ABSTRACT

MOHAN, MIDHUN. Spatial Modeling of Red-cockaded Woodpecker Non-Traditional Habitats: A Logistic Regression Analysis and LiDAR Approach. (Under the direction of Dr. Glenn P. Catts).

Despite the fact that Red-cockaded Woodpeckers (Picoides borealis) have a preference for old-growth longleaf pines with low or sparse understory (traditional), they also are known to exist in non-savannah like habitats having a wide range of biological features. In this paper, we present an application of GIS and Airborne Light Detection and Ranging (LiDAR) data analysis to identify underlying forest attributes of the nesting sites that could provide an explanation for this deviation. Initially cluster analysis was performed to locate hot spots inside the non-savannah regions and then quality level 2 LiDAR (2 returns\m2) acquired in 2014 was used to characterize the 3D structure of these existing active clusters to create a spatially explicit habitat suitability model. With experts' opinions on our analysis results we detected certain unrepresented parameters contributing towards the habitat suitability and performed logistic regression analysis to evaluate their contribution towards the predictive model. As most of the current models are based on traditional habitat characteristics, these models are inefficient when dealing with clusters existing in non-traditional habitat areas such as pocosin gradient or pond-pine dominated stands. It is expected that, by integrating new threshold limits of underlying habitat features obtained from our research, we can improve the existing models' habitat identification capability and thereby boost the quality of RCW conservation activities.

Spatial Modeling and Evaluation of Red-cockaded Woodpecker Non-Traditional Habitats: A Logistic Regression Analysis and LiDAR Approach

by
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DEDICATION

To everyone who believed in me and to everyone who helped me realize my potential,

Without their constant encouragement, advice, and all-round support,

I would not be where I am today!

Thanks for making me understand it is okay to dream big and remain a risk-taker, I really enjoyed the ride as a research graduate student at NC State and I promise to pass on the positive aspects of graduate life to the upcoming generations

BIOGRAPHY

Midhun Mohan a.k.a Mikey was born June 22, 1992 in Palakkad, Kerala, India. After finishing schooling from Amrita Vidyalayam, he started his undergraduate studies in mechanical engineering at Amrita University, India. Later, in his senior year he moved to California after getting selected for UC Davis Global Study Program. This marked the beginning of his research career and his love for Mathematics and Environment made him choose a graduate research career in Operations Research (OR) with a focus on environmental science related issues at NC State after his graduation.

Mikey started his research on optimization from the start of his first semester at NC State in August 2014 and under Dr. Joseph's Roise guidance, he was able to make a smooth transition to Forestry related OR problems. His initial research revolved around multi-objective mathematical modeling of Forest Carbon. While progressing on with his OR research, the author was exposed to various spatial modeling strategies by Dr. Glenn Catts, and Mikey realized his unfair advantage over application of GIS skills and decided to start a graduate certificate degree in the same. Also, soon enough with his mentors' encouragement and support Mikey had developed the necessary analytical and GIS skills required to approach real-world issues. During his third semester, he started his independent research on Habitat modeling of Red-cockaded woodpecker and realizing his love for the Forestry courses and field work, he enrolled for a parallel Master's degree in Forestry. The author

currently resides in Raleigh, NC and works for Center for Integrated Forest Science, USDA Forest Service as a Data Scientist.

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A Literature Review of Red-cockaded Woodpecker Habitat Favorability

LITERATURE REVIEW

The red-cockaded woodpecker (Picoides borealis) is a federally endangered, non-migratory bird endemic to southeastern United States and were once considered common throughout the open longleaf pine (Pinus palustris) ecosystem in the Piedmont and coastal plain of the south-eastern United States [1]. Its preference for longleaf pine and the destruction of that habitat from the start of 17th century, because of European settlement, lack of forest fires, urbanization, agriculture and widespread commercial timber harvesting have resulted in placing the RCWs on the federal list of endangered species [2]. Several RCW recovery and conservations plans have been implemented in recent years, based on new understanding of RCW biology and population dynamics, and they are trying to stabilize the existing RCW populations by altering the forest management strategies and implementing artificial cavities. However, most of the remaining populations are isolated and small, and hence need attention [13, 1].

RCW is different from other woodpeckers for the fact that it excavates cavities in living pine trees resistant to fire for roosting and nesting, and their major source of food is the invertebrates that they obtain primarily by scaling bark and pecking. Their selection of living pines might be an adaptation to the fire-maintained ecosystems in which they are usually found [43]. However, they have to account for a few challenges associated with excavating in live pines.

While excavating, cavity chamber cannot extend into the surrounding sapwood. It must be excavated in the tree's heartwood core. Cavity trees are of age 80 years or above are generally preferred as the diameter of heartwood is largely a function of age [44, 45]. Hence, a major cause of the decline of the woodpecker species is the disappearance of trees of sufficient age for cavity excavation. Cavity extraction is difficult because of the rigidity of heart-wood. Thus, birds usually excavate in trees in which the heartwood has been softened by decay due to infestation by fungus (Phellinus pini) [45]. Also, excavating an entrance tunnel into sapwood is often interrupted by sap leakage, and it limits the speed with which cavities can be constructed, which make the overall process take 3 years or more for completion.

Another major disadvantage to living pines are their vulnerability to predators. The rough surface of the trunk enables predators like snakes, to climb to the cavity. Red-cockaded woodpeckers try to avoid snakes climbing by maintaining resin wells, places where they chip into the sapwood, around their cavities. The resulting sap flow smooths the climbing surface and disrupts traction of ventral scales used by the snakes in climbing [46]. Absence of fire is another reason that increases the risk of predators. In this case, hardwood understory and midstory develops and this provides predators easy access to cavities [47, 48, 49].

Red-cockaded woodpeckers live in groups containing a breeding pair and 0-4 helpers, mostly comprised of males [50]. The role of helpers is to assist in incubation and feeding of nestlings and fledglings [51, 52]. Each woodpecker family group occupies a cluster of cavity trees

containing completed cavities and partially completed cavities. A group of cavities, both active (in use) and inactive (previously used), together form a “cluster” and each individual cluster comprises of 1-10 cavity trees [4, 5, 6, 7]. The typical cavity tree cluster is surrounded by foraging habitat comprised of low or sparse understory, and the territory is actively defended year-round by the resident group of birds [7, 4, 8]. These territories are usually large, ranging from 50-150 ha or more in size [53, 54]. Cavity trees are probably one of the most important factors determining territory quality and breeding success [9]. The cavities provide safe roosting places and are essential for nesting, and can be reused for years.

As creation of cavities is time consuming and difficult, red-cockaded woodpeckers prefer acquiring an existing set of cavities, even if reproduction is thereby delayed, rather than constructing a cavity set in a vacant area. From the population dynamics of these species it is found that the aforementioned reasons result in birds competing for territories with suitable existing cavities, rather than creating new cavity clusters, or inhabit territories with too few or poor cavities which further implies that most of the abandoned territories are not reoccupied [55, 56, 57, 58]. The low frequency with which the birds produce new clusters of cavity trees has been a major obstacle in efforts to manage this endangered species [9]. Therefore, a method of constructing artificial cavities would prove to be a valuable management strategy towards the recovery of these birds’ populations [8].

