Red-cockaded Woodpecker (*Picoides borealis*) habitat analysis via remote sensing

Scott Tweddale[1], H. Alexis Londo[2], Joelle M. Carney[3] David L. Evans[4], Scott D. Roberts[5], Robert C. Parker[6] and Stephen C. Grado[7]

[1]US Army Corps of Engineers, Construction Engineering Research Laboratory, Scott.A.Tweddale@erdc.usace.army.mil
[2]Department of Forestry, Mississippi State University, alondo@cfr.msstate.edu
[3]Department of Forestry, Mississippi State University, jcarney@cfr.msstate.edu
[4]Department of Forestry, Mississippi State University, devans@cfr.msstate.edu
[5]Department of Forestry, Mississippi State University, sroberts@cfr.msstate.edu
[6]Department of Forestry, Mississippi State University, rparker@cfr.msstate.edu
[7]Department of Forestry, Mississippi State University, sgrado@cfr.msstate.edu

Abstract

Multi-spectral imagery and multiple-return light detection and ranging (LIDAR) data were used to assess forest composition and structure for determining habitat suitability for red-cockaded woodpecker (*Picoides borealis;* RCW). Object-oriented classification of the imagery yielded covertype and distinguished between loblolly (*Pinus taeda*) and longleaf (*Pinus palustris*) pine with an accuracy of 80.8% when combining both pine species into one class and 73.7% when classifying pine species separately. The average stem diameter for pine areas was estimated using LiDAR data to identify and estimate individual stem heights. Field-derived height-diameter relationships were used to estimate diameter distribution. LiDAR-estimated mean basal area (BA - square meter/hectare) for canopy trees (14.05 m^2/ha) and canopy trees in the top quartile of height (7.03 m^2/ha) was not significantly different from field measurements of basal area for all trees (15.6 m^2/ha) and top quartile trees (8.05 m^2/ha) for 69 plots distributed across three sample areas ($\alpha = 0.05$). The density of midstory/understory hardwoods derived from LIDAR in 4 height strata; 0.5 – 2.1 m, 2.1–4.6 m, 4.6 m to height to live crown (HLC), and canopy, were correlated with field measurements of total cover, resulting in an R^2 of 0.0, 0.26, 0.36 and 0.60 for each stratum, respectively.

1. Introduction

The endangered red-cockaded woodpecker (*Picoides borealis*; RCW) of the Southern United States is the only species of woodpecker to excavate nest cavities within the trunks of living pine trees (preferably mature longleaf pine (*Pinus palustris*)) old enough to have developed sufficient heartwood (Zwicker and Walters 1999). Midstory and understory vegetation height and composition are important in characterizing the quality of RCW habitat. Rudolph et al. (2002) found that RCWs prefer to forage on trees where there was low density midstory vegetation and that foraging occurred at greater heights above ground on sites with greater midstory heights and densities. Zwicker and Walters (1999) stated RCWs were found to have preferences for pines >23 cm diameter at breast height (dbh) and avoided pines <13 cm dbh.

The basic information required for describing forest type and structure is often expensive and time consuming to collect in the field and requires periodic updates to remain valid (Xiao and McPherson 2004). Detailed identification of individual tree species or species groups has been demonstrated in analysis of digital multi-spectral imagery (Knight et al. 2004; Casey 1999;

Batten and Evans 1997; Hughes et al. 1986). Fusing spectral with light detection and ranging (LiDAR) data can take advantage of the strengths of both sensors for the purpose of improving estimates of forest stand characteristics (Leckie et al. 2003; McCombs et al. 2003).

