What Makes a Location into a “Favorable Habitat” under Changing Climate and Environmental Conditions? A Pilot Study Focused on Exploring the Differences between Natural and Non-natural Habitats using Airborne LiDAR

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Abstract. Recovery plans supported by conservation models are critical for the protection of endangered species. For developing these models, parameters are most commonly extracted via field survey or remote sensing based methods. However, at times, these models get narrowed down to specific habitat features associated with naturally occurring ecosystems, and thereby fail to detect suitable non-natural habitats that the animals have gotten adapted to in recent years - as a survival mechanism to cope up with the dynamic climate and environmental conditions. As a first step to address this issue, we considered the case of Red-cockaded woodpecker (RCW) species and undertook a pilot study to
explore the characteristics of non-natural locations that make it favorable for RCW nesting. On exploring the differences in habitat characteristics of natural and non-natural ecosystems - by employing airborne laser scanning data and logistic regression analysis method - we identified new prominent forest attributes and their variations for each habitat types. Based on our findings, we provide fruitful interpretations, recommendations and encourage discussions on less-studied conservation aspects and hope to stretch the horizons of ongoing biodiversity conservation efforts in the wake of global environmental change.

1. Introduction
Climate change, which broadly refers to the continuous change in climate patterns - evident at a local as well as global scale - primarily due to the increased levels of carbon dioxide in the atmosphere, has been transforming the environment at a dynamic rate, thereby, intervening in the life cycles of both humans and animals equally [1]. As a consequence, several animals respond to these changing environmental conditions by adapting themselves to the newly formed non-natural ecosystems, while numerous species flee or perish. Therefore, conservation models, which are critical for enhancing recovery operations of animals, need to be periodically modified to accommodate the varying habitat features. Nevertheless, these models, which are mostly built using habitat parameters derived through field surveys and remote sensing techniques, often get narrowed to specific habitat features associated with naturally occurring ecosystems, limiting the efficiency of the recovery processes.

Red-cockaded woodpeckers (RCW) (Picoides borealis Vieillot) are a group of non-migratory birds that are endemic to southeastern United States. Couple of decades back, in the Piedmont and coastal plains, they were very common throughout the open longleaf pine (Pinus palustris Mill) ecosystems [2]. However, RCWs’ preference for longleaf pine and their habitat destruction from the start of 17th century, caused by European settlement, naval stores, urbanization, agriculture and widespread commercial timber harvesting along with issues associated with change in environmental conditions, that caused increased fire suppression, forced the RCWs to be placed on the federal list of endangered species [3]. In the past few years, several RCW habitat conservation activities have been performed by the US Forest Service and similar agencies in the southeastern U.S [4,5]. Yet, most of these efforts were focused on modeling foraging zones of the “natural habitats”, which comprises of long leaf ecosystems with low (< 3 m) understory [6]. In these habitat models, the “non-natural” habitat environments, such as pocosins and pond pine ecosystems, where there have been RCW citing, fail to qualify for conservation initiatives.

Discerning the reasons for species adaptability in newly formed ecosystems can extensively assist in identifying and protecting suitable non-natural habitats, and in that way help enhance the ongoing habitat conservation efforts. However, different organisms behave differently to climate and environmental changes and quantifying the dynamic processes attributed to habitat favorability can be perceived as a challenging and time-consuming endeavor. Nevertheless, somewhere, we have to start, in order to progress. This pilot study is performed as a first step towards addressing this salient issue - using Light Detection and Ranging (LiDAR) data and logistic regression analysis method - and by taking the case of RCWs, as a representative species, we hope to stretch the horizons of conservation perspectives and encourage future research activities in directions that further explore the importance of upgrading habitat conservation models under changing climate and environmental conditions.