Apart from cavity trees, quality foraging habitat is considered as another essential component of RCW recovery. The foraging habitat guidelines for RCW recovery plan mainly focus on facilitating population expansion and maintaining existing population size. The threshold levels of key structural components considered include: 1) ≥40% herbaceous groundcover; 2) sparse hardwood midstory that is 2.1 m in height; 3) Basal Area and density of pines ≥35.6 cm dbh are ≥4.6 m2/ha and ≥45 stems/ha, respectively; 4) Basal Area of pines 25.4–35.6 cm dbh is ≤9.2 m2/ha; 5) Basal Area of pines ≥25.4 cm dbh is ≥2.3 m2/ha; 6) Basal Area and density of pines 25.4 cm dbh are ≤2.3 m2/ha and ≤50 stems/ha, respectively; 7) 30% hardwood overstory; and 8) foraging habitat that satisfies all the following conditions: 1) ≥30 years old; 2) Basal Area of pines ≥25.4 cm dbh is between 9.2 and 16.1 m2/ha; 3) Basal Area of pines 25.4 cm dbh is 4.6m2/ha; 4) sparse hardwood midstory that is 2.1 m in height; 5) total Basal Area, including overstory hardwoods, is 18.2m2/ha; and 6) stands satisfying these recommendations are not separated by more than 61 m [10].

Several habitat suitability models have been developed for locating optimal places for building artificial habitats with the combined efforts of biologists, foresters, technicians, researchers, and land managers working on private, state, national and federal properties where the birds survive. In 1989, the U.S. Fisheries and Wildlife Service published the "Criteria for Defining Foraging Habitat" in the Guidelines for preparation of biological assessments and evaluations for the red-cockaded woodpecker [10]. These guidelines outlined minimum criteria used in determining availability of red-cockaded woodpecker (RCW) foraging habitat. In Feb 2003, a

RCW foraging matrix application was developed to standardize foraging habitat evaluation meanwhile allowing flexibility to adapt the application to different foraging types. Over the years U.S.F.W.S. have been upgrading these foraging matrix applications and a RCW Matrix toolbar was developed by Intergraph Government Solutions in 2007 which was fully compatible with ArcMap [10]. Details on systems used to score stands and produce foraging maps in relation to criteria specified in recovery plan had been published in several other peer reviewed journals [11, 12, 13].

Research done on nesting habitats is very limited and most of the earlier habitat models developed were based on the traditional characteristics of the cluster i.e. long leaf savannah with sparse midstory. Despite the fact that Red Cockaded Woodpeckers have a preference for old-growth longleaf pines with low or sparse understory (traditional habitat), they are also known to exist in non-savannah like habitats having a wide range of biological features. For altering the models to identify such non-traditional sites such as pocosin gradient and pond pine dominated regions, we have to find the variation of threshhold limits and the unrepresented factors, that might have an influence on the habitat suitability. We believe that effective conservation of Red-cockaded woodpeckers requires insightful research on structure of their nesting habitats and that incorporation of our research findings can result in more efficient habitat models that can be used for designing successful management and recovery techniques.

CHAPTER 2

Evaluation and Spatial Modeling of Red-cockaded Woodpecker Non-traditional Habitats

INTRODUCTION

Over the years, advancement in airborne light detection and ranging (LiDAR) technology have created opportunities for applying technology and analysis methods for characterizing the forest structural attributes such as basal area (BA), stand height, biomass and stem volume in various parts of the world [13, 14, 15, 16, 17]. This has been particularly beneficial for ecological research as the high-resolution, three-dimensional data generated using LiDAR combined with field observations of wildlife populations provide the opportunity to examine animal–habitat relationships while accounting for the collective effects of fine-grained habitat characteristics, landscape composition, and landscape configuration [13]. Previous LiDAR based studies on exploring bird-habitat relationship includes studies done to investigate reproductive success [39, 29], habitat associations [40, 41, 42] and species richness [31, 30]. However, only limited research exists regarding application of LiDAR for assessing RCW habitats. A study done by Tweddale et al. (2008) was able to classify pine and hardwoods with 54 % and 13 % accuracy, respectively and reported moderate agreement between field- and LiDAR derived dbh and BA estimates. Smart et al. (2012) did a comparison of RCW nesting and foraging habitat using low-density discrete-return LiDAR (approximately 0.11 returns/m2) and found LiDAR-derived maximum tree height, variation of tree heights, and variation in canopy cover have the capability to statistically differentiate nesting and foraging habitat. Another study conducted by Garabedian et al. (2014) demonstrated a LiDAR based approach to evaluate RCW foraging habitat based on multiple habitat attributes and stated that mapping

habitat quality provided robust method to determine the potential range of habitat conditions and specific attributes that were limiting in terms of the amount of suitable habitat.

In this study, we explored the forest structure of traditional habitats, non-traditional habitats and no-bird zones to determine possible features that might provide an explanation for the existence of RCWs in the non-traditional habitats. The specific objective was to create a potential presence-absence predictive model with an assumption that existing RCW habitats can be considered as a measure of habitat suitability. This predictive model is expected to assist the researchers and biologists in identifying areas meeting threshhold structure requirement to introduce artificial cavities as a part of RCW recovery measures. We choose Multivariate statistical model approach for our study as they were proven to have potential for minimizing validation problems [18, 19]. Tweddale et al. (2008) reported LiDAR-derived habitat variables to possess potential for statistically differentiating nesting and foraging habitats, and suggested extraction of additional key habitat structural attributes for advancement of RCW research. As per their suggestion we coupled our statistical model with LiDAR analysis methods, which have the capacity to directly measure the vertical distribution of vegetation and the underlying topography [21], for obtaining accurate estimation of both vegetation height and ground elevation characteristics. From these models DEMs were generated. Spatial data on existing RCW habitat clusters were provided by U.S. Fisheries and Wildlife Service, and we used high density LiDAR (2 returns\m2) acquired in 2014 to characterize the three-dimensional structure of these clusters to define target habitat attributes.

Initially cluster analysis was done to check for any prominent underlying factors being responsible for habitat favorability. The statistical analysis results showed that the distribution of features was not occurring at random. Afterwards we determined the hot spots and evaluated those areas from a spatial as well as mathematical perspective. From our results and experts point of view, we selected three unrepresented variables and developed a predictive model using logistic regression analysis. This study aimed to assess the applicability of newly identified characteristics in explaining the deviation happening in the case of non-traditional habitats, and thereby offer suggestions for enhancing the predictive capacity of existing habitat identification models.

2. MATERIALS AND METHODS

2.1. Study Area

The geographic focus of this study is Palmetto-Peartree Preserve (see fig. 1), which was established by The Conservation Fund in 1999 with the funding from the North Carolina Department of Transportation. The preserve serves as an RCW mitigation bank and helps in offsetting RCW habitat loss due to road construction projects. It encompasses approximately 10,000 acres of land in the coastal plain of North Carolina and has an average slope of ≤1% (Figure 1).