Modern LiDAR systems generate x,y,z coordinate data from aerial platforms by laser ranging, operating at pulse rates of up to 200 kHz as noted in recent technology specifications from data providers. The spatial resolution, measurement accuracy and spectral response of these systems to vegetation have lead to a significant body of research on the use of LiDAR data for forest assessments. There are a variety of different approaches taken towards tree recognition and height determination (Popescu and Wynne 2004; Brandtberg et al. 2003; Persson et al. 2002; Zimble 2002; Eggleston 2001). The approach used in this project is based on the one described by McCombs et al. (2003). Tree locations with heights derived from LiDAR have a number of possible uses in defining the structural character of a stand, and thus the habitat suitability for different wildlife species (Hinsley et al. 2002; Zimble et al. 2003; Hill et al. 2004).

The overarching goal of this research was to demonstrate the use of high resolution multi-spectral imagery and LiDAR remote sensing technologies to generate a landscape-scale habitat preference variable expressed as geospatial layers available for habitat suitability modeling for the RCW. Specifically, the objectives were to: 1) determine pine and hardwood canopy species composition within forest stands, 2) determine the average size (diameter distribution) of pine dominated stands, and 3) assess the spatial distribution and total cover of midstory/understory hardwoods and other ground cover.

2. Methods

A 30 km^2 study area was selected for analysis that encompasses three separate forest tracts located along a corridor between 2 populations of RCWs in Hoke County, North Carolina. The tracts include: a private forest land managed partly for pine straw production, a state owned conservation area, and the southwest corner of a federally managed military base. The area is located within the Coastal Plain which is characterized by flat land to gently rolling hills and valleys. The vegetation of this region includes: grassland and early-successional habitats, pine woodland, and river bottoms. Elevation ranges from sea level near the coast to about 183 m in the Sand Hills of the Southern Inner Coastal Plain (Outcalt and Sheffield 1996, North Carolina Geographical Survey 2005).

2.1 Data Acquisition

LiDAR data were acquired July 13, 2005 at a nominal posting density of 4.0 points per m^2 and recorded as first, only (only 1 return was recorded), second, and third returns in Universal Transverse Mercator (UTM; NAD83, GRS80) x, y, and z coordinates. The data were used to generate canopy and ground elevation raster models at a resolution of 0.5 m for each of the study tracts. These models were used to determine locations of trees and their associated heights for evaluation of stand structure.

Airborne multi-spectral (CIR) imagery was acquired July 26, 2005 at 0.25 m resolution in four spectral channels: blue (450 nm), green (550 nm), red (650 nm), and NIR (850 nm). The individual frames were ortho-rectified to a ground digital elevation model (DEM) and mosaiced for each of the three study area tracts.

Field data were collected in November/December 2006 for training and validation of classifications made with the multi-spectral data and analysis of measurements calculated from the LiDAR data. Coordinates for 69 plot centers were randomly generated and circular plots were established at these points using a radius 11.3 m and nesting an inner plot of radius 8 m. These plots were distributed across all three study areas and their location recorded with real-time differential GPS. Within the larger plot, total number of stems and total tree height, dbh, location, height to live crown (HLC), crown diameter, and species of each overstory/midstory stem were recorded. Overstory/misdstory trees were defined as those trees with dbh greater than 2.54 cm. In the inner nested plot, understory vegetation measurements of total height, location, crown diameter, whether they were single or multiple stems, and species were recorded. The plot data were used to assess the accuracy of individual stem identification with LIDAR and to develop height-diameter relationships for prediction of stem diameters on LiDAR-detected pine trees. The midstory/understory observations were assessed for area coverage and coupled with LiDAR point densities to predict total cover of the vegetation under the main canopy (see section 2.4).

2.2 Canopy Species Classification

Field site inspections indicated that much of the longleaf pine tended to occur as either open-grown individuals or in small groups that could be readily distinguished from other targets. Broadleaf hardwoods tended to occur in clumps either in gaps between pine crowns or in contiguous stands at lower slope positions and along drainages. Because each target of interest occurs as a group of pixels rather than an individual pixel, a segmenting (object-based) image classification rather than pixel-based image classification technique was applied using eCognition 4.0.