2. Materials and Methods
2.1. Study Area, Data Collection and Processing
Two study sites were considered as a part of this research study: Palmetto-Peartree Preserve (P3) and Croatan national forest (CNF), both located at North Carolina, USA. Study plots (i.e., trees with RCW cavities) at P3 comprised of non-natural ecosystems and at CNF, the habitats primarily had pine forests. The P3 was in fact established by The Conservation Fund in 1999 to serve as an RCW mitigation bank.
to offset habitat loss happening from road construction projects. Active RCW nesting cavity locations that had been spotted within P3 were obtained via The Conservation Fund and U.S. Fish and Wildlife Service. In case of CNP, data were acquired through North Carolina Natural Heritage Program 2016, Division of Land and Water Stewardship. From natural habitats, non-natural habitats, and no-bird zones, 60 locations (20 locations from each category) were randomly selected for building the predictive models. Here, we define no-bird zones as areas that the birds have avoided for nesting, but, are similar to the non-natural habitats in terms of physical geography. These zones were selected from regions which were far (at least 8.05 km; i.e., 5 miles) away from identified RCW habitats – as the average flight distance of these birds were found to be less than 8 km. Also, we decided not to include the map of exact study locations in this paper as a gesture in support of the conservation endeavors.

Airborne LiDAR data used for this study were acquired in 2014 as a part of the NC Floodplain Mapping Program (Department of Public Safety). Field survey checkpoints (around 100 checkpoints per county) were used to evaluate the accuracy of LiDAR products; more details can be found in [7]. The major output derived from the LiDAR point cloud was the canopy height model (CHM); canopy structure metrics were derived from these CHMs. First, the LiDAR point clouds associated with the study sites were extracted and Digital Terrain Models (DTMs) were generated, from the points classified as ground. Subsequently, the point clouds were normalized to height above ground by subtracting the DTM elevation from each return, for generating Digital Surface Models (DSMs). The difference between DSMs and DTMs provided us with the respective CHMs. All LiDAR data processing were performed in ESRI ArcGIS 10.3 [8,9], by employing default settings of general raster processing tools such as LAS to Multipoint, Terrain to Raster and Raster Calculator function.

2.2. Spatial Analysis and Habitat Attributes Estimation

In case of RCW, spatially explicit information on the habitat distribution and structure of forest vegetation is required at broad scales for answering questions regarding their habitat selection criteria [6,7]. As an attempt to better understand the spatial pattern of habitat distribution and to improve the conservation practices, various classification and cluster analysis methods had been evaluated in previous studies [11]. Herein, we performed detailed visual analysis of non-natural study spots with the help of RCW experts, and this prompted us to assess the possibilities of having height difference between tree-crown and mid-story as a crucial factor for habitat suitability. Hence, in our habitat presence models we used height difference ($d$) as a primary variable, along with three other environmental variables - height density factor ($f$), percent openness ($p$) and tree height ($h$) - for quantifying the change in canopy cover with varying heights; parameters are explained in the following sections.

Initially, we developed forest CHMs for the randomly selected individual study sites for extracting the parameters of interest from the LiDAR data. We treated these individual fragments as a circular piece of land having a 30.34 m (100 feet) radius, so as to maintain uniformity and to standardize our values for making easier and fair comparisons. This kind of a smaller circumscribed circle around cluster center was used instead of the 0.8 km (½-mile) radius circle as adopted in the 2003 recovery plan, as our primary objective was the assessment of nesting sites [4,12]; spatial separation of foraging and non-foraging habitats was not considered in the model. Also, parameters associated with midstory and understory conditions had to be compromised as the accuracy and details contained by point-cloud data were low. Tree height, $h$, in our case, represented the maximum tree height within the circular plot. Since we were not able to clearly quantify the hardwood midstory as “sparse and less than 2.1m in height” as listed in the recovery standards [12], we derived a novel surrogate factor - "height-density factor ($f$)".

For quantitatively studying the vertical canopy structure, we first built conditional rasters from CHMs - using con tool provided by spatial analyst toolkit available in ArcGIS 10.3 [8,9] - and calculated the percent canopy cover difference for every 3.05 m (10 feet) interval starting from $h$ to the ground level. The Con tool works in a way such that, the output value for each cell is based on whether the cell value is evaluated as true or false (with respect to a conditional statement that we specify; for example: tree height > 10 m). At first, the interval width was also tested for 0.31 m (1 foot), 0.91 m (3 feet) and 1.52
m (5 feet), nonetheless, the canopy cover change with respect to interval width was comparatively less evident in these cases. Most of the times, plotting canopy height with relative difference in canopy cover over the intervals resulted in break points where a rapid change (maximum variation) was observed. Height-density factor can be defined as the center point of this height interval exhibiting maximum variation. Center point was selected as the variation of percent canopy cover within the 3.05 m (10 feet) intervals was found to be gradual. In short, f gives us an estimate on the change in canopy cover with respect to varying canopy height and is the canopy height where the % change in canopy cover is maximum. Whereas, the parameter p gives us the percent of unoccupied pixels in the CHM where canopy height is equal to f and parameter d denotes the absolute difference of h and f.

