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Base Facilities Environmental Quality

Remote Sensing Protocols for Parameterizing an Individual, Tree-Based, Forest Growth and Yield Model

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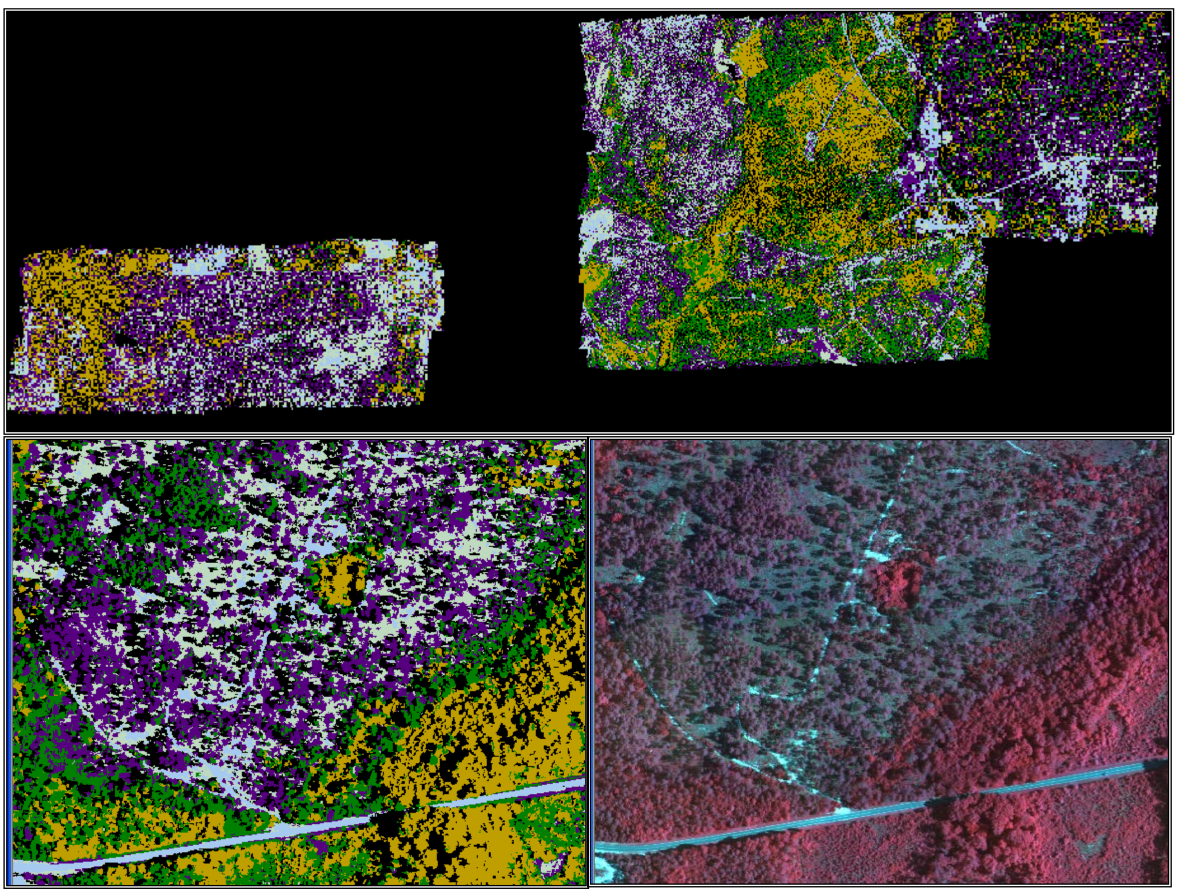

Construction Engineering Research Laboratory

Remote Sensing Protocols for Parameterizing an Individual, Tree-Based, Forest Growth and Yield Model

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Abstract

Potential impacts of climate change to southeastern U.S. pine ecosystems are of particular concern to the Department of Defense. The U.S. Forest Service-developed Forest Vegetation Simulator – Southern Variant (FVS-sn) forest growth model can project growth in southeastern U.S. pine ecosystems, and it has been modified to incorporate the effects of climate change. Stand inventories are typically utilized to parameterize FVS-sn growth models, but field-based inventories are cost-prohibitive to collect at landscape scales. Therefore, remote sensing protocols were developed to parameterize the FVS-sn model. More specifically, a tree-finding model was developed to estimate the location and height of individual stems using LIDAR data. Estimated stem locations from the tree-finding model matched 74% and 98% of field-mapped longleaf and loblolly stems, respectively. Using estimates of stem height, height to live crown, localized stem density, and crown area for a total of 160 matched stems as predictor variables in regression analysis explained 68% and 71% of the variation in field-measured diameter at breast height (dbh) for longleaf and loblolly stems, respectively. Using this protocol, a landscape-wide map of stem locations attributed with species, height, dbh, and crown length could then be used to parameterize the FVS-sn model.

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Preface

This study was conducted for the Office of the Assistant Secretary of the Army for Acquisition, Logistics, and Technology (ASA(ALT)) under Research, Development, Test, and Evaluation Program Element A896, “Base Facilities Environmental Quality,” and Work Unit #83KK3G, “Prediction and Adaptation of Military Natural Infrastructure in Response to Climate Change: Forest Modeling.” Technical monitors were Lorri A. Schwartz and Richard G. White at Headquarters Department of Army, Assistant Chief of Staff for Installation Management (HQDA ACSIM).