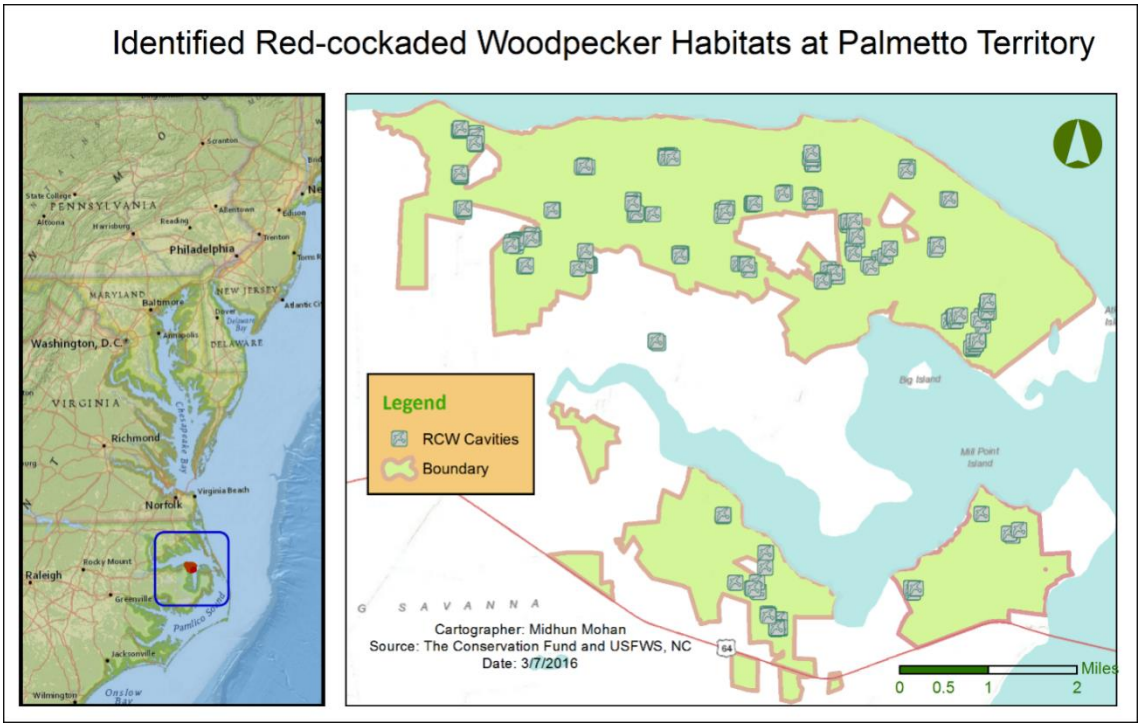

Figure 2.1: Identified Red-cockaded woodpecker clusters at Palmetto-peartree Preserve as for the year 2014

2.2. Methodology

Our research study is comprised of two stages: i) Spatial analysis done from a LiDAR-GIS perspective and ii) Regression analysis using the results obtained from the previous step. LiDAR analysis and related spatial procedures were performed using ArcGIS 10.3.1 and the free FugroViewer software by Fugro Geospatial Services. Quality Level 2 LiDAR (2 points/meter) dataset from 2014 (https://rmp.nc.gov/sdd/) acquired through North Carolina Spatial Data Download was used to characterize the 3D structure of RCW clusters to define

target habitat attributes (see appendix 1). The statistical operations were carried out in a mix of R, SAS and MS Excel environment.

Spatial Analysis

In case of Red-cockaded Woodpeckers, spatially explicit information on the habitat distribution and structure of forest vegetation is required at broad spatial scales for answering questions regarding their habitat selection criteria [36]. Various cluster analysis methods were implemented as an attempt to better understand the spatial pattern of habitat distribution in order to identify strategies which could help improve the conservation practices. We started with average nearest neighbor method and its z-scores revealed the possibilities of effective clustering. Using hot-spot analysis tool in ESRI ArcMap 10.3 we found the prominent sites which are supposed to be the oldest and most stable clusters of Palmetto territory. The Hot Spot Analysis tool calculates the Getis-Ord Gi* statistic for each feature in a dataset and the resultant Z score gives a estimate of locations where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features and to be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. [65]

After a detailed visual analysis of these hot spots, experts raised the chances of having height difference between tree-crown and mid-story might as a determining factor for habitat suitability. We further investigated the influence of this height difference as well as some of

its related factors to assess their applicability for developing a predictive model that can account for the anomalies.

Logistic Regression model

We choose Multivariate statistical model approach for our study as they were proven to have potential for minimizing validation problems [18, 19]. Tweddale et al. (2008) reported LiDAR-derived habitat variables to possess potential for statistically differentiating nesting and foraging habitats, and suggested extraction of additional key habitat structural attributes for advancement of RCW research. For our study, we coupled the statistical model with LiDAR analysis methods as they have the capacity to directly measure the vertical distribution of vegetation and the underlying topography [21], for obtaining accurate estimation of both vegetation height and ground elevation characteristics. From these measures, three-dimensional digital surface models (DSMs) and bare earth digital elevation models (DEMs) were generated. Spatial data on existing RCW habitat clusters was provided by U.S. Fisheries and Wildlife Service. Quality Level 2 LiDAR (2 points/meter) dataset from 2014 (https://rmp.nc.gov/sdd/) acquired through North Carolina Spatial Data Download was used to characterize the 3D structure of these clusters to define target habitat attributes. The LiDAR data was by default classified into Individual classes such as ground, vegetation, buildings, roads, and bridges.

For determining the dominant attributes, we constructed two separate models. The first model was built on parameter values derived from 20 non-traditional nesting sites and 20 no-bird

zones from Palmetto territory. No bird zones were selected from areas which were at least 8.05 km (5 miles) away from identified RCW habitats and these were chosen in a way that they had diverse range of tree heights. The second model was similar to the first model with an addition of 20 sites from Croatan National Forest which were traditional (see appendix 3). Ranges of maximum tree heights considered for individual case scenarios are represented below (Figure 2).

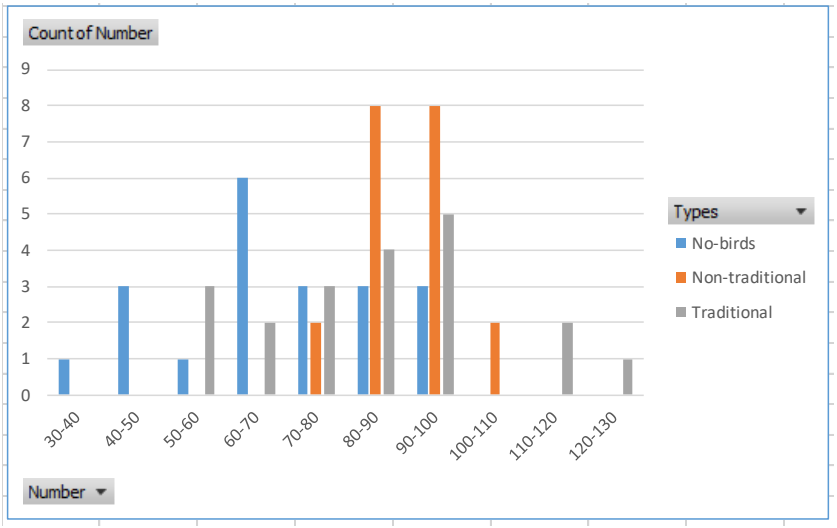

Figure 2.2: Total height frequency histogram for no-bird zones, traditional and non-traditional habitats

We conducted logistic regression analysis to develop a presence-absence model using the parameters identified through visual analysis of field plots. From the LiDAR data, we developed forest canopy models for the individual fragments and then later extracted parameters of interest. For maintaining uniformity and standardizing our values for easier

comparison we treated individual fragments as a circular piece of land having a 30.34 m (100 feet) radius. As we were more concerned in evaluating nesting sites, we adopted a smaller circumscribed circle instead of the 0.8 km (½-mile) radius circle around cluster center as used in the 2003 recovery plan [11, 12]. In this study, we did not attempt to analyze the spatial separation of foraging and non-foraging habitat either. We wanted to include midstory and understory conditions in our model but it was noted that point-cloud data lacked enough detail for representing these features with acceptable accuracy which actually agree with the observation Maltamo et al. (2005) had with his predictive model. As we were unable to explicitly quantify the hardwood midstory as "sparse and less than 2.1m in height" as stated per the recovery standards (12), we derived a new factor named "height-density factor (f)" as a surrogate.

Description of Model Parameters

The parameters of interest for our study were maximum tree height (h), height-density factor (f), percent openness (p) and height difference (d). For describing these variables, a sample study site (FID: 75) was chosen (figure 3, 4).

