regions of the USA, in particular the southeastern states.

LiDAR remote sensing has become more widely used and accepted in ecological and forest inventory studies in recent years (Means et al., 1999; Means et al., 2000; Lefsky et al., 2002; Reutebuch et al., 2005). 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 can be used to accurately predict PCC in a loblolly pine forest, as it is a direct measurement of the forest canopy (Griffin et al., in review).

This study attempts to compare MODIS data with a local scale LiDAR-derived PCC map in order to examine the relationship between local scale and regional scale estimates of PCC.

3.1.1 Objective

The overall goal of this study was to develop a use of LiDAR in evaluating the canopy parameter of PCC for pine and hardwood forests typical of the southeastern United States. The specific objective was to:

(1) Investigate the relationship between local scale LiDAR-derived PCC and regional scale MODIS-based PCC.

3.2 Materials and Methods

3.2.1 Study Area

The study area is located in the southern United States (30° 42’ N, 95° 23’ W), in the Piney Woods region of East Texas (Figure 3.1). It includes a portion of the Sam Houston National Forest, characterized by deciduous and pine stands with an urban interface and an area of 47.45 km^2. The study area is composed of 28.08 km^2 (59.17%) of pine forest, 10.84 km^2 (22.84%) of deciduous forest, and 8.54 km^2 (17.99%) of non-forested areas including urban areas, agricultural fields, etc. A mean elevation of 85 m, with a minimum of 62 m and a maximum of 105 m, and gentle slopes characterize the topography of the study area.

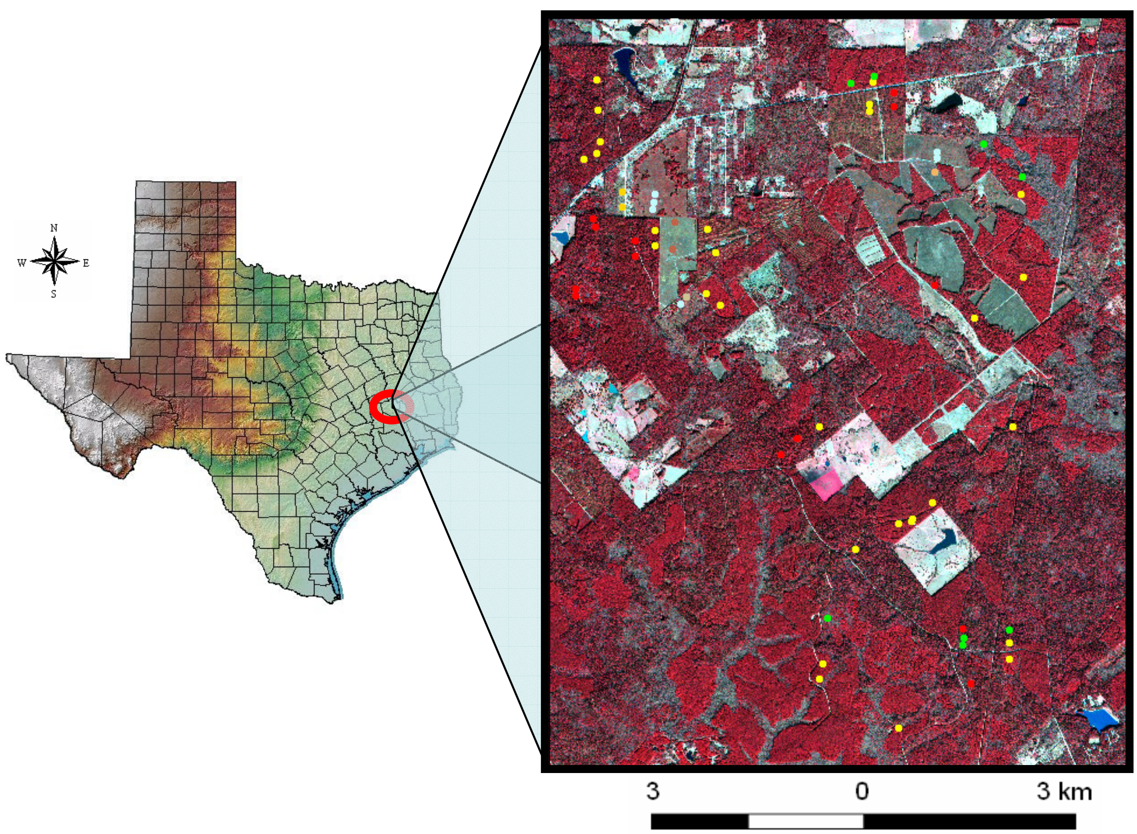

Fig. 3.1. A QuickBird multispectral image of the study area with plot locations included. Resolution is 2.5 m.

3.2.2 Field Measurements

The ground reference data were collected between May 2004 to July 2004 by photographing canopy characteristics on 53 circular plots (locations shown in Figure 2.1), of which 35 covered 1 hectare (1/10 acres) and 18 covered 1/10 hectare (1/100 acres). The 18 smaller plots were used 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. Plots were evenly distributed over the study area, coinciding with a separate dataset of profiling laser measurements collected at the time of this study. Plot-level ground reference values of PCC were quantified from the hemispherical photographs using HemiView Canopy Analysis Software (Delta-T Devices Ltd., Cambridge, UK) and methods described by Griffin et al. (in review). Ten plot photographs were removed from the data set during HemiView analysis due to unsuitable light conditions. 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. With that in mind, the results of this study will be most applicable to loblolly pine forest.