The work was performed by the Ecological Processes Branch (CN-N) of the Installations Division (CN), U.S. Army Engineer Research and Development Center – Construction Engineering Research Laboratory (ERDC-CERL). At the time of publication, Dr. Imee Smith was Acting Chief, CEERD-CN-N; Ms. Michelle Hanson was Chief, CEERD-CN; and Mr. Alan Anderson was the Technical Director for Military Ranges and Lands. The Deputy Director of ERDC-CERL was Dr. Kirankumar Topudurti, and the Director was Dr. Ilker Adiguzel.

COL Jeffrey R. Eckstein was the Commander of ERDC, and Dr. Jeffery P. Holland was the Director.

Unit Conversion Factors

Multiply	By	To Obtain
degrees Fahrenheit	(F-32)/1.8	degrees Celsius
feet	0.3048	meters
inches	0.0254	meters
square feet	0.09290304	square meters

Abbreviations

Term	Meaning
CIR	color infrared
dbh	diameter at breast height
DEM	digital elevation model
DoD	Department of Defense
ENVI	Environment for Visualizing Images (software)
FVS	Forest Vegetation Simulator
FVS-sn	Forest Vegetation Simulator–Southern Variant
GPS	global positioning system
GRS	Geodetic Reference System
HLC	height to live crown
LIDAR	light detection and ranging
MSU	Mississippi State University
NAD	North American Datum
RCW	red-cockaded woodpecker
RMSE	root mean squared error
TES	threatened and endangered species
UTM	Universal Transverse Mercator

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1 Introduction

1.1 Background

Several Department of Defense (DoD) policy initiatives are driving requirements for vulnerability assessments, planning, and adaptation strategies to address climate-change impacts on military lands. Climate change could alter compliance issues on DoD lands, including management of threatened and endangered species (TES) and habitats and impact natural resources that sustain the military training mission. Potential impacts of climate change to southeastern U.S. pine ecosystems is of particular concern to DoD due to the large number of military installations within this ecoregion and multiple natural resource management concerns related to these forest types, including their importance for multiple TES. The Forest Vegetation Simulator (FVS)-Southern Variant (sn) growth model developed by the U.S. Forest Service is capable of projecting growth in southeastern U.S. pine ecosystems, and modifications have been made by ERDC-CERL and by Virginia Polytechnic Institute and State University of Blacksburg, Virginia, to incorporate the effects of climate change including growth and mortality functions. Ground-based stand inventories are typically utilized to parameterize FVS-sn growth models, but field-based inventories are cost-prohibitive to collect at landscape scales. Therefore, remote sensing protocols utilizing airborne light detection and ranging (LIDAR) and multispectral data were developed to parameterize the FVS model with spatially explicit, landscape-scale map of stem locations, species, height, diameter at breast height (dbh), and crown length. Assessment of landscape-scale impacts of climate change on upland loblolly and longleaf pine ecosystems is necessary to inform current management practices at military installations.

1.2 Objective

The objective of this study was to develop remote sensing protocols to parameterize the FVS forest growth model at a landscape scale for a representative, upland loblolly and longleaf pine ecosystem test site.

1.3 Approach

Discrete-return LIDAR data was analyzed to produce digital elevation models of canopy height surface and bare earth. A model was developed to estimate the location and height of individual stems using both digital elevation models. Estimated stem height was used to estimate dbh for each stem. Additional forest structure parameters such as localized stem density and crown area were also estimated to improve predictions of dbh for estimated stem locations. Multispectral imagery was classified to identify species type of individual stems. Landscape-wide estimates of these parameters for individual stems could then be used to parameterize the FVS model to assess the potential effects of climate change on pine ecosystems in the southeastern United States.

1.4 Mode of tech transfer

Utilizing the protocols described in this report provides the capability to parameterize the FVS-sn growth model for the purpose of projecting growth in southeastern U.S. pine ecosystems while considering the effects of climate change.

2 Model background

FVS-sn is a stem-based model; therefore, to project forest growth with respect to climate-change scenarios across the landscape, a landscape-wide stem map is required to parameterize the model. Remotely sensed LIDAR data has some potential for parameterizing the FVS model at landscape scales (Hudak et al. 2006, 2008; Falkowski et al. 2010). Critical to parameterizing the FVS model is developing a method to spatially locate individual stems and to estimate stem height from LIDAR data. Multiple models for identifying individual stems from LIDAR data have been developed and tested across a variety of forest types (Persson et al. 2002; Kaartinen et al 2012; Leckie et al 2003a; Popescu and Wynne 2004; Packalen et al. 2008; Hyyppä et al. 2001; McCombs et al. 2003; Breidenbach et al. 2010). Similar to most other models of this type, this project utilized a local maximum-filtering approach to the canopy height surface with a variable filter size within pine-dominated stands with minimal hardwoods. In some studies, empirical relationships between field measurements of forest structure and LIDAR-derived estimates are stratified by species, age class, or site quality because different distributions of LIDAR returns could be expected with variation in these parameters, even within monoculture stands. Nelson et al. (1988) assessed plots with a mix of hardwoods and southern pine species, finding accuracy of biomass and volume estimates to be comparable with those where a single southern pine species was dominant. That work suggested that stratification was only worthwhile if there was a significantly larger deciduous component to the canopy (Nelson et al. 1988).