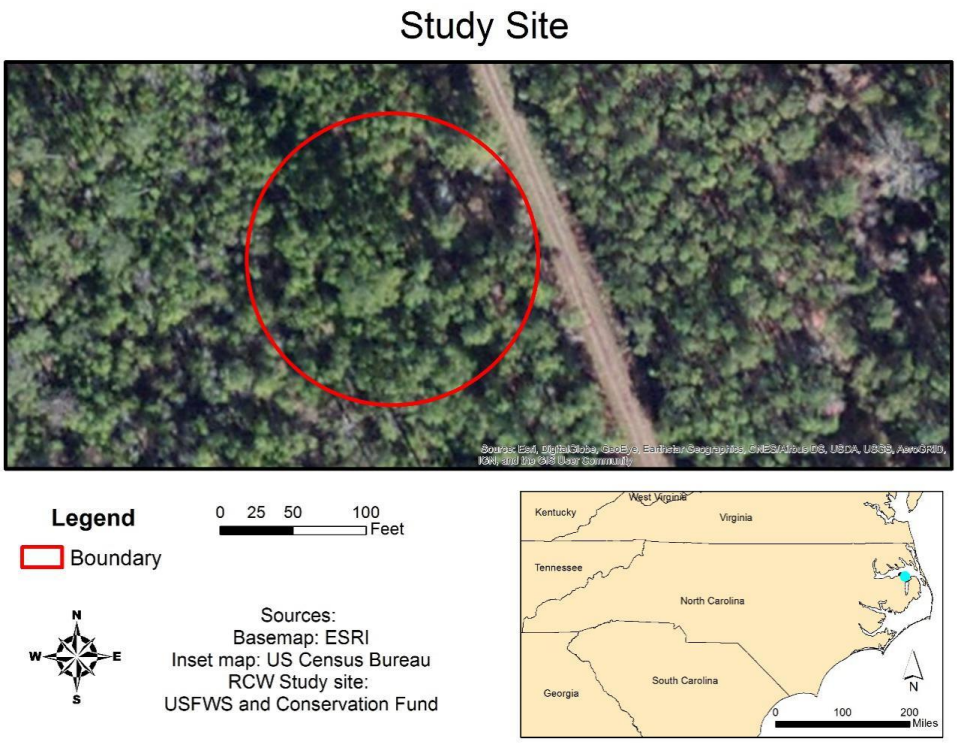

Figure 2.3: Sample circular subplot (FID: 75) of radius 100 feet

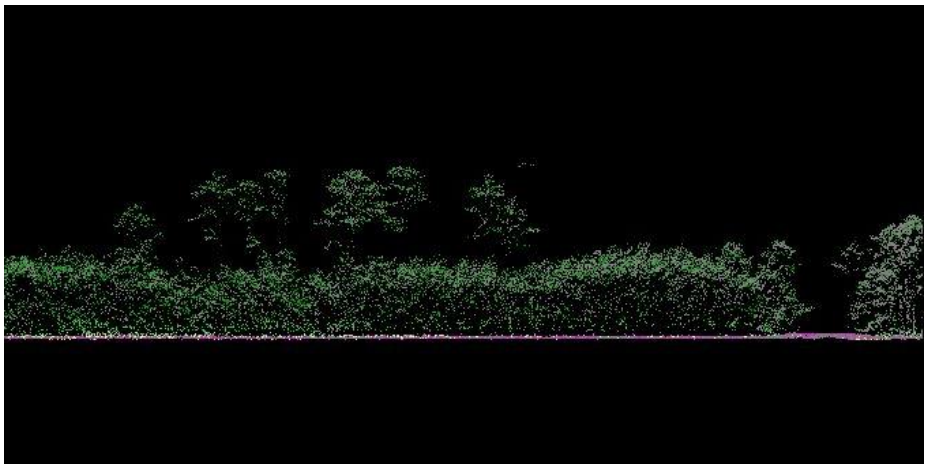

Figure 2.4: Side view of sample study site (FID: 75); Visualized using FugroViewer

Maximum tree height (h): Maximum height (in feet) obtained from the LiDAR-derived Canopy Height Model of the 30.34 m radius circular study plot. (92.2875 in figure 5)

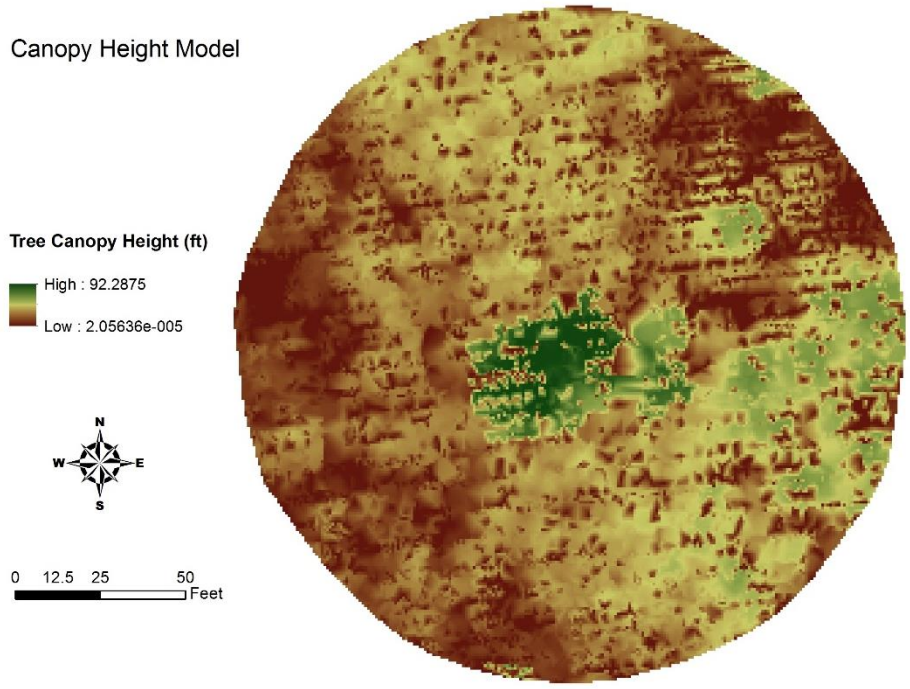

Figure 2.5: Canopy Height Model derived from LiDAR points for the sample subplot (FID: 75); developed using ArcMap 10.3

Height-density factor (f): For quantitatively evaluating the canopy structure we developed conditional raster from CHMs and calculated the percent canopy cover difference for every 10 foot interval starting from h to the ground level (figure 6). Initially, the interval width was also tested with 1 foot, 3 feet and 5 feet, however the change in canopy cover with interval width was comparatively less evident as with the case of interval width as 10 feet. In most of the

cases, plotting canopy height with relative difference in canopy cover over the intervals, resulted in break points where a rapid change (maximum variation) was observed (figure 7, point 1 in figure 8; see appendix 2). Height-density factor can be defined as the center point of this height interval exhibiting maximum variation (point 2 in figure 8). Center point was chosen as the variation of percent canopy cover within the 10 foot intervals was gradual (figure 9).