3.2.3 LiDAR Data and the Canopy Height Model

LiDAR data for the study area was collected in March 2004, during the leaf-off season, 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 20-30 cm and 15 cm, respectively, and a point density of 2.6 points/m^2. The average swath width was 350m, with 19 north-south flight lines and 28 east-west flight lines (see Figure 3.2). LiDAR point elevations were interpolated to form a digital surface model with a spatial resolution of 0.5 m, with only the highest laser hits per 0.5 m × 0.5 m cells being used in the interpolation to better characterize the top canopy surface. The canopy height model (CHM), a three-dimensional model of vegetation height with a resolution of 0.5 m, was created by subtracting ground elevation from the digital surface model using techniques described by Popescu and Wynne (2004). The CHM was interpolated to a cell size of 2.5 m prior to any calculations.

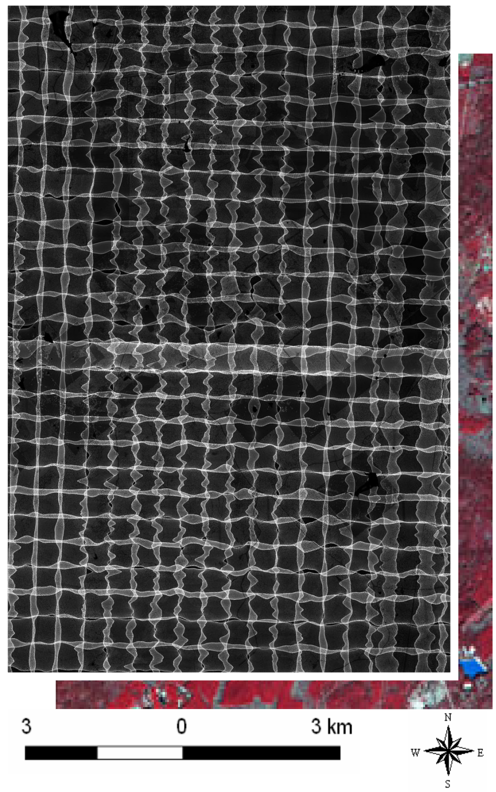

Fig. 3.2. LiDAR collection swath locations overlaid onto a QuickBird image of the study area.

Though the LiDAR data was collected during the leaf-off season, this was not expected to adversely impact the PCC estimates. The majority of the study area plots, 34 out of 43, 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).

3.2.4 LiDAR-derived Percent Canopy Cover

A LiDAR processing technique known as the "height bin method" was employed to derive PCC from LiDAR data. 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, in review). Height bins are created by subdividing normalized laser point returns into bins 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. The percentage of laser canopy hits is 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 (in review), with height ranges defined in Figure 3.3.

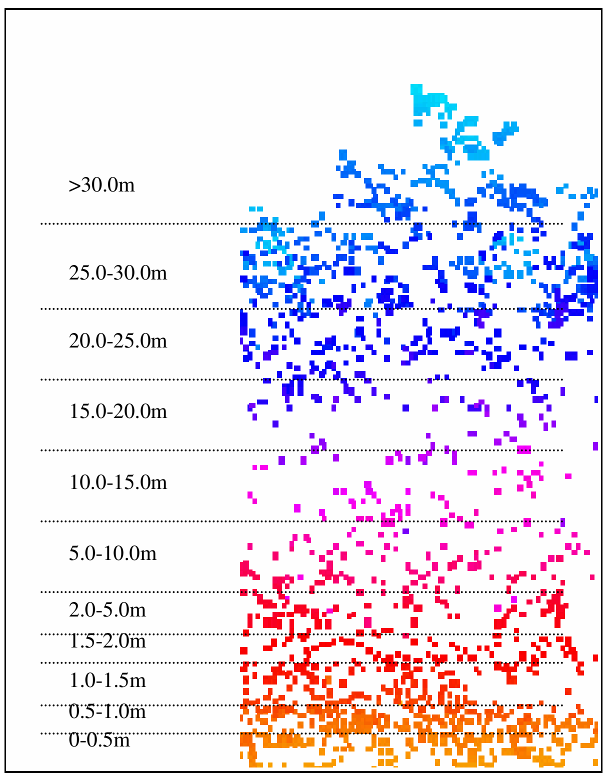

Fig. 3.3. The height bin method demonstrated on a LiDAR point cloud cross-section.

These height bins were generated as a multiband image of these predefined height intervals and 2.5 m × 2.5 m pixel dimensions (Figure 3.4). Each volumetric unit can be seen as a 2.5 m × 2.5 m × (varying) m voxel, a three-dimensional volume element corresponding to a pixel, also described by Popescu and Zhao (in review).