2.3. Quantitative Analysis and Habitat Modeling

Taking into account the binary nature of RCW tree cavity data, logistic regression and discriminant analysis were considered as appropriate modeling approaches. Nevertheless, logistic regression was considered as more fitting as available data on some of the independent variables (e.g. canopy openness) are qualitative and non-multivariate normal [13]. However, before that, univariate statistical tests were performed to evaluate the validity of individual model variables - and for obtaining a better understanding of each variable’s role. If the species did discriminate among sites based on the considered environmental factors, the mean values of these variables at favorable habitat locations should be different from locations they have avoided i.e., no-bird zones [13].

Logistic regression is a predictive analysis method, which is considered appropriate to conduct when the dependent variable is dichotomous (binary). In our case, the logistic model is used to estimate the probability (P) of RCW occurrence/favorability (binary response) based on h, f, p and d (independent variables). Unlike ordinary multiple regression, logistic regression analysis is efficient when applied to binary data and yields estimated probabilities (P) of RCW occurrence/favorability (binary re). This way, it allows us to evaluate the influence of an individual factor - using the measure of association, the odds ratio - in increasing the probability (by a specific percentage) of a given outcome. An odds ratio indicates how likely - with respect to odds - a particular event occurs in one group with reference to its occurrence in another group [14]. The general form of the equations are as follows:

\[
\logit(P_i) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \varepsilon_i, \quad (1)
\]

\[
\logit(P_i) = \log [P_i/(1-P_i)] \quad (2)
\]

\[
P_i = 1/[1 + e^{\logit(P_i)}]. \quad (3)
\]

Where, \(P_i\) is the probability that the event (active RCW habitat, for example) occurs in the \(i^{th}\) case, \(\log\) is the natural log (to the base e), \(\logit(P_i)\) is the logit transformation of the probability of the event, \(i\) is the indices of all cases (observations), \(\beta_0\) is the intercept of the regression line, \(\beta_1, \beta_2, \beta_3\) and \(\beta_4\) are the slopes of the regression lines, \(X_1, X_2, X_3\) and \(X_4\) are the predictor variables, \(\varepsilon_i\) is the error (residual) associated with each observation and \(e\) is the base of the natural logarithms. In our analysis, the probability cut level of \(P_i\) was chosen to be 0.50 and with this threshold, the yielded misclassification errors were found to be very limited.

For understanding the influence of individual parameters towards habitat favorability - along with determining the predominant attributes - we developed two separate habitat models. The first model was constructed on parameter values derived from 20 non-natural nesting sites and 20 no-bird zones located at P3. The second model was similar to the first model, but had additional 20 natural sites from CNF. Figure 1 provides an overview of the workflow. Statistical analysis and data exploration were carried out and tested in a combination of R and SAS environment [15,16].
3. Results

3.1. LiDAR derived metrics for describing forest structure

Primary parameters of interest for our study - $h, f, p, \text{ and } d$ - were derived from CHMs. For demonstration purpose, here, we considered the case of a non-natural sample study site (SSS) with the maximum tree height ($h$) being 28.13 m (92.3 feet). For calculating $f$, the CHM was first split into multiple bins of 3.05 m (10 feet) intervals. Here, for the SSS, since the $h$ was 28.13 m (92.3 feet), 9 conditional rasters were created - using point clouds greater than 27.43 m (90 feet), 24.38 (80 feet), 21.34 (70 feet) and so on, up to 3.05 m (10 feet). Figure 2 reveals how the canopy cover varies - i.e., gets denser - with decreasing canopy height. Figure 3a shows the percent openness (100 – % canopy cover) - an indicator of habitat favorability - associated with canopy heights. When the relative percent difference in % openness is plotted against canopy height (figure 3b), we notice an abrupt change in pattern when the canopy height is 12.19 m (40 feet). This indicates that the canopy cover was getting denser and denser gradually till 12.19 m (40 feet), and then there occurred a sizeable change. Since, the change in canopy cover is gradual, it can be presumed that the interval (9.14 m to 12.19 m i.e., 30 feet to 40 feet) is where the maximum relative change in canopy cover happened. For the same reason, we choose $f$ to be the mid-point of the interval (i.e., 35 feet or 10.67 m); $f$ can be perceived as a satisfiable surrogate to the mid-story height. Values of other parameters such as percent openness ($p$) and height difference ($d$), associated to height-density factor estimates, were 68.83 and 17.47 m i.e., 57.3 feet (92.3 – 35) respectively; similar procedures were followed for rest of the study sites as well.
Figure 2. Conditional rasters showing the variation of canopy openness for the sample study site.