The segmentation process was interactively guided to utilize scale, color, and shape parameters to generate image objects that covered individual tree crowns or groups of trees visible in the imagery. Member functions to separate shadow objects from non-shadow objects were instituted first followed by member functions to distinguish between vegetation objects and non-vegetation objects in the non-shadow areas. Member functions to ascertain longleaf, loblolly, hardwood, and other vegetation were subsequently applied to the vegetation objects. All multispectral bands and a Normalized Difference Vegetation Index (NDVI) were input into the classifier.

Classification accuracy was assessed using 552 points, including 109 samples for each of the 3 tree species and 75 samples each for shadow, bare ground, and low vegetation.
Classification accuracy was calculated from samples based on commonly reported methods of error matrix calculations (Congalton and Green 1999).

Due to the misregistration between LiDAR and the imagery, the final classification was generalized by calculating the majority class present in an aggregation window size of 6m-by-6m. This facilitated the ability to match vegetation types to LiDAR derived trees. This was an important step in determining the dominant stand type by size class in the RCW habitat evaluation process.

2.3 Pine Size Class Determination

Individual pine tree data from all field plots were analyzed to determine the relationship between tree height and stem diameter using regression procedures. This regression function was then applied to LiDAR-identified trees to estimate a diameter for each stem.

All probable canopy trees were identified and mapped within the three study tracts by use of the LiDAR elevation models and modified procedures adopted from those first described by McCombs et al. (2003). One difference between this procedure and that described in McCombs et al. (2003) was that spectral data were not incorporated into the identification function due to spatial misregistration between the multispectral and LiDAR data. The second and most important difference is that the new procedure introduces stem density and crown size dependent functionality in tree identification and therefore is more adaptable to ranges of conditions over which the model is applied.

The procedure consisted of two spatial process models which identified and estimated heights of probable tree locations in the main canopy of forest stands using the canopy and bare ground LiDAR surfaces. A smoothing filter was used to eliminate pits where LiDAR points penetrated the main canopy. The model identified clumps of pixels in the canopy height surface that were higher than a set percentage of neighboring pixels. Identification of these clumps of pixels was determined by using a focal rank utility with a variable search filter size keyed to the size of small, medium and large target tree crowns based on relative stem density. The resulting clumps were subjected to a sieving operation based on the estimated smallest tree crown to eliminate small groups of pixels that were not likely trees. The output clumps from this model, as well as the canopy and bare ground surfaces, were passed to the second model, which extracted the location and height value of the highest pixel in each clump as a tree location. A distance function was used to delete trees adjacent to, but shorter than nearby neighbors (probable false tree identified) based on tree height. Short trees were allowed to be closer together than tall trees. These geospatial data were used to develop the size class analysis for all pine areas.

The classification developed from the multi-spectral data was used to label all LiDAR-identified trees as to tree type (pine or hardwood). The diameter at breast height (dbh) to height relationship developed from the field data was applied to all LiDAR-identified pine trees to attribute those tree locations with estimated dbh. The last step was to examine the relative size of LiDAR-identified pines on a unit area basis to generate a geospatial layer of tree sizes grouped by the three diameter size classes: < 24.5 cm, 24.5 to 35 cm, and > 35 cm and pine type (loblolly or longleaf). These three pine size classes, along with evaluations of hardwood competition and midstory/understory total vegetation cover form the basis for identification of either areas currently suitable for RCW habitat or areas that, through proper management, could be made suitable for use by RCWs.

2.4 Midstory/Understory Density Analysis

Density of LIDAR returns in the canopy, > 4.6 m and > HLC, and three understory/midstory strata, 0.5 m to 2.1 m, > 2.1 m to 4.6 m, > 4.6 m and < HLC, were used to estimate understory/midstory vegetation total cover. The ground elevation value was subtracted from each LiDAR return height to determine height above terrain for each LiDAR point. The number of LiDAR returns in each height stratum were summed on 1.0 m grid cells to assign cell values representing return density by stratum. Total LiDAR shot density (first and only returns) was utilized to normalize the point densities at each level for changes in total shot density due to flight line overlap and scan line expansion and compression due to variable flying conditions. The normalized LiDAR density values were compared to field measurements of understory/midstory vegetation cover for all field plots.