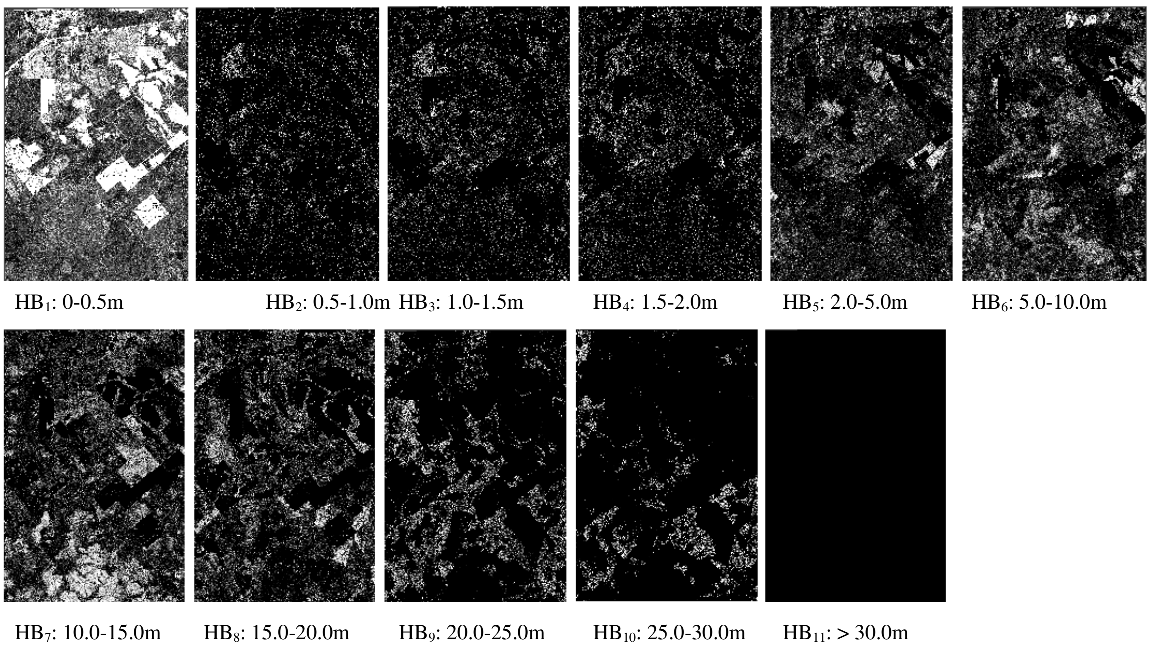

Fig. 3.4. Multiband image of the eleven height bins used in this study. Resolution is 2.5 m.

Plot-level LiDAR-derived PCC was derived from the bins. The first method assumes that the crowns of interest belong to trees with a height of over 2.0m and thus a sum of the seven highest height bins (HB_5 through HB_{11}) is used to model plot-level PCC:

$$PCC_{lidar,5-11} = \sum_{5}^{11} HB_n \tag{3.1}$$

where HB_n is a height bin image of number n (see Figure 3.4 for numbering).

3.2.5 Regression: Local Scale Predicted Percent Canopy Cover

Plot-level mean and standard deviation were taken from LiDAR-derived PCC:

- $x_{PCClidar,5\text{-}11}$
- $\sigma_{PCClidar,5\text{-}11}$

and plot-level maximum, mean and standard deviation were taken from the CHM:

- X_{chm}
- x_{chm}
- σ_{chm}.

SAS software (SAS Institute, Inc., Cary, NC, USA) was used to relate the LiDAR-derived PCC variables and CHM variables to plot-level observed values of PCC (HemiView). The PROC REG procedure of SAS was used to fit least-squares estimates of PCC to several linear regressions and stepwise selections were employed in the regressions to determine the variables remaining in each model. Variables retained in the regressions were significant at the 0.15 level. The models were checked for collinearity; variance inflation factor values for all retained variables were well below 10, thus there was no concern about collinearity. The following model was then selected to predict local scale PCC:

$$PCC_{pred} = 0.01 + 0.93x_{PCClidar,5-11} + 0.01X_{chm} - 0.01x_{chm}\,. \tag{3.2}$$

This model was selected because of its high coefficient of determination, (R^2= 0.84) and a low root mean squared error (RMSE = 9%). The model was then used to generate a map of local scale PCC for the study area, shown in Figure 3.5a. Because the selected model is an excellent predictor of local scale PCC, this map will be considered ground reference data for the purposes of this study.