The dbh measurement is a critical input parameter for modeling forest growth, but it cannot be measured directly with LIDAR. Therefore, once individual stems are located, allometric equations relating LIDAR-derived estimates of stem height, crown size, and relative stem density are typically used to estimate dbh for individual stems.

Similar to individual tree detection and height measurement, discrete-return LIDAR data with high sampling density has been utilized to delineate individual tree crowns and estimate their crown size by using a variety of complex approaches including valley-following within the canopy height model and region-growing approaches around individual stem locations

(Brandtberg et al. 2003; Leckie 2003a; Coops et al. 2004; Lee and Lucas 2007; Packalen et al. 2008). Object-oriented spectral classification procedures similar to those used in this research to segment multispectral imagery have also been utilized to estimate crown size (Leckie et al. 2003b). Estimated crown size (in addition to individual stem height) is often used as a predictive variable for estimating dbh (Wulder et al. 2000; Bechtold 2003; Popescu et al 2003; Hyyppä et al. 2001; Persson et al. 2002; Smith et al 1992).

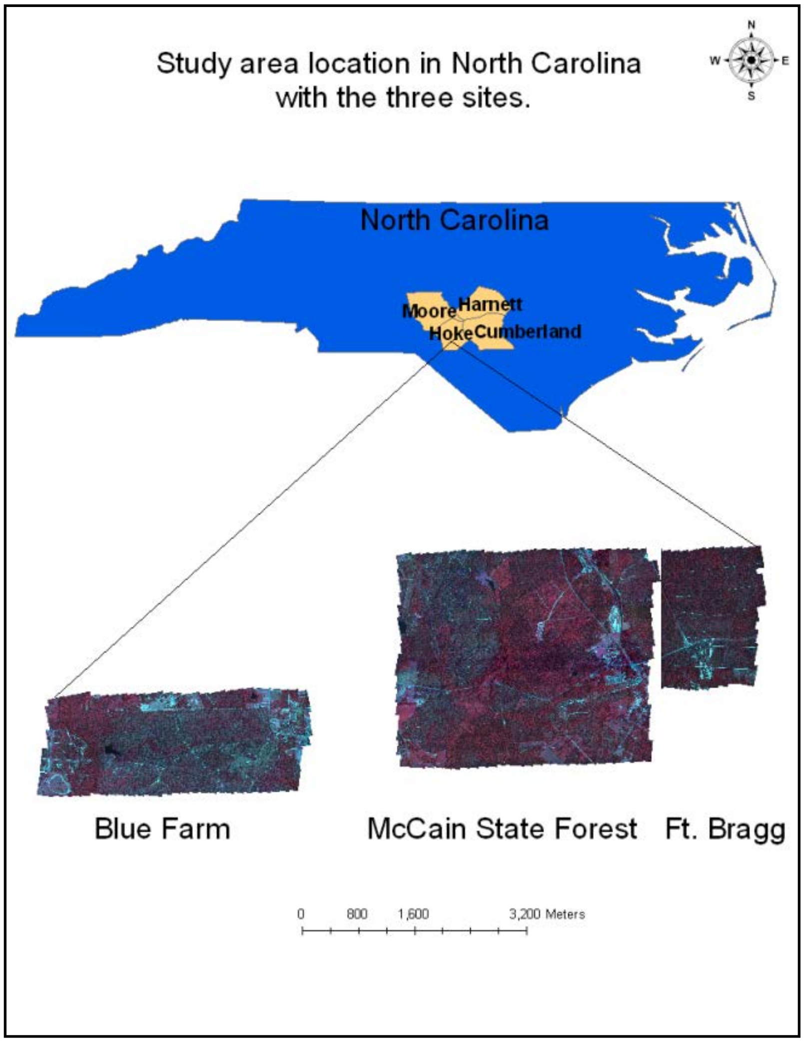
3 Methods

Geospatial data utilized to parameterize the landscape FVS model were primarily derived from a previous research project for this study site which was completed by Mississippi State University (MSU). The MSU study assessed the utility of remotely sensed data for assessing red-cockaded woodpecker (RCW) habitat (Evans et al. 2008; Tweddale et. al. 2008). A brief summary of the methods utilized in that research is provided in this report, and revisions to that method that were incorporated to improve dbh estimates are described below.

3.1 Study site

The study site for this analysis was the McCain tract, a state-owned conservation area located adjacent to Fort Bragg and Camp Mackall, North Carolina (Figure 1). The site is located in a critical corridor between two subpopulations of RCW in Hoke County, North Carolina, and is representative of a southeastern pine forest in the Sandhills region of North Carolina. The site is composed of flat land to gently rolling hills and valleys, with elevations ranging from sea level near the coast to about 600 ft. The primary vegetation types associated with this region include grassland and early-successional habitats, pine woodland, and river bottoms. The annual mean temperature is about 61.2 °F, with an annual precipitation of 46.7 in. (Evans et al. 2008). Field samples from plots in nearby tracts (Blue Farm and Fort Bragg) were utilized as part of this analysis for assessing diameter estimates derived from stem heights and for assessing accuracy of a multispectral image classification. Landscape-wide stem mapping and attribution for the purpose of parameterizing the FVS-sn growth model was only completed for pine-dominated stands within the McCain tract.

Figure 1. Location of study site in Hoke County, North Carolina (Evans et al. 2008, 13).