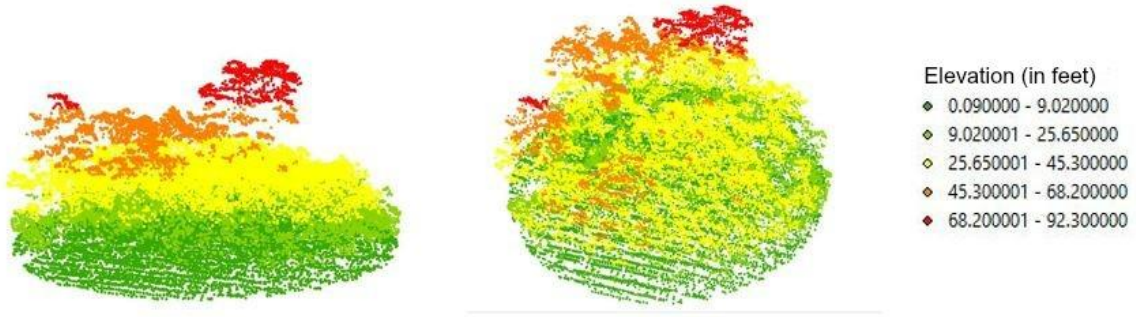

Figure 2.6: LiDAR point cloud representation based on height for the sample study site (FID: 75); developed using ArcScene

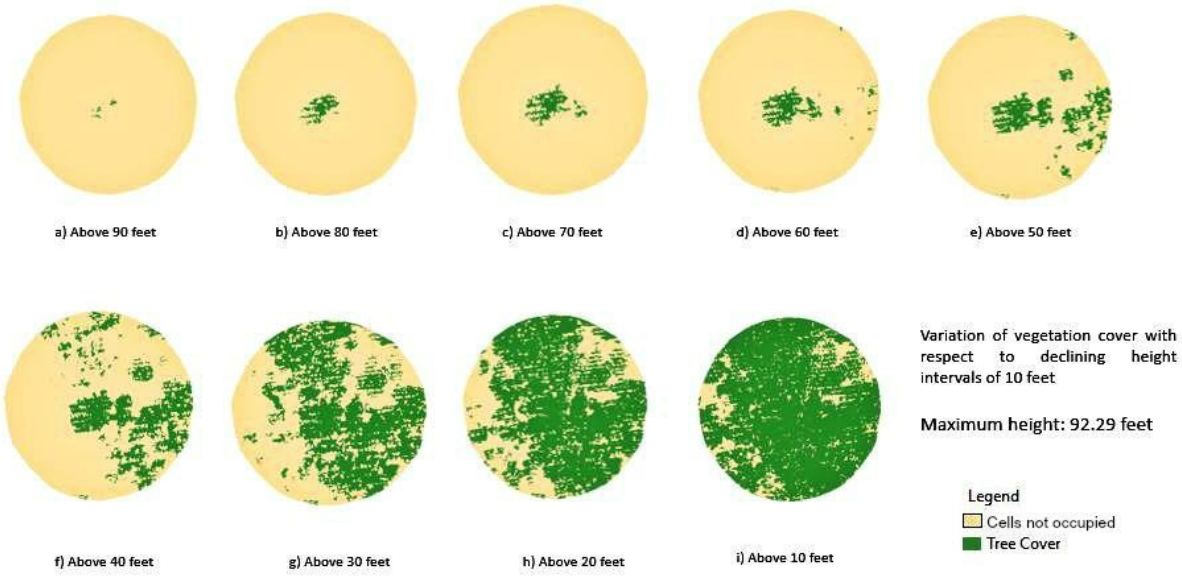

Figure 2.7: Variation of mid-story cover with respect to changing height intervals of 10 feet each (Study site FID: 75); conditional rasters developed using ArcMap 10.3

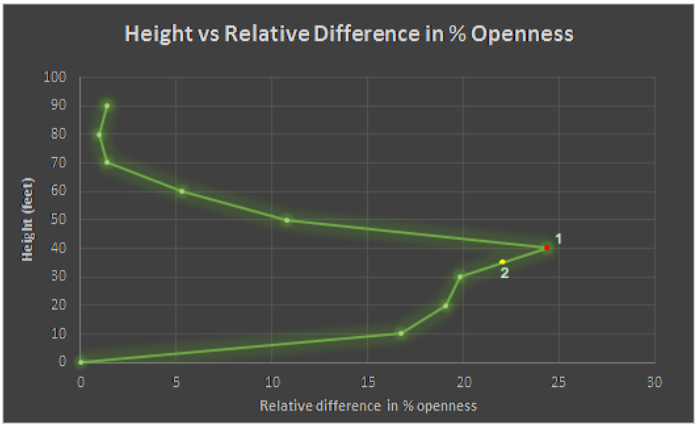

Figure 2.8: Graph showing relationship between height and relative difference in percent openness (Study site FID: 75)

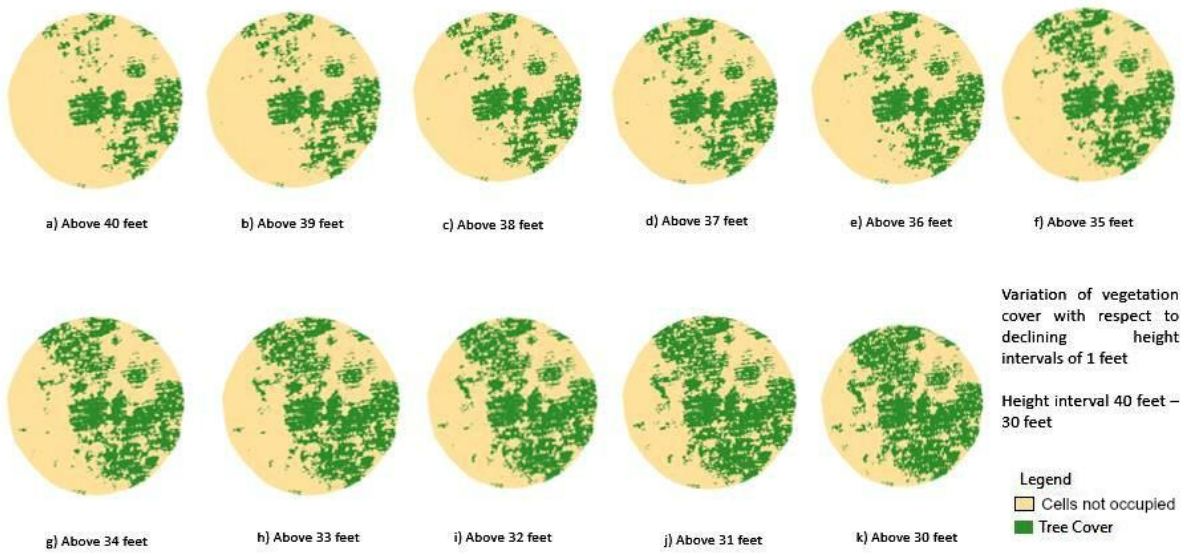

Figure 2.9: Gradual change of percent cover per feet within the 10 feet interval (Study site FID: 75)

Percent openness (p): It is percentage of unoccupied pixels in the canopy height model at the height-density factor. (cells not occupied in figure 7)

Height difference (d): Difference in height (in feet) between Tree height and Height-density factor.

ANALYSIS AND RESULTS

Initially, height-density factor (f), total height (h), openness percent (p) and height difference (d) were considered as factors for developing the logistic regression model. Total height (h) was included due to its high correlation with stand age, which was a criterion described in the previous recovery plans [111, 113]. Univariate statistical analysis was performed to assess the validity of individual model variables as it was listed as a suitable preprocessing technique for understanding each individual variable's role [18, 19, 23]. In this case d was found to have the highest c-value (0.836) among the 4 variables. Here the c-value is equivalent to the well-known measure ROC and as the value nears to 1, it means that the model is capable of perfectly discriminating the response. Later the model was updated by removing h as it was found to be positively correlated ($r = 0.71611$, $p < 0.001$) with d. Then p, f, and the interaction terms were included separately, and it was found that f contributed the most towards the model's c-value (0.866). There were no statistically significant interactions found between the two independent variables. Then further experimentation was performed with inclusion of p in the model as it has shown to be a significant factor in similar studies [11, 12, 35]. However, in our case, it appeared to have a negative effect on the c-value (0.855). Hence, it was not considered in the final model.