An analysis of the field data indicated the mean HLC occurred at 10.5 m for all dominant/co-dominant pine tree observations. However, HLC varies spatially, so a method was developed to characterize the spatial variation in HLC and adjust the threshold that separated understory/midstory and canopy returns accordingly.

The LiDAR detected trees with associated heights were first attributed for the height to base of live crown using a regression relationship derived from field measurements of total height to HLC . The HLC values at tree locations were then spatially "grown" in all horizontal directions using a focal analysis kernel to create a continuous raster layer that characterized the canopy cutoff height based on the spatial variation of crown base height. This was then used to classify all points as either canopy or subcanopy points. Establishment of a raster surface that characterized spatial variation in HLC allowed the threshold height separating the midstory from canopy to be varied across the terrain rather than using a constant HLC to establish the threshold height. The comparisons of field measures of understory/midstory total cover and LiDAR return density was performed for the modified definition of height classes as described in the previous section.

3. Results and Discussion

3.1 Canopy Species Composition

The overall accuracy of the resulting classification after separating the pine cover type into loblolly and longleaf was 73.73%, with an overall kappa statistic of 0.682. The overall classification accuracy increased to 80.80% when loblolly and longleaf were combined into one pine cover type, and the overall kappa statistic increased to 0.737.

3.2 Pine Size Class Determination

The tree identification model identified most canopy trees and some smaller trees in canopy gaps and open areas. The comparison of dominant/co-dominant plot trees to LiDAR-identified trees revealed some inconsistencies in this procedure's ability to detect all trees. Due to imprecision in the ground based GPS measurements, tree matching of field measured trees was difficult. This was largely attributed to assumed errors in GPS fixes on plot locations and the field measurement errors in tree location establishment relative to these GPS positions.

LiDAR derived trees were matched to the overstory/midstory field measured observations where possible in order to assess the accuracy of the tree finding model. Some adjustment for plot location was necessary to match LiDAR derived trees with field observations. These procedures produced 476 matched trees (65 hardwood and 411 pine) from a possible 730 trees for a detection rate of 65.21%. The privately managed area (71.96% agreement) and state managed tract (65.66% agreement) performed better than the federally managed tract (58.96% agreement). Overall, this is theorized to be due to the variations in growing conditions and site qualities. As expected, LIDAR detection of pine trees (54.0% agreement) proved more successful than hardwood detection (13.0% agreement).

After assessing the performance of the tree finding model using all field measured trees as validation, a subset of the field measured trees was selected in an attempt to identify dominant and co-dominant stems in the canopy. For each plot, the limiting height for the upper quartile (top 25%) was determined and was used to subset the field data by only retaining stems with height in the upper quartile. This subset provided a total of 335 possible trees (70 hardwood and 278 pine) of which 28 hardwood and 195 pine were matched for an agreement of 66.57%. Again the privately managed tract (76.09% agreement) and state managed tract (68.52% agreement) performed better than the federally managed tract (58.52% agreement) (Table 1).

Table 1. Site and overall accuracy results of the pairing of LiDAR derived trees with field observations of trees in the upper quartile of total tree height by plot.