3.2 Remotely sensed data

Airborne LIDAR data was collected by LandAir Mapping* for this site on 23 July 2005. LIDAR data were acquired at a nominal posting density of 4.0 points per square meter and recorded as first, only (i.e., 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. The canopy models were created using the first and only returns by use of point cloud filtering methods provided

* LandAir Mapping, Inc. of Peachtree City, Georgia.

in Environment for Visualizing Images (ENVI) software.* The ground models were generated using a combination of first returns and last returns using point cloud filtering methods provided in LIDAR Analyst 3.05.02 module of ArcGIS 9.0, as described in Evans et al. (2008). These digital surface models of canopy height and bare earth were used to determine locations of trees and their associated heights for evaluation of stand structure.

Airborne color-infrared (CIR) imagery for the study site was acquired 26 July 2005 by GeoData Airborne at 0.25-m resolution in four spectral channels: blue (450 nm), green (550 nm), red (650 nm), and near infrared (NIR; 850 nm). The individual frames were ortho-rectified to a ground digital elevation model (DEM) and mosaiced for the study site (Evans et al. 2008).

3.3 Field data

Field data were collected in November and December 2006 by MSU 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 with a radius of 11.3 m. These plots were distributed across the McCain tract and adjacent tracts, and their location was recorded with real-time differential global positioning system (GPS). 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 for each plot. Overstory and midstory trees were defined as those trees with dbh greater than 2.54 cm. 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 stem locations (Evans et al. 2008). Using a forest stand map for the McCain tract, stands that were dominated by longleaf and/or loblolly were retained, and other stands (such as those dominated by bottomland hardwoods) were eliminated from analysis. A total of 22 field plots were ultimately used for this analysis within pine-dominated stands in the McCain tract.

* ENVI software is a product of Exelis Visual Information Solutions, www.exelisvis.com.

3.4 Image classification

Prior to development of a stem-mapping procedure, multispectral imagery was classified by MSU by using an object-oriented classifier with eCognition 4.0* to identify canopy species type. Advantages of using object-oriented classifiers for identifying species of individual tree crowns have been demonstrated using a variety of high resolution multi-spectral data (Leckie et al. 2003b.; Ke et al. 2010). In this project, MSU utilized the following object-oriented classification approach as described below.

> "...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 nonvegetation 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) (near infrared reflectance –red reflectance/ near infrared reflectance + red reflectance) were input into the Classifier.." (Evans et al. 2008).

Classification accuracy was assessed by using 552 field observations that included 109 samples for each of the three 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; Evans et al. 2008; Tweddale et al. 2008).

3.5 LIDAR-based stem mapping

All probable canopy trees were identified and mapped by MSU within the McCain tract, using the LIDAR-derived surface models of the canopy and the bare earth along with modified procedures adopted from those models as first described by McCombs et al. (2003). One difference in the methods utilized by MSU from that described in McCombs et al. (2003) was that spectral data were not incorporated into the identification function due to spatial registration problems between the LIDAR data and the or-

* Software developed by Trimble Geospatial Imaging of Munich, Germany. Trimble Navigation, Ltd. of Westminster, CO is the U.S. distributor (www.ecognition.com).

tho-corrected multispectral imagery. The second and most important difference between the methods is that the new procedure introduced stem density and crown size dependent functionalities in tree identification, making the new model more adaptable to ranges of conditions over which it was applied (Evans et al. 2008).

The MSU procedure utilized two spatial process models developed in Erdas Imagine* which identified and estimated heights of probable tree locations in the main canopy of pine-dominated forest stands in the McCain tract. The first model utilized the LIDAR-derived canopy and bare-ground surface models as input. Generally, the highest pixels (or local maximums) in the canopy height surface should correspond to the location of probable individual canopy trees. Prior to identification of individual stems, a smoothing filter was applied to eliminate "holes" in the canopy surface caused by LIDAR points that penetrated the main canopy.

The model then identified clumps of pixels that could be trees through identification 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 moving focal rank utility and was a function of the size of the search filter utilized. The key to selection of the search filter size was to use a size that was similar to the typical size of the canopies to be detected. This selection minimized the inclusion of pixels from neighboring canopies when determining the focal rank and decreased errors of omission and commission. The model utilized one of three possible radial search filters sizes to identify small, medium, and large crowns. The size of these search filters reflected the typical size of small, medium, and large canopies identified in the field at representative sites. A relative stem density function was utilized to determine which size search filter was utilized as stem density varied spatially. The premise of using a relative stem density function to alter the search filter size is that as stem density increases, crown size typically decreases. Therefore, as stem density increases and crown size decreases, a smaller search filter is utilized to identify smaller crowns or smaller clumps of pixels that are higher than their neighboring pixels. Relative stem density was determined by calculating local stem density as a percentage of maximum stem density for the entire study area.

* Erdas Imagine is a suite for geospatial data-authoring software by Hexagon Geospatial, Inc. with headquarters in Madison, Alabama (www.hexagongeospatial.com).

Using the methods described above, clumps of pixels that were identified as higher than a set percentage of neighboring pixels were subjected to a sieving operation based off the estimated smallest tree crown; thus, the sieving operation eliminated small groups of pixels that were not likely trees. The output clumps from this model, as well as the canopy and bare ground surface models, were then passed to the second model which extracted the location and height value of the highest pixel in each clump as a tree location (Evans et al. 2008, Tweddale et al. 2008).