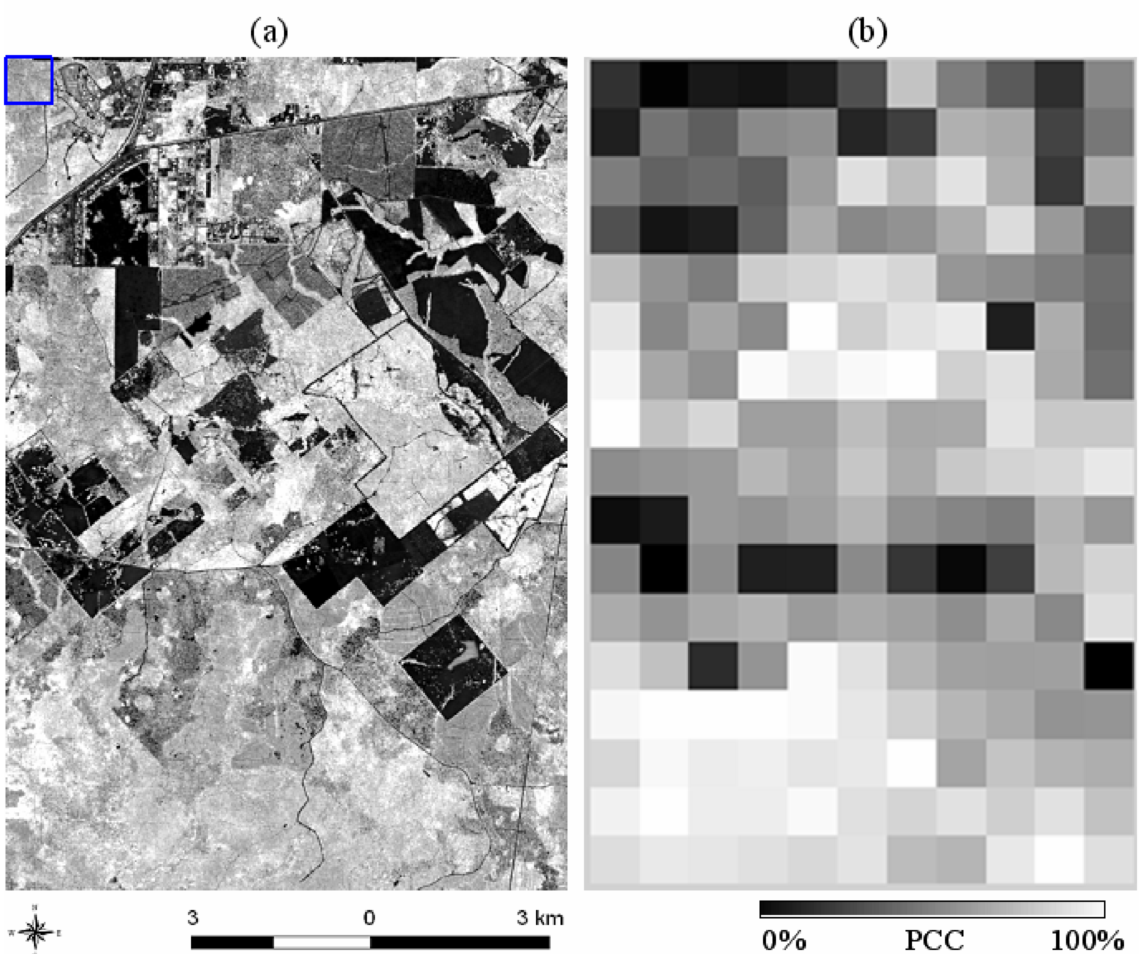

Fig. 3.5. (a) Local scale percent canopy cover (PCC) derived from linear regression and LiDAR measurements of the study area. The spatial resolution is 2.5 m. The blue square represents the area over which values were averaged to aggregate map. (b) Regional scale PCC from MODIS vegetation continuous fields (VCF). The spatial resolution is 500 m.

3.2.6 MODIS Information

Regional PCC data, also referred to as percent tree canopy cover, was taken from the MODIS 500m Global Vegetation Continuous Fields (VCF) (Hansen et al., 2003). The VCF PCC was created from seven MODIS imagery bands employing approximately one year of data. A nonlinear, distribution-free automated regression tree algorithm is one step used to create the VCF PCC, using classified Landsat training data as the dependent variable. Landsat images are aggregated to the MODIS grid, and then classified into four classes of tree cover, each class having a mean PCC label. Outputs from the regression tree are further modified by a stepwise regression and bias adjustment (Hansen et al., 2002b). The final output is PCC per 500 m MODIS pixel; MODIS VCF PCC is defined as the amount of skylight obscured by tree canopies equal to or greater than 5 m in height (Hansen et al., 2003). Figure 3.6 shows the North America VCF; PCC is shown in red, herbaceous cover in green, and bare cover in blue. A portion of the MODIS VCF PCC map corresponding to the study area (30° 42' N, 95° 23' W) was extracted from the North America map. Figure 3.5b shows this area.

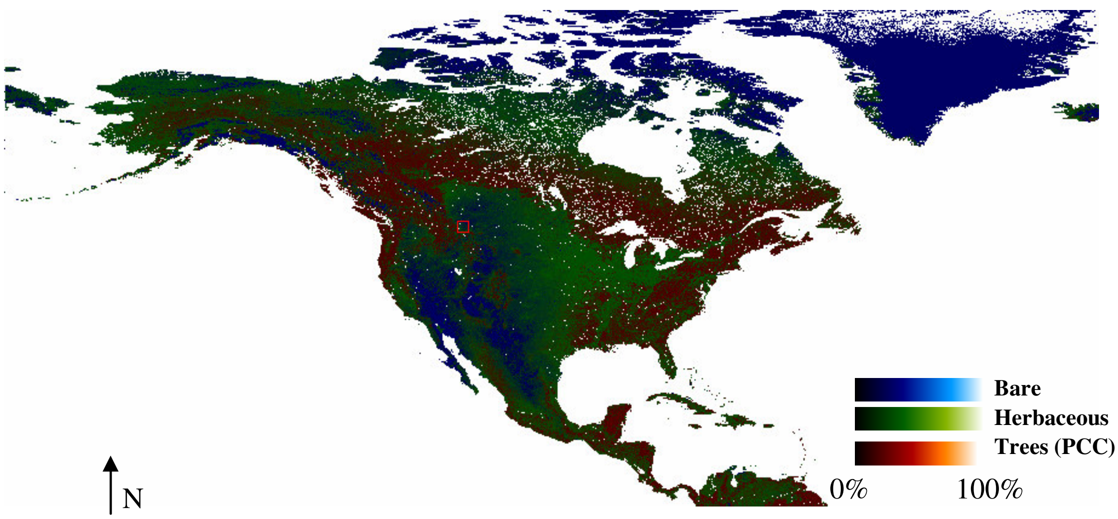

Fig. 3.6. North America MODIS global vegetation continuous fields (VCF) including percent canopy cover (PCC) at regional scale. The spatial resolution is 500 m.