	Privately Owned					
Field Samples					**LiDAR Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	7	63	4	59	**Matched**	70
Omission	23	21	3	18	**Commission**	22
Total	30	84	7	77	**Total**	92
% Matched	23.33	75.00	57.14	76.62	**% Matched**	76.09
% Omission	76.67	25.00	42.86	23.38	**% Commission**	23.91
	Federally Managed					
Field Samples					**LiDAR Samples**	
	Hardwood	Pine	Loblolly	Longleaf		Model
Matched	16	63	4	59	**Matched**	79
Omission	15	54	8	44	**Commission**	56
Total	31	117	12	103	**Total**	135
% Matched	51.61	53.85	33.33	57.28	**% Matched**	58.52
% Omission	48.39	46.15	66.67	42.72	**% Commission**	41.48
	State Managed					
Field Samples					**LiDAR Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	5	69	31	38	**Matched**	74
Omission	4	8	4	4	**Commission**	34
Total	9	77	35	42	**Total**	108
% Matched	55.56	89.61	88.57	90.48	**% Matched**	68.52
% Omission	44.44	10.39	11.43	9.52	**% Commission**	31.48
	All Three Tracts Combined					
Field Samples					**LiDAR Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	28	195	39	156	**Matched**	223
Omission	42	83	15	66	**Commission**	112
Total	70	278	54	222	**Total**	335
% Matched	40.0	70.1	72.2	70.3	**% Matched**	66.57
% Omission	60.0	29.9	27.8	29.7	**% Commission**	33.43

The tree finding model assigned the LiDAR measured height for each tree location. Using the LiDAR height measurement, it was possible to attribute each tree with an estimate of its diameter using the diameter height relationship developed from all field measured pine:

$$\ln(dbh) = -0.640235 + 1.0165769 * \ln(\text{Total Height}) \quad (1)$$

with an R^2 of 0.73 and RMSE of 0.26. This equation was developed from 689 intact pine trees greater than 7.62 cm in dbh. After assigning a height and dbh attribute to each LIDAR identified pine stem, LIDAR derived estimates of basal area were determined.

Comparisons between LiDAR derived estimates of height, dbh, and basal area and field measurements of these variables showed height estimates derived from LIDAR to be highly correlated with field measurements (R^2=0.91). LIDAR derived estimates of dbh and basal area (BA– square meter per hectare) were not as highly correlated with field measures (R^2=0.54 and R^2=0.46 respectively). Diameter estimates were based on height-diameter relationships which partially explain variations in diameter as a function of height. Therefore, errors associated with diameter estimates derived from height were compounded when these diameter estimates were used to estimate basal area.

Errors in omission and commission with the tree finding model also contributed to the errors in stem density and BA estimation, although omission and commission errors tended to cancel each other thus resulting in a fairly accurate estimation of stem density. The effects of the omission and commission trees on basal areas estimates were examined by evaluating the average of field measured BA compared to the average of LiDAR estimated BA by site for all overstory/midstory pine trees. These were separated into relevant dbh classes as defined in the RCW recovery guidelines (USFWS 2003). Significant differences were seen between the LiDAR estimates and the field measurements for the privately managed tract and the federally managed tract but across all the sites, there were no significant differences found. The analysis was repeated using only trees in the top quartile of height for each plot. Although significant differences can be seen in some of the diameter classes, field measured mean pine BA was not significantly different from mean LiDAR derived estimates of pine BA for each site separately and for all sites combined (LiDAR estimate = 14.03m^2/ha vs. field measurement = 15.59 m^2/ha). The errors in BA calculations by diameter classes can be attributed to the effect of the bias in the LiDAR estimated height on the calculated dbh value as well as the inclusion of omitted and committed trees into each diameter class.

3.3 Midstory/Understory Density Analysis

All returns from the LiDAR data were used in the midstory/understory density analysis. For each return, a ground elevation value and a HLC value was determined. The ground elevation value was required to calculate height above ground for each LiDAR return. The ground value was determined by matching the coordinates of each LiDAR return with the ground elevation model. The HLC value for each LiDAR return was determined by matching the coordinates of each LiDAR return with a raster model that characterized the spatial variation in HLC. The raster model of HLC was created using a two step process. First, HLC values for individual stems identified with LIDAR in the raster stem map were estimated using the regression relationship derived from field measurements of total height to HLC:

$$HLC = 0.69415 * \text{Total Height} - 1.51926 \quad (2)$$

with an R^2 of 0.78 and RMSE of 2.50. Next all tree locations in the raster stem map with total heights 4.6 m or less were removed. Moving a 3.5 m X 3.5 m kernel across the raster stem map, the HLC values estimated for each stem location were extended from the stem location to pixels in close proximity to the stem (areas under canopy and between stems) by assigning the lowest HLC value for any stems in the kernel to all remaining pixels in the kernel. In order to accurately characterize the spatial extent of the canopy while not extending the spatially variable HLC surface into open areas with no canopy, the algorithm was repeated three times These values and the ground elevation values were added as attributes for each LiDAR data point.