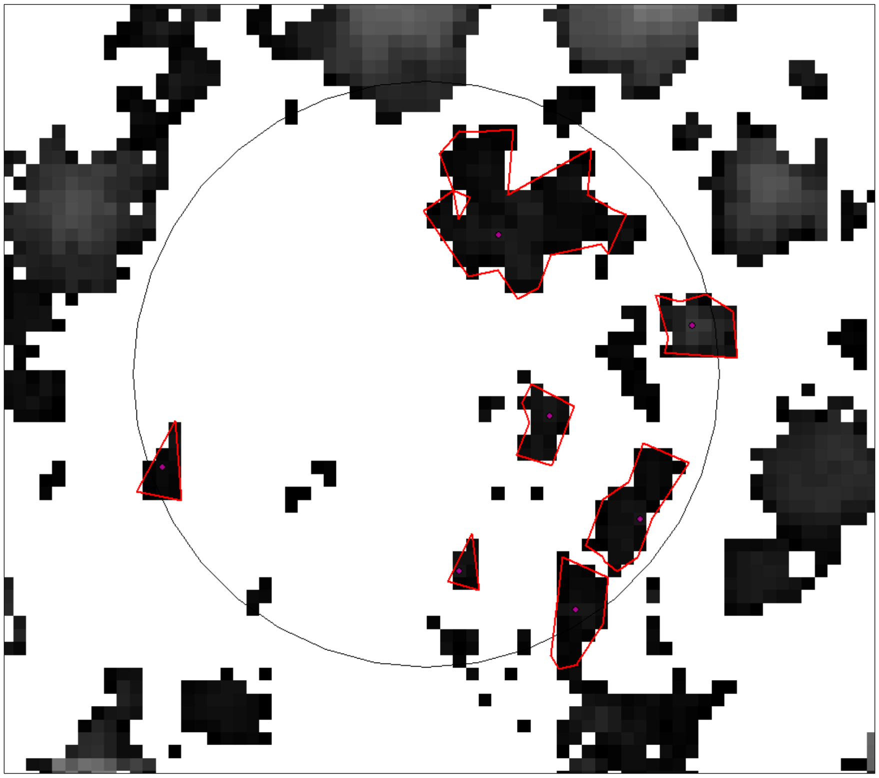
Estimated stem locations derived from analysis of LIDAR data were overlaid on field-mapped stem locations. LIDAR-derived estimates of stem locations that matched field-mapped stem locations were identified for 22 plots in the McCain tract. In addition, commission and omission stems were identified to assess the accuracy of the stem-mapping spatial models.

3.6 Estimation of crown area

In addition to stem height, HLC, and stem type (hardwood vs. loblolly vs. longleaf),the canopy size, and the localized stem density were also estimated for matching stems. Various crown area delineation programs are summarized in the literature. However, all of the programs are proprietary and complex. In addition, the multispectral data could not be used to estimate crown area because the spectral data was not ortho-corrected to the LIDAR-derived canopy surface model which resulted in misregistration between the two data layers. Therefore, a simplified two-step approach was implemented to estimate crown area.

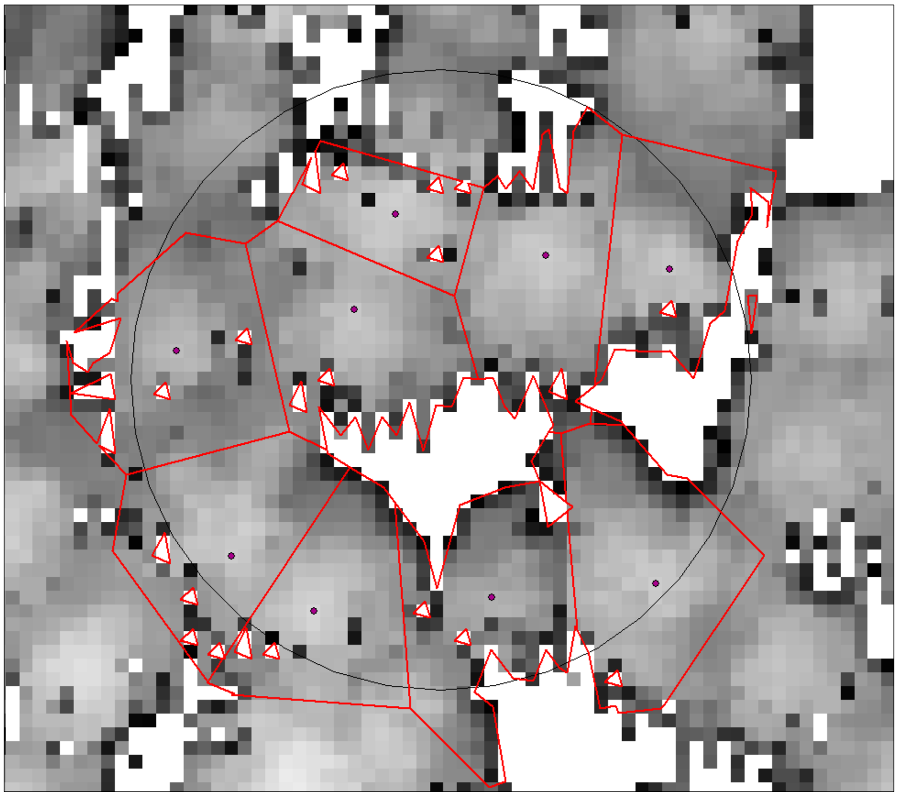
First, a mask was applied to the LIDAR-derived canopy surface model to eliminate all pixels <7 m above ground, thereby identifying individual tree crowns or clumps of crowns and eliminating background low vegetative cover and bare ground. The intent was to parameterize the FVS-sn model with all stems >4 in. dbh. Using the relationship between height and diameter from field-sampled stems, a 7-m height threshold was determined. For open-grown stems that did not overlap adjacent tree canopies, the total area defined by individual clumps of pixels >7 m in height was used as an estimate of crown area (Figure 2).