The local scale predicted PCC map was aggregated to a resolution of 500m, taking the mean average over each newly created cell to determine the corresponding value with the MODIS tree cover map.

3.2.7 Regression Analysis

A simple linear regression model was fitted between LiDAR PCC values and MODIS PCC values to examine the relationship. Local scale LiDAR-generated PCC (PCC_{pred}), treated as ground reference values in this regression, was considered as the dependent variable and MODIS VCF PCC ($PCC_{MODIStree}$) was considered as the independent variable.

3.3 Results and Discussion

3.3.1 Results

The regression variable properties such as mean average, maximum and minimum are reported in Table 3.1. Each variable had a fairly normal distribution.

Table 3.1
Summary statistics of data used in linear regression analysis

Values/Units	Mean	Maximum	Minimum	Range	n (# observations)
PCC_{pred} (%)	31.46	51.7	0	51.7	187
$PCC_{MODIStree}$ (%)	61.44	82	26	56	187

The model resulting from the linear regressions for calibrating regional estimates of PCC based on local estimates was:

$$PCC_{pred} = 0.41 PCC_{MODIStree} + 6.29 \,. \qquad (3.3)$$

The r^2 of Equation 3.3 was 0.19 and root mean squared error (RMSE) was 9.81%. A plot of the data points and linear regression fit is shown in Figure 3.7.

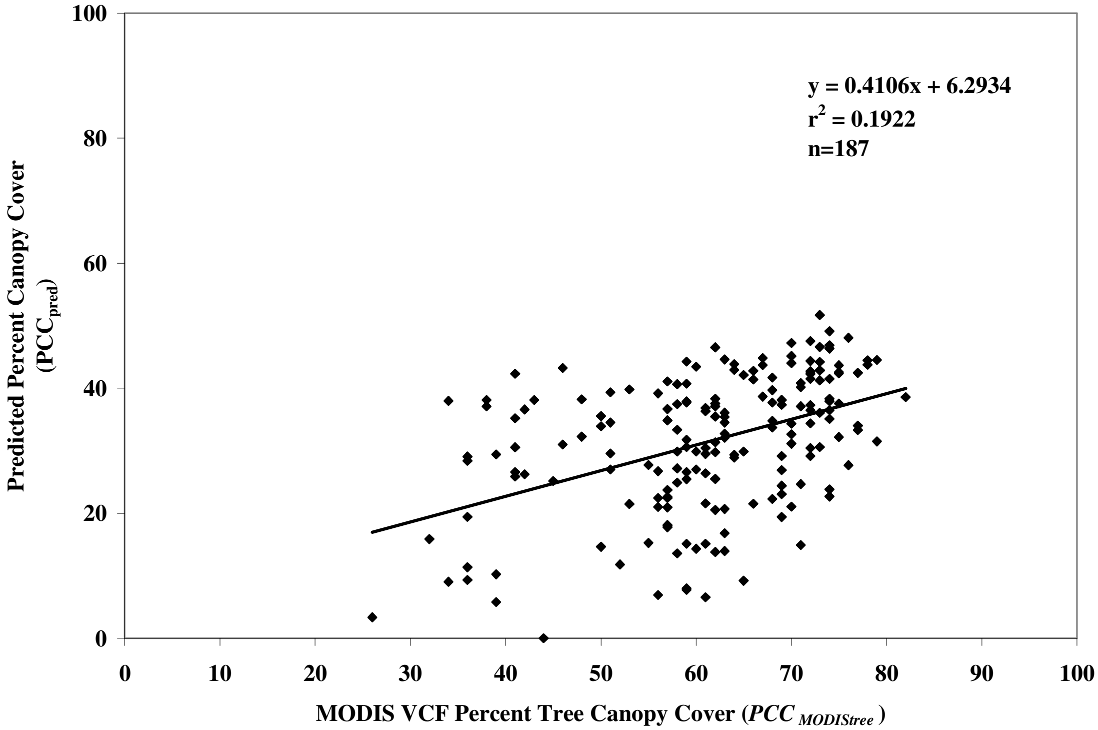

Fig. 3.7. Regression results, MODIS relationship

It can easily be observed from both Table 3.1 and Figure 3.7 that the local scale maximum PCC value is much lower than the regional scale maximum PCC value. This is most likely due to the differing scales. When local scale (2.5 m) PCC was aggregated to a regional (500 m) scale, the average of each subset of pixels was taken. Since there was a wide range of local scale PCC values in each 500 m × 500 m area, the mean for each area was probably quite a bit lower than the maximum for that area. Thus, the averaged aggregation caused an overall lowering of the local scale PCC values towards the mean. As shown in this overall study (Chapter II), LiDAR is a direct measure of PCC; at local scales, LiDAR data was an accurate predictor of field values of PCC both through multiple regression models and as a direct measure of PCC.