Figure 3. Graphs showing (a) percent canopy openness vs tree height (b) tree height vs relative difference in percent openness.
3.2. Logistic Regression Model

The performance of logistic regression based habitat presence models indicated that LiDAR-derived parameters are efficient in RCW habitat structural assessment and for determining the roles of underlying habitat parameters. Also, in general, variation of parameter means was found to be comparatively higher in no-bird zones. On performing univariate statistical analysis, we assessed the validity of individual model variables and parameters \(d\) and \(h\) were found to have similar \(c\)-values, greater than the other two variables - \(p\) and \(f\). Here, when the \(c\)-value nears to 1, it means that the model is capable of perfectly discriminating the response; this is equivalent to the well-known measure ROC (receiver operating characteristic) [14,17]. Correlation plots for the selected parameters revealed high association \((r = 0.71611, \ p < 0.001)\) between \(h\) and \(d\). On testing different combinations of the 4 variables, the best case (highest \(c\)-value; 0.866) was obtained for the model with \(d\) and \(f\) as independent variables. There were no statistically significant interactions found between the two variables \((p > 0.001)\). \(p\) has been found to be a significant factor in similar studies [4,12], however, in our case, it had a negative impact on the \(c\)-value (0.855) and thus was removed at a later stage. Here, equation 4 represents the general form of model I; the overall model was found to be significant (Likelihood Ratio chi-square test value: 21.045; \(Pr < 0.001\)). The odds ratio estimates indicate that for every one-unit increase in \(d\), the chances of finding RCW increased by 14\% when the effects of other factors are kept constant and the RCW favorability increased by 6\% when the \(f\) increased by one unit keeping the effects of other variables constant.

\[
P = 0.1343 \ d + 0.0561 \ f - 8.9556
\]  

An alternative model (model II) was built on similar procedures, though it included data from additional 20 natural sites from CNP as well. This helped us evaluate how the performance of our model was influenced by the inclusion of parameters dictating the favorability in natural habitats. In this case, univariate statistical analysis resulted in \(h\) having the highest \(c\)-value (0.763) and hence the model II had \(h\) replace \(d\), unlike in model I. The general form of model II is listed in equation 5.

\[
P = 0.0634 \ h + 0.0439 \ p - 7.2225
\]  

Both the models were further evaluated based on their predictive performance; by comparing their ability to identify the presence of non-natural habitat conditions. For this validation process, 10 new non-natural study sites in Palmetto-Peartree Preserve were considered. Model I successfully identified 8 out of the 10 total sites at 75\% confidence interval, whereas model II could classify only 6 of them correctly. A 75\% confidence interval was chosen as it was reported as a decent measure in similar studies done in the ecological modeling domain.

4. Discussion

Findings from our study suggest that nesting habitats at natural and non-natural sites might have different underlying parameters contributing at varying degrees towards RCW favorability. From our results, the importance of difference in distance between the tree top and mid-story towards habitat favorability is evident and incorporating this parameter in the existing models might enable advancement of RCW conservation activities in non-natural habitat locations. The habitat model I, made of parameters extracted from 20 non-natural and 20 no-bird zones, showed \(f\) and \(d\) as dominant parameters whereas when data from additional 20 natural zones were included the primary factors changed to \(h\) and \(p\). This in fact states that, increasing \(h\) and decreasing \(f\) results in increasing RCW presence within non-natural habitats - i.e., a positive correlation between \(d\) and habitat favorability. Also, the model II, with \(h\) and \(p\) as parameters, performed with comparatively lesser accuracy with non-natural habitat identification. This further implies that considering the exact parameters of RCW habitats in natural sites might not be able to successfully locate RCW habitat zones in non-natural habitats. Additionally, LiDAR structural
assessment of the forest canopy revealed the similarity of \( f \) to the mid-story height and the logistic regression analysis results underscore the role of \( f \) in habitat prediction models. Even then, as a whole, it is difficult to affirm whether the results (8 from 10 with 75% confident interval) can prove the suitability of the proposed approach for RCW cluster mapping in non-natural sites due to limited study samples. More data collection and analysis need to be performed for bolstering our interpretations. Also, since, our major focus was on detecting non-natural habitats, and due to lack of enough high quality data of additional natural habitats at the time of study, we did not further test the applicability of models for identifying natural sites or no-bird zones. However, testing and comparing the performance of our models on variant ecosystems as well the models’ compatibility with increased levels of confidence intervals are planned in upcoming studies to draw more convincing inferences. It would be also interesting to know how the habitat suitability models developed earlier would perform compared to the new models developed here using the newly found attributes. Extraction of key variables included in the earlier models from the field plot data and including those in the current models’ feature selection procedures is also another prospective worth investigating; this will enable us to check if the newly identified LiDAR-features outperforms the existing ones used for model creation purposes.