Figure 2. Example of delineation of tree canopies for isolated stems (outlined by red polygons) within a circular plot (11.3 m radius), using a mask to eliminate canopy-height model pixels <7 m above the ground (ERDC-CERL).



In cases where individual canopies overlapped, the same boundary created from the mask was used to define the outer edge of overlapping trees. In order to estimate the interior boundary between overlapping stems, Thiessen polygons were calculated and intersected with the outer boundaries derived from the mask (Figure 3).

Figure 3. Example of delineation of tree canopies for clumped/overlapping stems (outlined by red polygons) within a circular plot, using the intersection of a mask to eliminate canopy height model pixels <7 m above ground to define outer canopy boundaries and Thiessen polygons to define the interior canopy boundaries between overlapping canopies (ERDC-CERL).



3.7 Estimation of localized stem density

Using all probable stem locations identified with the stem-mapping model, a moving circular (11.3 m radius) focal sum utility was utilized to count the number of stems for each center pixel of the moving kernel, thereby providing an estimate of stems per hectare for each pixel in the study area. The stem locations identified in the tree finding model were then intersected with the stem density model to attribute each individual stem location with a neighboring stem-density attribute.

3.8 Diameter estimation

Using 160 LIDAR-identified stem locations across 22 plots that matched field-identified stem locations, field-measured dbh was regressed with four independent variables that were estimated with LIDAR data: (1) stem height, (2) HLC, (3) crown area, and (4) localized stem density.

4 Results

4.1 Image classification

The classification was performed by using an object-oriented classification approach using eCognition 4.0 and based on membership functions defined for six classes: (1) longleaf pine, (2) loblolly pine, (3) hardwood, (4) low vegetation, (5) shadow, and (6) bare, as described below (Evans et al. 2008, 25–26):

> The process of image segmentation was instrumental in isolation of groups of pixels that represented majority portions of overstory tree crowns. This made it possible for the analyst to train the membership functions based on individual trees or groups of trees rather than use the classical pixel-based training techniques utilized in other classification protocols. For the original pixel size of 0.25m, the following segmentation parameters seemed to generate the best (visually compared to original imagery) representation of tree cover: scale = 12, and shape = 0.1 (with shape being qualified by values of compactness = 0.5 and smoothness = 0.5). Bands used in segmentation were red, green, and blue. All three bands were treated equally given a weight value of 1.0 when considered for contribution.
>
> A hierarchical classification scheme that used membership functions was a good combination of logical ordering of image elements based on spectral and photo-interpretive properties. Shadow and non-shadow were differentiated by use of mean brightness for each image object. This object value is the relative brightness (magnitude of reflectance) of all input channels taken together. The function used for shadow distinction had a cutoff value of 66; object brightness values above this number were considered non-shadow. The non-shadow class was further subdivided by use of a membership function based on the derived NDVI value of 65 to separate non-vegetation and vegetation. Green vegetation has high reflectance in the near-infrared and low reflectance in the visible wavelengths of light, thus making it highly distinguishable from non-vegetation by use of the NDVI.
>
> The vegetation class was further subdivided into herbaceous, hardwood, and pine classes based on overlapping fuzzy membership functions and

finally, the pine class was subdivided into loblolly and longleaf. The resulting classification (Figure 4) provides a detailed spatial representation of the vegetative components on the study tracts. The classification was then tested for accuracy by use of individual tree locations in the plot data and other observations for the non-tree classes made throughout the study area.

The overall accuracy after separating the pine cover type into loblolly and longleaf was 73.73% (Table 1). The overall kappa statistic was 0.6819 while individual cover type kappa values ranged from 0.9210 for shadow cover type to 0.5085 for hardwood cover (Table 2).

Figure 4. Classification of all three study tracts plus enlarged portion of part of the McCain tract, illustrating the relative detail in the output product: purple = Longleaf Pine (*Pinus palustris*), green = Loblolly Pine (*Pinus taeda*), tan = hardwood (Evans et al. 2008, 27).