MODIS VCF PCC values, on the other hand, are formulated and validated through a series of averaging and scaling information up to larger scales (Hansen et al., 2002a;

Hansen et al., 2003). The averaging does not work in making an accurate product at local scales. MODIS VCF products are released at a resolution of 500 m, implying that the data is accurate for use at that scale. However, this study has clearly demonstrated that the MODIS VCF PCC, at least at local scales, is not accurate.

3.3.2 Conclusions

Estimation of land cover and percent tree cover at the regional and global scales is considered important for the monitoring and modeling of ecological and environmental processes (Schwarz & Zimmermann, 2005). The goal of this study was to compare regional MODIS estimates of percent tree cover with local LiDAR-derived estimates of PCC through a linear regression. Information was taken from both a local scale LiDAR-derived PCC map and corresponding regional MODIS PCC estimates. These two datasets were compared through simple linear regression. The determined relationship shows that the accuracy of MODIS VCF PCC at local scales is questionable.

This study found that LiDAR can be used to estimate local PCC at a resolution of 2.5 m with an R^2 of 0.84 and an RMSE of 9%, demonstrating the accuracy of LiDAR in predicting local scale PCC. Hansen et al. (2002a) found that the 500 m MODIS VCF PCC map had an overall RMSE of 8.5% when compared to a canopy cover map derived from ETM+ data, IKONOS data and field measurements. The larger scale tree cover map was designed for use in change detection studies at the global scale, not the regional or local scale (Hansen et al., 2003). This study has clearly demonstrated that the MODIS VCF PCC map is not accurate at local scales.

Further investigation is required to determine whether it is possible to calibrate the MODIS VCF PCC values to be accurate at local scales. One possible solution is for scanning LiDAR data to be collected over strategic areas of each continent, for use in calibrating the regional scale PCC estimates. LiDAR has been proven to be a direct and accurate measure of PCC and other forest biophysical parameters (Riaño et al., 2004; Popescu et al., 2004; Griffin et al., in review). Using LiDAR to calibrate MODIS data could improve the future accuracy and usefulness of the MODIS VCF maps.

CHAPTER IV
SUMMARY AND CONCLUSIONS

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, in fact, 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.

A third objective was to generate PCC and LAI maps of the study area. Maps were produced using the prediction models in Equations 2.7 and 2.8. These maps could have been produced from LiDAR-derived PCC with similar accuracy levels. Finally, the overall objective of the first part of this study (Chapter II) 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 and generate high-resolution maps of these characteristics at a local scale, using multiple regression.

A series of linear regressions incorporating independent variables from two LiDAR-derived canopy cover estimates, a LiDAR-derived CHM, TreeVaW-derived PCC values and NDVI was generated. Results indicate a strong relationship between LiDAR variables and observed PCC values, with the most predictive regression model having an R^2 value of 0.84. The best model prediction of LAI, also using only LiDAR variables, is nearly as strong with an R^2 value of 0.78.

This correlation is in keeping with the observed trend of previously cited studies, which also found a strong correlation between LiDAR-estimated canopy characteristics and observed LAI or PCC. The PCC estimation in particular was a good use of LiDAR because the coefficient of determination was near those of previous studies (Lovell et al., 2003; Popescu et al., 2004; Riaño et al., 2004).

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 and crown fuels (Mutlu, in review). The height bin methods 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, in review).

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, N.J.J., 2003; Coops et al., 2004). Doing so may have increased the agreement between the estimated LAI and ground reference values in this study.

Estimation of land cover and percent tree cover at the regional and global scales is considered important for the monitoring and modeling of ecological and environmental processes (Schwarz & Zimmermann, 2005). The goal of this study was to compare regional MODIS estimates of percent tree cover with local LiDAR-derived estimates of PCC through a linear regression. Information was taken from both a local scale LiDAR-derived PCC map and corresponding regional MODIS PCC estimates. These two datasets were compared through simple linear regression. The determined relationship shows that the accuracy of MODIS VCF PCC at local scales is questionable.

This study found that LiDAR can be used to estimate local PCC at a resolution of 2.5 m with an R^2 of 0.84 and an RMSE of 9%, demonstrating the accuracy of LiDAR in predicting local scale PCC. Hansen et al. (2002a) found that the 500 m MODIS VCF PCC map had an overall RMSE of 8.5% when compared to a canopy cover map derived from ETM+ data, IKONOS data and field measurements. The larger scale tree cover map was designed for use in change detection studies at the global scale, not the regional or local scale (Hansen et al., 2003). This study has clearly demonstrated that the MODIS VCF PCC map is not accurate at smaller scales.

Further investigation is required to determine whether it is possible to calibrate the MODIS VCF PCC values to be accurate at local scales. One possible solution is for scanning LiDAR data to be collected over strategic areas of each continent, for use in calibrating the regional scale PCC estimates. LiDAR has been proven to be a direct and accurate measure of PCC and other forest biophysical parameters (Riaño et al., 2004; Popescu et al., 2004; Griffin et al., in review). Using LiDAR to calibrate MODIS data could improve the future accuracy and usefulness of the MODIS VCF maps.

REFERENCES

Avery, T.E. & Burkart, H.E. (1994). *Forest Measurements, 4th Edition*. (p.408) New York: McGraw-Hill, Inc.