In addition to RCW, this framework is transferable to several other species - such as California spotted owl (\textit{Strix occidentalis occidentalis} Xantus de Vesey) and Fisher (\textit{Martes pennant} Erxleben), whose habitat mapping is guided by properties of stand structure [18,19]. In these cases, field inventory methods can be outrun by LiDAR-based techniques as well as other remote sensing methods such as aerial and satellite imagery, as it allows for a vertical characterization of nesting habitat structures [10]. Multi-return high resolution LiDAR have been used for monitoring large residual trees which facilitate selection of habitats by spotted owls, and to measure number, density, pattern of trees and canopy cover for evaluating the associated nesting habitats [19]. For testing the influence of canopy cover variation in these situations, inclusion of height-density factor in the models could be found helpful.

Considering the high cost associated with LiDAR technology, and advancements in Structure-from-Motion algorithms, as a future alternative, habitat characteristics can be derived using stereo imagery obtained via Unmanned Aerial Vehicles (UAVs) as well [20,21]. This will help eradicate the limitations associated with absence of consecutive years’ data; another possible way to tackle this situation is by modeling and including predictive forest growth where habitat changes can be simulated as a function of land cover change [22]. Either way, the time difference between field data collection and remotely sensed data acquisition should be proved not to be significant for the study sites (i.e., to prove that the forest stands did not change too much over the years) for providing validity to the research interpretations [23]. In this study, landscape connectedness with existing clusters was not considered; including those parameters may add more variables and/or relevant factors to the model. In that case, several areas located by our model as possible habitat zones might not be found suitable for accommodating RCW clusters if they are adjacent to existing clusters. This is because of the territorial nature of RCWs i.e., they often have individual groups that compete against each other for territory [24]. Also, it has been reported that the artificial cavities need to be at least 8.05 km (5 miles) away from the existing clusters for relocation to happen and further exhaustive research - and related model upgradations - has to be done for accurately demonstrating the effect connectivity has on habitat favorability.
Another potential parameter which should be explored is the distance between habitats and roads. In most of the existing models, we find the roads being masked [25]; nonetheless, inspecting several of our spots near roads led us to speculate that open, scarcely-used roads had acted as sparse forging zones and increased the habitat favorability, considering the change in pattern observed while calculating $f$ for these sites (see figure 4b). Herein, using spatially explicit and detailed LiDAR-derived habitat attributes we are able to gather new insights into RCW nesting habitat relationships and this can be further underpinned by employing supplementary field plot data [26]. Also, development of thematic potential RCW presence-absence map from these kinds of models based on environmental characteristics is also a possibility; it can then be used to assess the impact of various human activities such as rising urbanization and land use change on habitat quality. For this study, we analyzed only nesting sites, however, we anticipate a similar framework to be extended to foraging habitats as well; ideally, a structural overlay of social or biological model can be developed for pursuing future research.