All LiDAR points were categorized into the height class bins in which they occurred. The height classes used in this portion of the study to create each bin were 0.5 m to 2.1 m, > 2.1 m to 4.6 m, > 4.6 m and < HLC, and > 4.6 m and > HLC. For each height class, the number of returns per 1.0 m pixel were summed and assigned to the pixel value. LiDAR returns below 0.5 m were not included in the analysis to eliminate confusion between near ground and ground returns.

For each field plot and for each height class, the sum of total area coverage for each midstory/understory tree canopy was calculated using the zonal sum statistic. All pixels representing coverage were summed for each plot yielding the zonal sum of coverage by plot. The number of pixels for each field plot was converted to square meters to determine total vegetation cover in each midstory/understory height class. Additionally the sum of the number of LiDAR returns intercepted in the same height class strata was summed for each plot.

The relationship between the sum of area for midstory/understory canopy coverage for each plot and the number of LiDAR interceptions for each height class was positively correlated. The correlations were greatest in the HLC to top of canopy (R^2=0.60) and second highest in the > 4.6 m to HLC strata (R^2=0.36). On the privately owned sited and the state managed site the second highest stratum (> 4.6 m to HLC) (R^2=0.82 - private and R^2=0.94 - state) performed better than the higher stratum (HLC to top of canopy) (R^2=0.68 - private and R^2=0.70 - state) (Table 2).

Table 2. Results of midstory/understory analyses between percent area coverage observed (square meters) and LiDAR interception density for each midstory/understory height class.

	Privately Owned		**Federally Managed**		**State Managed**		**All Combined**	
	R square	**RMSE**	**R square**	**RMSE**	**R square**	**RMSE**	**R square**	**RMSE**
0.5 to 2.1 meters	0.04	27.42	0.06	8.51	0.26	27.42	0.00	26.37
2.1 meters to 4.6 meters	0.31	12.38	0.65	7.86	0.20	15.64	0.26	13.02
4.6 meters to HLC	0.82	6.10	0.41	33.90	0.94	6.43	0.36	37.14
HLC to Canopy Top	0.68	17.10	0.47	32.24	0.70	21.05	0.60	23.94

3.4 Landscape-scale Habitat Model

The results from this study outline methods to utilize multi-spectral imagery and LiDAR data to evaluate a series of forest stand parameters associated with RCW habitat that can not be feasibly assessed across extensive landscapes with traditional inventories alone. Not only do these methods provide detailed habitat information at landscape scales and at reduced costs, but they also provide the capability to assess and monitor RCW habitat suitability in areas that are inaccessible to field surveys, including impact area safety zones on military installations and adjoining private land. Synoptic assessment and monitoring of RCW habitat suitability across a variety of land uses and ownership provides vital information to wildlife management professionals and other stakeholders in efforts to manage and monitor habitat conditions at regional and landscape scales. Information is also valuable to military land managers as they strive to manage pine forest to sustain the primary training mission while also managing forest conditions to maintain or improve habitat suitability for the species.

References

Batten, S. and D.L. Evans. 1998. Forest stand assessments with high-resolution multispectral frame camera data. In: *Proceedings of the First International Conference on Geospatial Information in Agriculture and Forestry*. Volume I, 1998 June 1-3, Lake Buena Vista, FL. ERIM International, Inc., Ann Arbor, Michigan. p. 95-101.

Brandtberg, T, T.A. Warner, R.E. Landenberger, J.B. McGraw. 2003. Detection and analysis of individual leaf-off tree crowns in small-footprint, high sampling density LiDAR data from the eastern deciduous forest in North America. Remote *Sensing of Environment* 85(2003), pp. 290-303.