Baret, F. & Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*, 35, 161-173

Berterretche, M., Hudak A.T., Cohen W.B., Maiersperger, T.K., Gower, S.T. & Dungan, J. (2005). Comparison of regression and geostatistical methods for mapping Leaf Area Index (LAI) with Landsat ETM+ data over a boreal forest. *Remote Sensing of Environment*, 96, 49-61

Bréda, N.J.J. (2003). Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. *Journal of Experimental Botany*, 54 (392), 2403-2417

Casanova, D., Epema, G.F. & Goudriaan, J. (1998). Monitoring rice reflectance at field level for estimating biomass and LAI. *Field Crops Research*, 55, 83-92

Chapin, F.S., Matson, P.A. & Mooney, H.A. (2002). *Principles of Terrestrial Ecosystem Ecology*. (p.108) New York: Springer Science and Business Media, Inc.

Chen, J.M., Rich, P.M., Gower, S.T., Norman, J.M., & Plummer, S. (1997). Leaf are index of boreal forest: Theory, techniques, and measurements. *Journal of Geophysical Research*, 102(D24), 429-444

Chen, Q., Baldocchi, D., Gong, P., & Kelly, M. (2006). Isolating individual trees in a savanna woodland using small footprint lidar data. *Photogrammetric Engineering and Remote Sensing*, 72(8), 923-932

Coops, N.C., Smith, M.L., Jacobson, K.L., Martin, M. & Ollinger, S. (2004). Estimation of plant and leaf are index using three techniques in a mature native eucalypt canopy. *Austral Ecology*, 29, 332-341

Curran, P.J., Dungan, J.L. & Gholz, H.L. (1992). Seasonal LAI in slash pine estimated with Landsat TM. *Remote Sensing of Environment*, 39, 3-13

Duranton, H., Soudani, K., Trautmann, J. & Walter, J. (2001). Comparison of optical methods for estimating canopy openness and leaf area index in broad-leaved forests. *Comptes Rendus de l'Académie des Sciences*, 324(4), 381-392

Englund, S.R., O'Brien, J.J. & Clark, D.B. (2000). Evaluation of digital and film hemispherical photography and spherical densiometry for measuring forest light environments. *Canadian Journal of Remote Sensing*, 30, 1999-2005

ENVI Software. (2006). Version 4.2. ITT Industries Inc., Boulder, CO, USA

Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., & Schaaf, C. (2002). *Remote Sensing of Environment*, 83, 287-302

Gill, S.J., Biging, G.S., & Murphy, E.C. (2000). Modeling conifer tree crown radius and estimating canopy cover. *Forest Ecology and Management*, 126, 405-416

Griffin, A.M.R., Popescu, S.C. & Zhao, K. Using LiDAR and normalized difference vegetation index to remotely determine LAI and percent canopy cover. (in review, *Remote Sensing of Environment*)

Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Carroll, M., Dimiceli, C., & Sohlberg, R.A. (2003). Global percent tree cover at a spatial resolution of 500 meters: First results of the MODIS vegetation continuous fields algorithm. *Earth Interactions*, 7(10), 1-15

Hansen, M.C., DeFries, R., Townshend, J.R., Carroll, M., Dimiceli, C., & Sohlberg, R. (2003). 500m MODIS Vegetation Continuous Fields. Data. College Park, Maryland: The Global Land Cover Facility

Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Marufu, L., & Sohlberg, R. (2002a). Development of a MODIS tree cover validation data set for Western Province, Zambia. *Remote Sensing of Environment*, 83, 320-335

Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Sohlberg, R., Dimiceli, C., & Carroll, M. (2002b). Towards an operational MODIS continuous field of percent tree cover algorithm: Examples using AVHRR and MODIS data. *Remote Sensing of Environment*, 83, 303-319

HemiView Canopy Analysis Software. (1999). Version 2.1. Delta-T Devices Ltd., Cambridge, United Kingdom

HemiView User Manual. (1999). Version 2.1. Cambridge, United Kingdom: Delta-T Devices Ltd.

Interactive Data Language. (2006). ITT Industries Inc., Boulder, CO, USA

Jonckheere, I., Muys, B., & Coppin, P. (2005). Allometry and evaluation of in situ optical LAI determination in Scots pine: A case study in Belgium. *Tree Physiology*, 25, 723-732

Koch, B., Heyder, U. & Weinacker, H. (2006). Detection of individual tree crowns in airborne lidar data. *Photogrammetric Engineering and Remote Sensing*, 72(4), 357-363

Lefsky, M.A., Cohen, W.B., Parker G.G., & Harding, D.J. (2002). Lidar remote sensing for ecosystem studies. *BioScience*, 52(1), 19-30

Lovell, J.L., Jupp, D.L.B., Culvenor, D.S. & Coops, N.C. (2003). Using airborne and ground-based ranging LiDAR to measure canopy structure in Australian forests. *Canadian Journal of Remote Sensing*, 29, 607-622

Means, J.E., Acker, S.A., Fitt, B.J., Renslow, M., Emerson, L. & Hendrix, C. (2000). Predicting forest stand characteristics with airborne scanning lidar. *Photogrammetric Engineering and Remote Sensing*, 66(11), 1367-1371

Means, J.E., Acker, S.A., Harding, D.J., Blair, J.B., Lefsky, M.A., Cohen, W.B., Harmon, M.E. & McKee, W.A. (1999). Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the western Cascades of Oregon. *Remote Sensing of Environment*, 67, 298-308