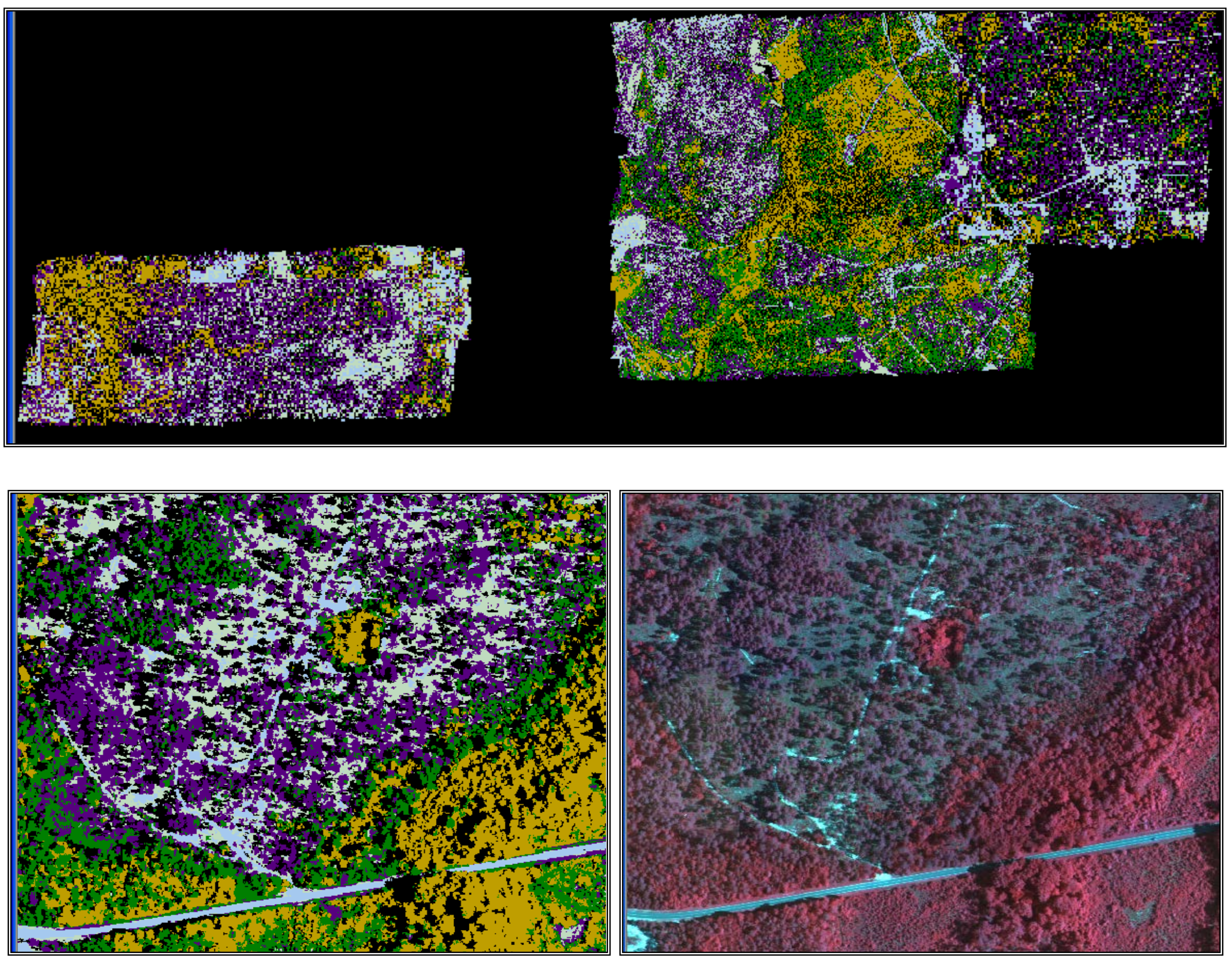


Table 1. Classification error matrix for the separation of the all cover types for the 2005 images of the three study areas: McCain tract and adjacent sites (Evans et al. 2008, 27).

Classified	Reference: LL[1] Pine	Lob[2] Pine	HW[3]	Shadow	Bare[4]	Low Veg[5]	Totals
LL[1]	99	31	24	2	0	12	168
Lob[2]	8	67	22	0	0	0	97
HW[3]	2	11	63	2	0	0	78
Shadow	0	0	0	70	4	12	86
Bare[4]	0	0	0	0	60	3	63
Low Veg[5]	0	0	0	1	11	48	60
Totals	109	109	109	75	75	75	552
N =	552		Overall Accuracy:	73.73%			

[1] LL = Longleaf Pine – (*Pinus palustris*), [2] Lob Pine = Loblolly Pine (*Pinus taeda*), [3] HW = Hardwood, [4] Bare = bare ground, and [5] Low Veg = low vegetation.

Table 2. Class accuracies and kappa statistics for the classification error matrix of all class cover types for the 2005 images of the McCain tract and adjacent sites (Evans et al. 2008, 28).

	Ref Total	Class Total	Correct	Producer Accuracy	Users' Accuracy	Kappa
LL[1]	109	168	99	90.83%	58.93%	0.8681
Lob[2]	109	97	67	61.47%	69.07%	0.5325
HW[3]	109	78	63	57.80%	80.77%	0.5085
Shadow	75	86	70	93.33%	81.40%	0.9210
Bare[4]	75	63	60	80.00%	95.24%	0.7742
Low Veg[5]	75	60	48	64.00%	80.00%	0.5961
					Overall Kappa:	0.6819

[1] LL = Longleaf Pine – (*Pinus palustris*), [2] Lob Pine = Loblolly Pine (*Pinus taeda*), [3] HW = Hardwood, [4] Bare = bare ground, and [5] Low Veg = low vegetation.

4.2 Matching LIDAR-estimated and field-measured stem locations

All stem locations identified using the LIDAR-based stem identification algorithm were intersected with the image classification in order to attribute each identified stem with a vegetation type. Using these attributed stems locations (244 total stems) across 22 plots on the McCain tract, 160 LIDAR-identified stem locations were visually matched with corresponding stem-mapped locations for field-measured stems with dbh > 4 in. Results from this stem-matching process for 22 plots located on the McCain tract are summarized into correctly identified (matched), omission, and commission stems (Table 3). Overall, the percentage of LIDAR-derived stem locations that were correctly matched with field-mapped stem locations was 66%. However, this overall percentage included the low percentage of hardwood stems that were matched (23%). Using a local maximum-based stem-finding model (such as the one developed and utilized for this research) typically does not identify hardwoods with a high degree of accuracy due to their crown morphology. However, the objective of this project was to parameterize the FVS-sn forest growth model for longleaf and loblolly stem locations, which had overall correctly matched percentages of 74% and 98% respectively.