The updated predictive model was of the form $p = 0.1343\ d + 0.0561\ f - 8.9556$. From the odds ratio estimates it was found that for every one unit increase in d, the chances of finding RCW increased by 14 % and every one unit increase in f increased the chances by

approximately 6 %. The model's efficiency in predicting habitat suitability of 10 non-traditional habitats was then tested and it resulted in 80% accuracy. The high success rate of models show that d and f are able to explain the variability in the model with an 80% confidence level. (see appendix 4)

For the second model, an additional 20 traditional test sites from Croatan National Forest were included. Here, a large change in range of mean values as compared to the non-traditional habitats was identified (figure 2). In this case h was found to have the highest c-value (0.763) and the final predictive model was of the form $p = 0.0634h + 0.0439p – 7.2225$. This model gave a 60% accuracy when used for predicting the same 10 non-traditional habitats which was used for testing the first model.

DISCUSSION

The findings from this study suggest that f (height-density factor) and d (difference of height between f and crown height) have the potential for helping in the identification of non-traditional RCW habitats, albeit to a moderate degree. It is well-publicized that a midstory height less than 3 m is favorable for RCWs, but under this criterion, most of the non-traditional habitats were found unsuitable [36]. Using this model developed from the newly identified predictor variables, I was able to predict the presence of RCW non- traditional habitats elsewhere with 80% success rate and the overall success rate was 70 % for a total of 20 testing sites. Even though these individual features are not sufficient to predict the habitat suitability by themselves, integrating them with pre-established variables may offer possibilities for

extending the threshhold limits and thereby help in development of habitat suitability indices that can account for feature deviations from the traditional criteria. In short, the results of our study suggest that habitats that do not satisfy all the requirements of recovery plan [12] can still have the potential for supporting healthy and growing RCW populations. In my second model, we saw that addition of values obtained from traditional habitats affected the overall predictive capacity of our model. This might be due to the range in mean of height differences in case of traditional habitats were lower than that of non-traditional habitats or even due to the ongoing management for RCWs in these traditional habitats. As the primary goal of this paper is to evaluate the underlying parameter responsible for the favorability of RCW non-traditional habitats, I did not investigate further the second model.

As it is easier, faster, and comparatively cheaper to calculate total tree height rather than calculating height difference from the LiDAR data, we tried replacing d with h in our first model and the resultant model had a slightly higher c-value (0.880). In this case p was found to be insignificant at 80 % confidence. Thus, I checked for a model with h and f, and the resulting model had a c-value of 0.883 at 80% confidence interval with both the parameters being significant. Even though individual contribution of h towards c-value was lesser than that of d, adding f made the former model more efficient comparative to a model developed using h and h as parameters. This in fact states that, increasing total height and decreasing f results in increasing presence, which in turn reinforces our previous argument about the positive correlation between height difference and habitat favorability.

The above trend regarding the model might be a result of f and p explaining the same kind of relationship as d. Thus, there is a need to look for parameters related to structural composition such as tree size and/or minimum diameter. But for doing that we need to have additional field measurements along with LiDAR data. From a LiDAR perspective, our research method proves beneficial and gives a method for looking deep into the nesting tree habitat structure. Our work suggests that the RCWs might have become adapted to new kind of ecosystems over the years. Another possible scenario might be that the non-traditional areas were once long leaf fire maintained ecosystems with RCWs in them, and later the vegetation changed over time for a range of reasons. There is also a chance that maybe our sample size was not large enough and was not representative of all non-traditional habitats elsewhere. We need to assess the success rate of the model on more sites to test the aforementioned possibilities. Image analysis can be helpful in this context as it helps in tracing the changes and tracking habitat structure over time.

For this study, I preferred LiDAR over image-based approaches as they are limited to DSM generation when vegetation cover is present and the ground is obscured [24, 21]. Also, LiDAR-derived data have been found to be a statistically significant indicator in the case of habitat suitability analysis as they improve the predictive power of models and help refine the spatial distribution of suitable habitats when creating higher accuracy maps [25, 26, 27, 28]. An analytical approach for quantifying the trade-offs between prediction reliability and scalability of LiDAR-derived habitat, and the related uncertainty is addressed in detail by Garabedian et

al. (2014). However, imagery might provide better results when we deal with areas having variation in slopes such as mountain ranges assuming that the ground is not obscured [24].

It is important to recall that the habitat analysis data from which the model was developed corresponded to just a series of 4 years and may be insufficient for long-term management purposes of an endangered species. However, such limitations are supposed to be overcome through integration of predictive forest growth where habitat changes can be simulated as a function of landscape dynamics [41]. It should be noted that I haven't included landscape connectedness with existing clusters in our studies, and including those parameters may add some additional variables and/or constraints to our model. Also, few of the areas identified by our model as potential habitat zones may not be able to accommodate RCW clusters if they are adjacent to existing clusters. This is because RCWs are territorial birds having individual groups that compete against each other for territory [37, 38, 39]. For relocation to happen, it was found that the artificial clusters need to be at least 5 miles away from the existing clusters. More research has to be done for accommodating the effect of connectivity in mathematical models used for determining habitat zones.

Another potential parameter which should be explored is distance of habitats from roads. In existing models, we see them usually being masked [13], but on inspecting several of our spots during our research we assumed that open roads had acted as sparse forging zones and increased the habitat favorability, given the assumptions that the traffic flow was less than 20 vehicles per day. The accuracy of the current model can be further improved by delineating

individual trees for determining the underlying parameters. Use of higher resolution imagery such as UAV-imagery can be considered in this regard. Spatially explicit and detailed LiDAR-derived habitat attributes provided new insight into RCW nesting habitat relationships and can be further reinforced using field plot data [13, 31, 32]. A thematic potential RCW presence-absence map can be developed from these kinds of models based on environmental characteristics, and it can be used to assess the impact of certain human activities such as expanding urban settlement and land use patterns on nearby habitat zones. Optionally, a choropleth map patterned in proportion to the degree of habitat favorability based on environmental parameters could also be considered appropriate. For this study, only nesting sites were analyzed, but the same can be applied to foraging habitats and a structural overlay of social or biological model can be made for pursuing future research.

In addition to Red-cockaded Woodpeckers, this methodology can be applied for mapping potential habitat for other species such as California spotted owl (Strix occidentalis occidentalis) and fisher (Martes pennanti), whose management is guided by stand structure habitat requirements. In these cases, Airborne LiDAR-based methods outperform field data driven modeling and other remote sensing techniques such as aerial and satellite imagery, as it enables characterization of vertical structure of nesting habitats [61, 62]. Multi-return high resolution LiDAR have been used for identifying large residual trees which facilitate selection of habitats by spotted owls, and to measure number, density, pattern of residual trees and canopy cover for assessing the forest structure surrounding the nesting habitats [60]. Incorporation of height-density factor here would help in testing for the influence of variation

of canopy cover in these situations. The fisher in Sierra Nevada uses tall trees as resting sites, which contributes to their population success [63], and Air-borne LiDAR can be used to extract tree-level characteristics for developing habitat suitability models. Bradbury et al. [64] utilized Airborne LiDAR for analyzing the influence of vegetation structure on bird-habitat. They derived crop type and field boundary height, and pointed out its potential in predicting the distribution of breeding Sky Larks (Alauda arvensis) in a farmed landscape. Thus, management of these and similar species could benefit from the development of LIDAR-based structural metrics to parameterize predictive bird–habitat association models.

