ASSESSING THE INFLUENCE OF SOCIAL INFORMATION AND HABITAT STRUCTURE ON CERULEAN WARBLER BREEDING DISTRIBUTION IN SOUTHERN INDIANA

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CERULEAN WARBLER SETTLEMENT CUES: A CONSPECIFIC ATTRACTION STUDY

ABSTRACT

Distributions of breeding birds are often aggregated rather than evenly or randomly distributed across suitable habitat, suggesting that settlement cues go beyond habitat characteristics. The Cerulean Warbler (*Setophaga cerulea*) has a distribution that is loosely clustered within large tracts of seemingly suitable habitat, and research reporting habitat structure within Cerulean Warbler territories has been largely inconsistent across its range. I assessed the influence of three forms of social information on male Cerulean Warbler breeding site selection: 1) locational cues, or pre-breeding cues 2) public information, or post-breeding cues, and 3) clustered locational cues, or breeding aggregation cues. I did this by broadcasting conspecific song in mature deciduous forests that have not had an established Cerulean Warbler territory in the past six years. In 2013, I broadcasted conspecific song during the pre- and post-breeding period. In 2014, I used a clustered speaker arrangement and broadcasted song during the pre-breeding season to portray a mock breeding aggregation. The broadcast systems were deployed in Morgan-Monroe State Forest, Indiana on 15 April and taken down on 23 July 2013. They were deployed again on 15 April and taken down on 10 May 2014. Point counts were conducted in treatment and control plots every 3-6 days. In 2013, only two detections occurred and breeding territories were not established in control or treatment plots, suggesting that locational cues during the settlement period do not influence breeding site selection. Treatment and control plots in these same areas were surveyed in 2014, and no detections occurred and no territories were established near treatment or control plots, suggesting post-breeding cues do not influence breeding site selection the following year. Lastly, treatment and control plots from
2014 mock breeding aggregations sites had only two detection and no territories were established, suggesting that breeding aggregations do not influence settlement due to a reproductive advantage.
INTRODUCTION

Breeding bird habitat selection is the behavioral response of avifauna to external cues, resulting in the preference for environmental components that increase survival and fitness (Block and Brennan 1993). External cues that elicit avian habitat selection exist on a continuum of spatial scales, from a broad-scale macrohabitat, such as an appropriate geographic region, to a fine-scale microhabitat, such as an area containing a specific foraging substrate (Block and Brennan 1993). Researchers have historically defined settlement cues by correlating a species’ occupancy to climate, geology, and vegetative characteristics (Grinnell 1917, Kendeigh 1945, MacArthur et al. 1962). However, bird territories are often found to be aggregated even within large tracts of seemingly suitable habitat (Darling 1952). These aggregations suggest that either preferred microhabitat has not yet been defined (e.g., Bakermans and Rodewald 2009) or that behavioral phenomena beyond habitat quality influence settlement decisions, such as conspecific attraction (Stamps 1988). Conspecific attraction may seem contradictory for territorial species; however, theory suggests that settling near conspecifics provides many benefits that outweigh the costs of competition (Stamps 1988).

The benefits of conspecific attraction are often rendered from social information (Danchin et al. 2004). A behavioral response to social information is a four part process: a signal (event or state), an observation of the signal, a decision based on the observation, and the consequence of the decision (Seppänen et al. 2007). Social information is only valuable if it increases a species’ survival and fitness; therefore, the value of social information is rendered from the consequences of using social information (Danchin et al. 2005).
A signal can be either intentional or inadvertent. Intentional social information is an evolved signal, developed to convey a specific message and is effectively received with its intended purpose by another individual (Danchin et al. 2004, Seppänen et al. 2007). Bird song and alarm calls are two avian signals that have evolved with specific intent (Smith 1986, Falls 1992). Birds use song as a signal to attract a mate and deter competition; aggregations may form as a way to increase signal strength and thus increase mate attraction (Bradbury and Gibson 1983). In addition, females may seek out aggregations due to increased mate choice and the opportunity for extra-pair copulations (Wagner 1997). Aggregations may also occur as a way to decrease predation by using an attack abatement strategy that also provides increased predator detection and defense through the implementation of alarm calls (Smith 1986, Turner and Pitcher 1986).

Inadvertent social information (ISI) is a signal that has been perceived with unintended meaning, and can be in the form of locational cues or public information (Danchin et al. 2004). Locational cues and public information both impart the presence of resources; however, public information also imparts the quality of resources (Danchin et al. 2004). A singing male is indeed producing an intentional signal to attract a mate (Falls 1992), but it is also inadvertently producing a locational cue, indicating appropriate nesting habitat to other prospecting conspecific males (Danchin et al. 2004). Such a locational cue would benefit inexperienced male breeders under temporal constraint to select a territory when arriving at breeding grounds in early spring (Alatalo et al. 1982, Muller et al. 1997). Another example of ISI is the presence of fledglings, which are interpreted as a direct representation of habitat quality because they would not occur if the surrounding habitat did not possess adequate resources to attract a mate, construct a nest, and feed young (Danchin et al. 2004). This public information would benefit
dispersing individuals in an asynchronous nesting population, such as young of the year or failed breeders (Danchin et al. 2004). These individuals may prospect areas containing fledglings and settle there the following spring (Doligez et al. 2002, Parejo et al. 2007, Betts et al. 2008, Parejo et al. 2008). Aggregations are likely to form from intentional or inadvertent social information when the benefits of using these cues outweigh the costs of assessing the environment through trial-and-error (Seppänen et al. 2007).