Merilo, E., Heinsoo, K. & Koppel, A. (2004). Estimation of leaf area index in a willow plantation. *Proceedings of the Estonian Academy of Sciences, Biology, Ecology*, 53(1), 3-13

Microsoft Excel 2002. (1985-2001). Microsoft Corporation, Redmond, WA, USA

Mussche, S., Samson, R., Nachtergale, L., De Schrijver, A., Lemeur, R. & Lust, N. (2001). A comparison of optical and direct methods for monitoring the seasonal dynamics of leaf area index in deciduous forests. *Silva Fennica* 35(4), 373-385

Mutlu, M., Popescu, S.C., Stripling, C. & Spencer, T. Mapping surface fuel models using LIDAR and multispectral data fusion for fire behavior. (in review, *Remote Sensing of Environment*)

Nelson, R. (2006). Personal conversation, properties of scanning LiDAR. Sept. 29, 2006

Nelson, R., Krabill, W. & MacLean, G. (1984). Determining forest canopy characteristics using airborne laser data. *Remote Sensing of Environment*, 15, 201-212

Nemani, R.R., Keeling, C.D., Hashimoto, H., Jolly, W.M., Piper, S.C., Tucker, C.J., Myneni, R.B., Running, S.W. (2003). Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science*, 300, 1560-1563

Pocewicz, A.L., Gessler, P. & Robinson, A.P. (2004). The relationship between effective plant are index and Landsat spectral response across elevation, solar insolation, and spatial scales in a northern Idaho forest. *Canadian Journal of Remote Sensing*, 34, 465-480

Popescu, S.C. & Wynne, R.H. (2004). Seeing the trees in the forest: Using LIDAR and multispectral data fusion with local filtering and variable window size for estimating tree height. *Photogrammetric Engineering and Remote Sensing*, 70(5), 589-604

Popescu, S.C., Wynne, R.H. & Scrivani, J.A. (2004). Fusion of small-footprint LiDAR and multispectral data to estimate plot-level volume and biomass in deciduous and pine forests in Virginia, USA. *Forest Science*, 50, 551-565

Popescu, S.C., Wynne, R.H., & Nelson, R.H. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29(5), 564-577

Popescu, S.C., Wynne, R.H., & Nelson, R.H. (2002). Estimating plot-level tree heights with lidar: Local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture*, 37(1-3), 71-95

Popescu, S.C. & Zhao, K. LiDAR tomography of forest vegetation: An application for estimating crown base height for deciduous and pine trees. (in review, *Remote Sensing of Environment*)

Reutebuch, S.E., Anderson, H. & McGaughey, R.J. (2005). Light Detection and Ranging (LIDAR): An emerging tool for multiple resource inventory. *Forest Science*, 103(6), 286-292

Riaño, D., Valladares, F., Condés, S. & Chuvieco, E. (2004). Estimation of leaf area index and covered ground from airborne laser scanner (LiDAR) in two contrasting forests. *Agricultural and Forest Meteorology*, 124, 269-275

Ritchie, J.C., Everitt, J.H., Escobar, D.E., Jackson, T.J. & Davis, M.R. (1992). Airborne laser measurements of rangeland canopy cover and distribution. *Journal of Range Management*, 45, 189-193

Roberts, S.D., Dean, T.J., Evans, D.L., McCombs, J.W., Harrington, R.L. & Glass, P.A. (2005). Estimating individual tree leaf area in loblolly pine plantations using LiDAR-derived measurements of height and crown dimensions. *Forest Ecology and Management*, 213, 54-70

SAS Software. (2002-2003). Version 9.1. SAS Institute, Inc., Cary, NC, USA

Schlerf, M. & Atzberger, C. (2006). Inversion of a forest reflectance model to estimate structural canopy variables from hyperspectral remote sensing data. *Remote Sensing of Environment*, 100, 281-294

Schwarz, M. & Zimmermann, N.E. (2005). A new GLM-based method for mapping tree cover continuous fields using regional MODIS reflectance data. *Remote Sensing of Environment*, 95, 428-443

Weltz, M.A., Ritchie, J.C. & Fox, H.D. (1994). Comparison of laser and field measurements of vegetation height and canopy cover. *Water Resources Research*, 30, 1311- 1319

White, J.D., Running, S.W., Nemani, R., Keane, R.E. & Ryan, K.C. (1997). Measurement and remote sensing of LAI in Rocky Mountain montane ecosystems. *Canadian Journal of Remote Sensing*, 27, 1714-1727

White, M.A., Shaw, J.D., & Ramsey, R.D. (2005). Accuracy assessment of the vegetation continuous field tree cover product using 3954 ground plots in the south-western USA. *International Journal of Remote Sensing*, 26(12), 2699-2704

VITA

Alicia Marie Rutledge Griffin received her Bachelor of Science degree in aerospace engineering from Texas A&M University in 2004. She entered the Forest Science program at Texas A&M University in January 2005, and she received her Master of Science degree in December 2006. Her research interests include remote sensing with an emphasis in Light Detection and Ranging (LiDAR). She hopes to pursue a doctoral degree in planetary science.

Ms. Griffin may be reached at the Spatial Sciences Laboratory, Texas A&M University, 1500 Research Parkway, Suite B223, 2120 TAMU, College Station, TX 77843-2120. Her e-mail address is alicia.rutledge@gmail.com.