CONCLUSION

Overall this research study suggests that height difference and height density factor are slightly, although not with high statistical significance, able to predict the presence of Red-cockaded woodpeckers nesting habitats especially in non-traditional regions of southern United States. The research also points to the potential value of incorporating these variables to the existing models for enhancing their predictive capabilities. While my analyses were developed to extract nesting-habitat metrics based on a novel method of RCW habitat quality, our methods can also be utilized for assessing habitats of other similar bird species as well as for the foraging habitats of RCWs. It must be borne in mind that the inputs for developing the models presented in this study were only gathered from a small number of sites over a short period of time. Thus, further research on a larger scale is required for determining the long-term effects of

connectivity, predators, competition, foraging habitat, and biological implications on the newly identified parameters, before establishing generalized conclusions.

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APPENDICES

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Appendix A

Characteristics of LIDAR utilized

Source: North Carolina Spatial Data Download (https://rmp.nc.gov/sdd/)

(North Carolina Risk Management Office in Coordination with NC Department of Transportation)

Base data: Quality Level 2 LiDAR (2 points/meter) dataset from 2014

QL2 specs:

Phases 1-3 (P3 is included) were done with a linear aerial sensor (traditional), collected at 2 points per meter in 2014. All data includes multi-return and intensity values and is collected to support a 9.25 cm or 3.36 inches RMSEz for Non Vegetated areas based on NDEP guidelines.

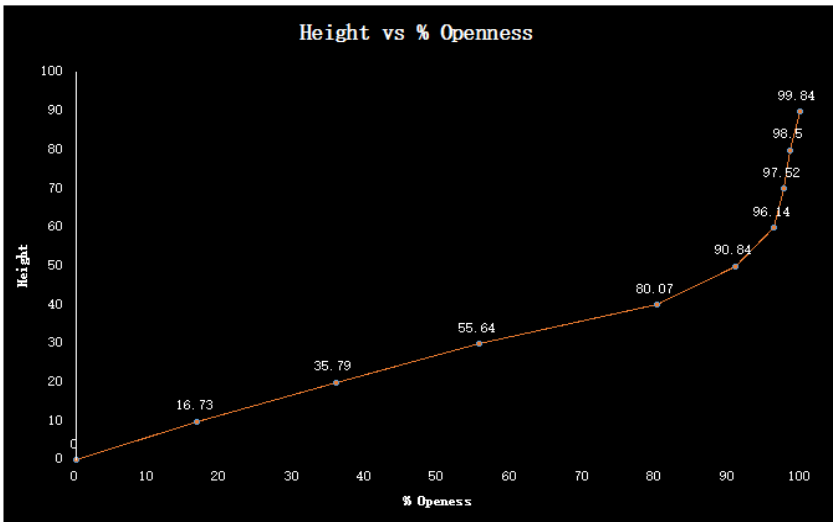
Individual classes: Ground, strata/vegetation, buildings, roads, bridges

Projection: All geospatial deliverables were produced in NAD83 (2011) North Carolina State Plane Coordinate System, US survey feet; NAVD88 (Geoid 12A), US survey feet.

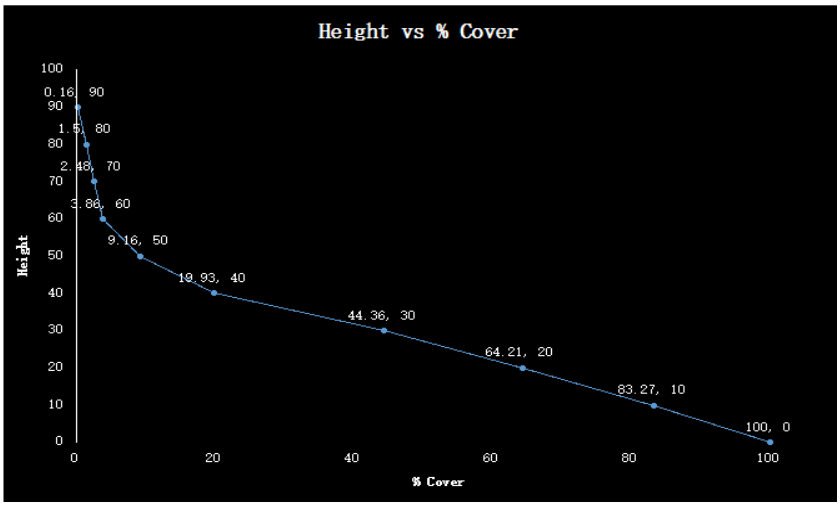
Data download format: .las files

Appendix B

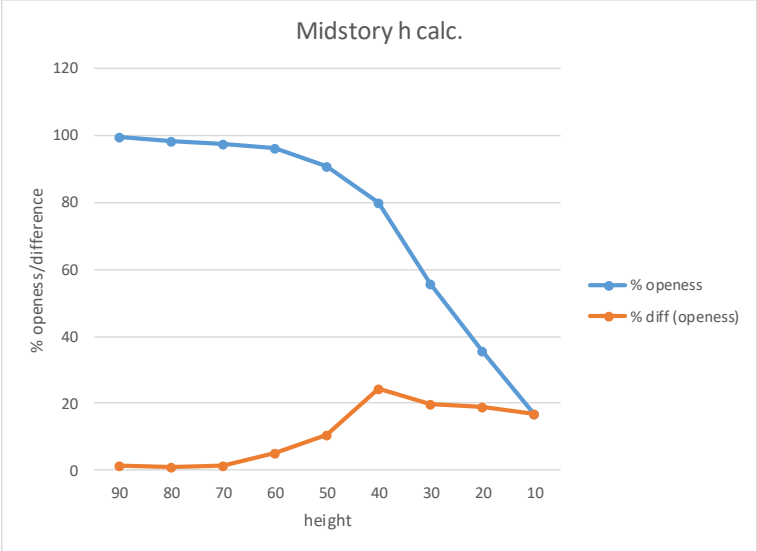
Graphs related to height-density factor (f) calculation for the sample study plot (FID: 75)



Graph 1: Height vs % Openness graph for the sample study plot



Graph 2: Height vs % canopy cover graph, which is a mirror image of h vs % openness graph



Graph 3: Example of height-density factor estimation. Here we have % openness and relative difference on the x-axis and height on the y-axis. In this figure we can see that 35' would be selected as the f.

height	% openess	range	% diff (openess)	0	1
90	99.84	90 - 80	1.34073531	47661	74
80	98.50	80 - 70	0.982507594	47021	714
70	97.52	70 - 60	1.384728187	46552	1183
60	96.14	60 - 50	5.295904473	45891	1844
50	90.84	50 - 40	10.77406515	43363	4372
40	80.07	40 - 30	24.42442652	38220	9515
35	68.83			32856	14879
30	55.64	30 -20	19.84916728	26561	21174
20	35.79	20 - 10	19.06358018	17086	30649
10	16.73	10 -0	16.72986278	7986	39749
0	0.00			0	47735

Table 1: Calculation table for sample site; Here "0" and "1" represents the number of pixels belonging to the categories "openness" and "canopy cover" respectively.

Appendix C

Attribute table for 1) Non-traditional habitats 2) No-bird zones and 3) Traditional habitats.

Note: “Midstory height” in the following tables represents “Height-density factor”.