In sum, even though, this pilot study cannot function as a stand-alone research to provide convincing conclusions regarding why RCWs favor certain non-natural sites, for sure, the results of our study are able to develop a hypothesize that habitats that do not meet all the conditions set by well-established recovery plans can yet have the potential for nurturing healthy and advancing RCW populations. This discovery is crucial for enhancing the decision making processes associated with conservation strategies - for not just RCWs, but of similar species of birds and animals as well - in the present era influenced by rapid climate change and environmental transformation. Parameters such as $f$ and $d$, which are not considered in existing models, proved to be helpful in non-natural habitat identification. Inclusion of these newly found features may offer additional options for extending the threshold limits of pre-established features and thereby help in creation of habitat suitability indices that can account for feature deviations prominent in non-natural ecosystems. However, data acquisition from non-natural sites can be a big challenge, as these locations are not widely known. For enhancing our understanding of RCW habitat favorability and for improving the predictive range of habitat models, future studies in the direction of merging nesting habitats with foraging habits for structural analysis will be very helpful. By taking the proposed measures, we can improve the ways RCW conservation measures are integrated into
the forest management methodologies and thereby create a win-win situation for both forest managers and RCW conservationists [27,28]; we also envision applications of advanced geostatistical as well as other cutting edge remote sensing techniques - such as multispectral lidar - to assist the model development initiatives [29,30,31,32]. Whilst this study focused on RCWs, we expect the proposed framework to be applicable for a wide range of endangered species and look forward to seeing climate and environment adaptable habitat models in mere future.

5. Conclusions
From this research study, we were able to hypothesize that there exist differences in values of underlying characteristics for natural and non-natural habitats, and underscores the influence height difference and height density factor have towards Red-cockaded woodpeckers’ habitat favorability. However, it must be borne in mind that, since the existence of several endangered species in non-natural habitats is not widely publicized or studied, the inputs for developing respective models can be difficult to obtain. Nonetheless, by sharing our results we intend to encourage the readers, researchers and biologists to pursue studies on a larger scale in the proposed direction for determining the longer-term effects that environmental and climate changes will have on habitat favorability of various animal species. This way, effective and adaptive habitat conservation models can be developed, which can further contribute towards the protection and well-being of numerous endangered species of animals and birds.

References
[1] Dore M H 2005. Climate change and changes in global precipitation patterns: what do we know?. Environment international, 31(8), 1167-1181.
[2] Jackson J A 1971. The evolution, taxonomy, distribution, past populations and current status Of the red-cockaded woodpecker. Ecology and management of the red-cockaded woodpecker. US Bureau of Sport Fishing and Wildlife and Tall Timbers Research Station, Tallahassee, FL 1971: 4-29.
[3] Myers G 2016. North Carolina Wildlife Resources Commission.
[4] Lipscomb D J, Thomas M W 2006. Evaluating some proposed matrices for Scoring sub-optimal red-cockaded woodpecker foraging habitat in relation to the 2003 recovery plan. Gen. Tech. Rep. SRS-92. Asheville, NC: US Department of Agriculture, Forest Service, Southern Research Station. pp. 10-16.
[5] U.S. Fish and Wildlife Service; Red-cockaded Woodpecker Recovery; RCW Foraging Matrix Application; Available online: http://www.fws.gov/rcwrecovery/matrix.html (accessed on 15 December 2015)
[6] Bruggeman D J, Michael L J 2008. "Should habitat trading be based on mitigation ratios derived from landscape indices? A model-based analysis of compensatory restoration options for the red-cockaded woodpecker. Environmental Management 42.4 (2008): 591-602
[7] NCfloodmaps; LiDAR and Digital Elevation Data; Available online: http://www.ncfloodmaps.com/pubdocs/lidar_final_jan03.pdf (accessed on 21 October 2015)
[8] ESRI 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.
[9] Scott L M, Janikas M V 2010. Spatial statistics in ArcGIS. Handbook of applied spatial analysis, 27-41.
[10] Mohan M 2016. Spatial Modeling and Evaluation of Red-cockaded Woodpecker Non-Traditional Habitats: A Logistic Regression Analysis and LiDAR Approach. NCSU Library.
[11] Garabedian J E, Moorman C E, Peterson M N, Kilgo J C 2018. Relative importance of social factors, conspecific density, and forest structure on space use by the endangered Red-cockaded Woodpecker: A new consideration for habitat restoration. The Condor, 120(2), 305-318.
[12] U.S. Fish and Wildlife Service. 2003. Recovery plan for the red-cockaded woodpecker (Picoides borealis): second revision. Atlanta, GA: U.S. Fish and Wildlife Service. 296 p.

[13] Pereira J, Itami R 1991. GIS-based habitat modeling using logistic multiple regression- A study of the Mt. Graham red squirrel. *Photogrammetric engineering and remote sensing*, 57(11), 1475-1486.