Table 3. Confusion matrix of LIDAR-based stem identification compared to field-mapped stems >4 in. dbh on 22 plots on McCain tract (ERDC-CERL).

Field Data				Lidar Data	
	Hardwood	Loblolly	Longleaf		
Matched	10	49	101	Matched	160
Omission	34	1	36	Commission	84
Total	44	50	137	Total	244
Percentage Matched	23	98	74	Percentage Matched	66
Percentage Omission	77	2	26	Percentage Commission	34

4.3 Landscape-scale estimation of stem diameter (dbh) for LIDAR-estimated stem locations

A total of 160 stems that were correctly identified from the LIDAR stem-mapping model and validated with field-mapped stem locations were used to develop species-specific linear regression models to estimate dbh for all LIDAR-derived stem location estimates across the landscape. This allowed for landscape-wide parameterization of the FVS-sn forest growth model by providing estimates of individual stem diameters. LIDAR-derived estimates of stem height were highly correlated with field-measured stem height for matched stems (coefficient of determination R^2=.92; root mean squared error [RMSE] = 1.79 m). Similarly, field measurements of HLC were correlated with field measurements of stem height (R^2=0.78; RMSE = 2.50 m). Using this relationship, HLC was estimated for LIDAR-identified stem locations. However, for the purpose of estimating dbh of LIDAR-derived stem locations, stem height and HLC crown were only moderately correlated with dbh. Therefore, in addition to LIDAR-estimated height and HLC crown, two additional predictive variables (crown area and localized stem density) were estimated and included to improve dbh estimates for individual LIDAR-identified stems. The species-specific linear regression models for hardwood, loblolly, and longleaf pine are provided below for 160 LIDAR-estimated stem locations that were matched to field-mapped stem locations with dbh > 4 in.

4.3.1 Hardwood

Adjusted $R^2 = 0.08$ (n=10)

LIDAR_stem diameter(dbh, inches) = 4.3466842 + (0.2856989*LIDAR_height(meters)) + (0.0053212* LIDAR_stem density(stems per_hectare)) – (0.470026* LIDAR_height_to_live_crown (meters)) + (0.1292488* LIDAR_crown area (sq. meters))

4.3.2 Loblolly

Adjusted $R^2 = 0.71$ (n=49)

LIDAR_stem_diameter(dbh, inches) = 0.2860809 + (0.7666321* LIDAR_height(meters)) – (0.005573* LIDAR_stem_density(trees_per_hectare)) – (0.312897 *LIDAR_height_to_live_crown(meters)) + (0.0234666* LIDAR_crown_area(sq. meters))

4.3.3 Longleaf

Adjusted $R^2 = 0.68$ (n=101)

LIDAR_stem_diameter(dbh, inches) = 2.8894785 + (0.6245536* LIDAR_height(meters)) – (0.00671* LIDAR_stem_density(trees per hectare)) – (0.323546 *LIDAR_height_to_live_crown(meters)) + (0.0768556 *LIDAR_crown_area(sq. meters))

5 Conclusions

The FVS-sn forest growth model developed by the U.S. Forest Service is capable of projecting growth in southeastern U.S. pine ecosystems, and modifications have been made by ERDC-CERL and Virginia Polytechnic Institute and State University to incorporate the effects of climate change including growth and mortality functions. Ground-based stand inventories are typically utilized to parameterize FVS-sn growth models, but field-based inventories are cost-prohibitive to collect at landscape scales. The methods demonstrated in this research allowed for estimation of stem location and diameter of approximately 65,000 individual longleaf and loblolly pines distributed across the McCain tract that otherwise would not be feasible. This will allow an assessment of the effects of projected climate change on this representative study site, including growth and mortality. It is likely that more complex, proprietary software developed for estimating radii of individual crowns would have likely improved estimates of crown area, which in turn may have resulted in more accurate estimates of stem diameter for all stems.

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14. ABSTRACT

Potential impacts of climate change to southeastern U.S. pine ecosystems are of particular concern to the Department of Defense. The U.S. Forest Service-developed Forest Vegetation Simulator – Southern Variant (FVS-sn) forest growth model can project growth in southeastern U.S. pine ecosystems, and it has been modified to incorporate the effects of climate change. Stand inventories are typically utilized to parameterize FVS sn growth models, but field-based inventories are cost-prohibitive to collect at landscape scales. Therefore, remote sensing protocols were developed to parameterize the FVS-sn model. More specifically, a tree-finding model was developed to estimate the location and height of individual stems using LIDAR data. Estimated stem locations from the tree-finding model matched 74% and 98% of field-mapped longleaf and loblolly stems, respectively. Using estimates of stem height, height to live crown, localized stem density, and crown area for a total of 160 matched stems as predictor variables in regression analysis explained 68% and 71% of the variation in field-measured diameter at breast height (dbh) for longleaf and loblolly stems, respectively. Using this protocol, a landscape-wide map of stem locations attributed with species, height, dbh, and crown length could then be used to parameterize the FVS-sn model.

15. SUBJECT TERMS
climate change, natural resources management, remote sensing, pine ecosystems, modeling, southeastern U.S. forests, LIDAR, Forest Vegetation Simulator (FVS)

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