Casey, W. A. (1999) Forest species group classification using digital frame camera imager, MS Thesis, Mississippi State University, Starkville, MS, 55 p.

Congalton, R. G. and K. Green. 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis, Boca Raton, FL, 137 p.

Eggleston, N.T. 2001. Tree and Terrain Measurements using Small-footprint Multiple-return Airborne LiDAR Data from Mixed Douglas-fir Forest in the Pacific Northwest. M.S. Thesis. Mississippi State University. 135 p.

Hill, R.A., S.A. Hinsley, D.L.A. Gaveau and P.E. Bellamy. 2004. Predicting habitat quality of Great Tits (Parus major) with airborne laser scanning. *International Journal of Remote Sensing* 25(22): 4851-4855.

Hinsley, S.A., R.A. Hill, D.L.A. Gaveau, and P.E. Bellamy. 2002. Quantifying woodland structure and habitat quality for birds using airborne laser scanning. *Functional Ecology* 16: 851-857.

Hughes, J. S., D.L. Evans, and P.Y. Burns. 1986. Identification of two southern pine species in high resolution aerial MSS data. *Photogrammetric Engineering and Remote Sensing* 52(8):1175-1180.

Knight, T.C., A.W. Ezell, D.R. Shaw, J.D. Byrd, and D.L. Evans. 2004. Identifying loblolly pine and four common competing hardwood species using multispectral reflectance analysis. *Proceedings of the 12th Biennial Southern Silvicultural Conference*. p. 336-342.

Leckie, D., F. Gougeon, D. Hill, R. Quinn, L. Armstrong, and R. Shreenan. 2003. Combined high-density lidar and multispectral imagery for individual tree crown analysis. Canadian Journal of Remote *Sensing* 29: 633-649.

McCombs, J., S. D. Roberts, and D. L. Evans. 2003. Influence of fusing lidar and multispectral imagery on remotely sensed estimates of stand density and mean tree height in a managed loblolly pine plantation. *Forest Science* 49(3):457-466.

North Carolina Geographical Survey 2005. Division of Land Resources. Raleigh, NC http://www.geology.enr.state.nc.us/Mineral%20resources/mineralresources.html.

Outcalt, K., and R. Sheffield. 1996. The longleaf pine forest: trends and current conditions, Resour. Bull. SRS-9. Ashville, NC: U.S. Department of Agriculture Forest Service. Southern Research Station. 1-23.

Persson, A., J. Holmgren, and U. Söderman. 2002. Detecting and measuring individual tree using an airborne laser scanner. *Photogrammetric Engineering and Remote Sensing*

68(9):925-932.

Popescu, S. C. and R. H. Wynne (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.

Rudolph, D., R. Conner, and R. Schaefer. 2002. Red-cockaded Woodpecker foraging behavior in relation to midstory vegetation. *Wilson Bulletin* 114(2):235-242.

U.S. Fish and Wildlife Service. 2003. Red-cockaded Woodpecker (*Picoides borealis*) Recovery Plan: *Second Revision*. U.S. Fish and Wildlife Service, Atlanta, Georgia, USA.

Xiao, Q., and E. McPherson. 2004. Using AVIRIS data and multiple-masking techniques to map urban forest tree species. *International Journal of Remote Sensing* 25(24):5637-5654.

Zimble, D. 2002. Characterizing vertical forest structure using small-footprint multi-return airborne LiDAR. M.S. Thesis, Mississippi State University, Department of Forestry. 39 p.

Zimble, D., D.L. Evans, G. Carlson, R. Parker, S.C. Grado, and P. Gerard. 2003. Characterizing vertical forest structure using small-footprint airborne lidar. *Remote Sensing of the Environment* 87:171-182.

Zwicker, S., and J. Walters. 1999. Selection of pines for foraging by Red-Cockaded Woodpeckers. *Journal of Wildlife Management* 63:843-852.