[14] Dayton C M 1992. Logistic regression analysis. *Stat*, 474-574.

[15] R Core Team 2015. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, accessed Oct. 15 2015, <http://www.R-project.org>.

[16] Alison P D 2012. Logistic regression using SAS: Theory and application. SAS Institute.

[17] Fawcett T 2006. An introduction to ROC analysis. *Pattern recognition letters*, 27(8), 861-874.

[18] Purcell K L, Mazzoni A K, Mori S R, Boroski B B 2009. Resting structures and Resting habitat of fishers in the southern Sierra Nevada, California. *Forest Ecology and Management*, 258(12), 2696-2706.

[19] García-Feced C, Tempel D J, Kelly M 2011. LiDAR as a tool to characterize wildlife habitat: California spotted owl nesting habitat as an example. *Journal of Forestry*, 109(8), 436-443.

[20] Mohan M, Silva C A, Klauberg C, Tat J, Catts G, Cardil A, Hudak A T, Dia M 2017. Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest. *Forests*, 8(9), 340.

[21] Gonzalez L F, Montes G A, Puig E, Johnson S, Mengersen K, & Gaston K J 2016. Unmanned Aerial Vehicles (UAVs) and artificial intelligence revolutionizing wildlife monitoring and conservation. *Sensors*, 16(1), 97.

[22] Mueller J, Moning C, Baessler C, Heurich M, Brandl R 2009. Using airborne laser scanning to model potential abundance and assemblages of forest passerines. *Basic and Applied Ecology*, 10(7), 671-681.

[23] Silva C A, Klauberg C, Hudak A T, Vierling L A, Jaafar W S W M, Mohan M, Garcia M, Ferraz A, Cardil A, Saatchi S 2017. Predicting stem total and assortment volumes in an industrial *pinus* taeda L. Forest plantation using airborne laser scanning data and random forest. *Forests*, 8(7), 254.

[24] Hooper R G, Niles L J, Harlow R F, Wood G W 1982. Home ranges of red-cockaded woodpeckers in coastal South Carolina. *The Auk* (1982): 675-682.

[25] Copeyon C K, Walters J R, Carter III J H 1991. "Induction of red-cockaded woodpecker group formation by artificial cavity construction. *The Journal of wildlife management*: 549-675 556.

[26] Garabedian J E, McGaughey R J, Reutebuch S E, Parresol B R, Kilgo J C, Moorman C E, Peterson M N 2014. Quantitative analysis of woodpecker habitat using high-Resolution airborne LiDAR estimates of forest structure and composition. *Remote Sensing of Environment*, 145, 68-80.

[27] Roise J P, Harnish K, Mohan M, Scolforo H, Chung J, Kanieski B, Catts G P, McCarter J B, Posse J, Shen T 2016. Valuation and production possibilities on a working forest using multi-objective programming, Woodstock, timber NPV, and carbon storage and sequestration. *Scandinavian Journal of Forest Research*, 31(7), 674-680.

[28] Roise J P, Chung J, Lancia R 1991. Red-cockaded woodpecker habitat management and longleaf pine straw production: an economic analysis. *Southern Journal of Applied Forestry*, 15(2), 88-92.

[29] Jat P, Serre M L 2018. A novel geostatistical approach combining Euclidean and gradual-flow
covariance models to estimate fecal coliform along the Haw and Deep rivers in North Carolina. 

Stochastic Environmental Research and Risk Assessment, 1-13.

[30] Huo L, Silva C A, Klauberg C, Mohan M, Zhao L, Tang P, Hudak A T 2018. Supervised Spatial Classification of Multispectral LiDAR Data in Urban Areas. PLOS ONE, 13(10): e0206185.

[31] Wan Mohd Jaafar W S, Woodhouse I H, Silva C A, Omar H, Hudak A T 2017. Modelling individual tree aboveground biomass using discrete return lidar in lowland dipterocarp forest of Malaysia. Journal of Tropical Forest Science, 465-484.

[32] Wan Mohd Jaafar W S, Woodhouse I H, Silva C A, Omar H, Maulud K N A, Hudak A T, Klauberg C A, Mohan M 2018. Improving Individual Tree Crown Delineation and Attributes Estimation of Tropical Forests Using Airborne LiDAR Data. Forests.

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