Predictors for Regression Analysis Model						
SL no:	OBJECTID	RCW probability	height diff.	openess %	midstory height (ft~)	Total height
1	71	1	60.7	74.4	25	85.72
2	96	1	62.3	67.3	15	77.27
3	98	1	76.8	50.5	15	91.78
4	114	1	69.4	79.8	25	94.39
5	117	1	60.8	84.7	25	85.82
6	119	1	68.4	82.4	15	83.42
7	120	1	67.4	87	25	92.38
8	60	1	63.5	48.5	35	98.46
9	61	1	71.6	65.4	35	106.59
10	62	1	62.8	62.1	45	107.803
11	140	1	65.9	60.3	15	80.93
12	141	1	71.6	46.8	15	86.61
13	142	1	60.72	74.4	25	85.72
14	144	1	74.42	54.9	15	89.42
15	56	1	62.3	67.3	15	77.27
16	64	1	79.5	29.9	15	94.51
17	66	1	76.8	50.5	15	91.78
18	69	1	84.5	57.9	15	99.5
19	74	1	73.5	56.6	15	88.47
20	75	1	57.3	68.8	35	92.29

Table 1: Non-traditional habitat attributes of study sites from Palmetto territory

Predictors for Regression Analysis Model						
SL no:	OBJECTID	RCW probability	height diff.	openess %	midstory height (ft~)	Total height
1	1	0	44.5	76.3	55	99.53
2	2	0	46.2	71.2	15	61.2
3	3	0	25.1	55.7	15	40.06
4	4	0	79.7	52.1	15	94.68
5	5	0	16.3	48.3	25	41.3
6	6	0	38.6	71.4	55	93.63
7	7	0	28.6	74.4	55	83.59
8	8	0	22.3	41.9	25	47.34
9	9	0	17.8	63.1	55	72.78
10	10	0	23.3	50.9	45	68.31
11	11	0	69.4	85.3	15	84.39
12	12	0	52.8	50.5	25	77.79
13	13	0	63.1	61.1	15	78.12
14	14	0	41.2	53.5	15	56.65
15	15	0	73.6	71.2	15	88.63
16	16	0	53.09	40.3	15	68.09
17	17	0	26.4	54.8	35	61.4
18	18	0	50.01	57.2	15	65.01
19	19	0	10.46	87	25	35.46
20	20	0	51.59	71.7	15	66.59

Table 2: No-bird zone attributes of study sites from Palmetto-territory

Predictors for Regression Analysis Model						
SL no:	OBJECTID	RCW probability	height diff.	openess %	midstory height (ft~)	Total height
1	1	1	20.7	77.05	35	55.7
2	2	1	16.7	80.51	35	51.7
3	3	1	21.3	68.61	35	56.3
4	4	1	29.6	89.63	95	124.6
5	5	1	22.9	74.61	75	97.9
6	6	1	35.1	85.34	80	115.1
7	7	1	24.9	62.4	75	99.9
8	8	1	49.6	61.12	35	84.6
9	9	1	48.1	73.88	40	88.1
10	10	1	22.4	83.6	75	97.4
11	11	1	45.2	42.92	30	75.2
12	12	1	60.4	79.79	25	85.4
13	13	1	33.9	91.57	65	98.9
14	14	1	36.3	79.97	75	111.3
15	15	1	16.1	84.94	55	71.1
16	16	1	18.9	83.87	55	73.9
17	17	1	17.4	92.81	45	62.4
18	18	1	24.9	82.48	45	69.9
19	19	1	25.1	77.52	65	90.1
20	20	1	18.3	76.56	65	83.3

Table 3: Traditional-habitat attributes of study sites from Croatan National Forest

Appendix D

SAS Tables

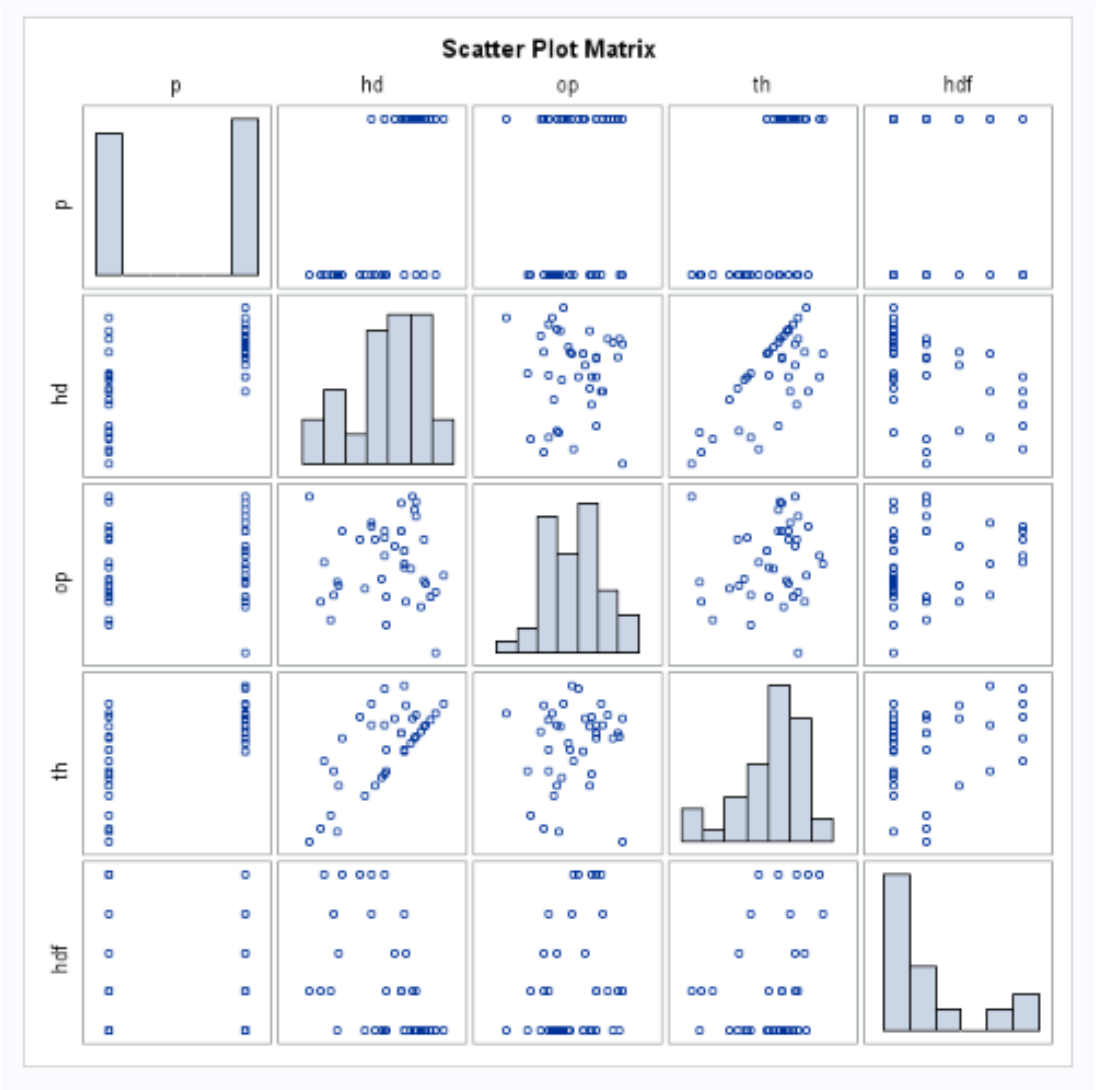


Figure 1: Correlation matrix – you can notice the high correlation between maximum height (th) and height difference (hd)

Probability modeled is p='1'.

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	57.452	40.407
SC	59.141	45.473
-2 Log L	55.452	34.407

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	21.0450	2	<.0001
Score	16.1539	2	0.0003
Wald	9.4604	2	0.0088

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-8.9556	3.3585	7.1105	0.0077
hd	1	0.1343	0.0447	9.0347	0.0026
hdf	1	0.0561	0.0402	1.9495	0.1626

Odds Ratio Estimates			
Effect	Point Estimate	75% Wald Confidence Limits	
hd	1.144	1.086	1.204
hdf	1.058	1.010	1.108

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	86.5	Somers' D	0.732
Percent Discordant	13.3	Gamma	0.734
Percent Tied	0.3	Tau-a	0.376
Pairs	400	c	0.866

Figure 2: Fit Statistics and Odds Ratio Estimates