Researchers have found that both locational cues and public information increase site selection of male birds for some species (Ahlering et al. 2010), even within sub-quality habitat (Farrell et al. 2012). Betts et al. (2008) examined the effects of public information on Black-throated Blue Warbler (Setophaga caerulescens) settlement patterns by broadcasting adult and fledgling vocalizations across a habitat gradient during the end of the breeding season. The authors found that males were 4.1 times more likely to settle in treatment conditions than control conditions the following spring, and there was no difference in the amount of settlement across the habitat gradient. However, second-year male settlement was greater than after-second-year settlement in sub-quality habitats, and female settlement had a higher correlation to male location than to treatment conditions. These settlement patterns indicate that past experience will influence settlement decisions; however, experienced breeders will be more discerning of habitat quality when using social information. Farrell et al. (2012) examined the effects of locational cues on Golden-cheeked Warbler (Setophaga chrysoparia) settlement patterns by broadcasting male vocalizations across a habitat gradient during the beginning of the breeding season. The authors found that territory densities were on average four times higher in treatment conditions than control conditions, and there was no difference in territory density, pairing, or fledging success across treatment conditions. These results indicated that males use conspecifics to select
breeding habitat and aggregations may be more important for mate attraction and reproductive success than habitat quality.

The behavioral traits of the Cerulean Warbler (*Setophaga cerulea*) suggest that it may benefit from conspecific social information for breeding site selection. The Cerulean Warbler is a small, Neotropical migratory wood warbler that breeds high in the canopy of large mature deciduous forests of central and eastern North America (Buehler et al. 2013). Although it was once abundant, it is now considered one of the fastest declining Neotropical wood warblers in North America (Buehler et al. 2013). Its population declined 70% from 1966 to 2006 (Sauer et al. 2011) and it is listed as a “Species of Concern” by the U.S. Fish and Wildlife Service (2012) and endangered in the state of Indiana (Indiana Department of Natural Resources 2012). Cerulean Warbler males arrive in southern Indiana during mid- to late April (Buehler et al. 2013). Arrival occurs during a time when many trees are still budding and information on prey abundance and habitat structure are incomplete (van Asch and Visser 2007, Newell and Rodewald 2012, Wagner 2012). It would be costly for inexperienced male breeders to select a territory so early in the season through trial-and-error sampling of habitats, suggesting that locational cues from experienced breeders would be advantageous for site selection. In further support of locational cues possibly influencing settlement, territory distributions of Cerulean Warblers have been described as loosely clustered (Roth and Islam 2007), even when seemingly suitable unoccupied habitat is nearby (K. Barnes, pers. obs.). In addition, Stamps (1988) suggested that if locational cues are an important component in site selection then inexperienced breeders should be aggregated around experienced breeders, who settle earlier due to knowledge of habitat quality gained from past experience. Dibala (2012) found that Cerulean Warbler territories followed this clustering pattern, and that second-year male territories were closer to
after-second-year males within clusters. In addition, studies that define habitat preferences across the Cerulean Warbler’s range have been largely inconsistent beyond reporting the preference for large tracts of mature deciduous forests (Rosenberg et al. 2000). Inconsistencies in habitat preference could arise from social information having a stronger influence on habitat selection than the quality of habitat structure.

My research objectives were to (1) determine if conspecific vocalizations during the settlement period induce male Cerulean Warbler settlement, (2) determine if conspecific vocalization during the 2013 breeding and post-breeding period induce male Cerulean Warbler settlement in 2014, (3) determine if aggregated conspecific vocalizations during the pre-settlement and settlement period induce male Cerulean Warbler settlement, and (4) determine if conspecific vocalizations elicit a stronger settlement response than habitat quality. In addition, if settlement is induced, pairing status and reproductive success will be measured for all individuals. In 2013, I broadcasted male Cerulean Warbler vocalizations from speakers in areas that have not had an established territory in the past six years to determine if conspecific vocalizations induce settlement. During this time, I broadcasted vocalizations within higher and lower quality habitat to determine if conspecific vocalizations elicit stronger settlement response than suitable habitat structure. In 2014, I broadcasted male Cerulean Warbler vocalizations from speakers in an aggregated arrangement during the settlement period in areas that have not had an established territory within the past 2-7 years.

**METHODS**

*Study site and experimental site selection*
The social attraction experiment was conducted in south-central Indiana’s Morgan-Monroe State Forest, approximately 30 km north of the city of Bloomington. Treatment and control plots were selected within two 225 ha long-term monitoring units (Units 1 and 2) composed of mature deciduous forest. These units are two of nine units that make up the Hardwood Ecosystem Experiment (HEE). Point count surveys have been conducted in these units since 2007 to measure the relative abundance of male Cerulean Warblers within Morgan-Monroe and nearby Yellowwood state forests. Multiple organizations and agencies created the HEE to determine the effects of different timber harvesting methods on local flora and fauna. In fall 2008, Unit 1 received eight small patch cuts (> 0.4 < 2 ha) and single tree removal (target basal area 16.1-23 m²/ha) throughout the remainder of the unit. Unit 2 is a control unit which has not received silvicultural treatments.

Unit 1 had the lowest relative abundance of Cerulean Warblers of all nine units. From 2007 to 2012, the mean relative abundance was 0.51 males/km² ± 0.83 (mean ± SD) and there was only one confirmed established territory. Unit 2 had the second lowest relative abundance of all nine units. From 2007 to 2013, the mean relative abundance was 2.11 males/km² ± 1.37 (mean ± SD) with 11 confirmed established territories. In 2012, the year prior to conducting the social attraction experiment within Unit 2, there were no detections or territories established within this unit. Although the study sites contain suitable habitat, minimal Cerulean Warbler settlement has occurred since 2007, ensuring that induced male Cerulean Warblers settlement due to a social attraction broadcast system is not the result of drawing males from nearby areas within the unit.

In 2012, eight treatment and eight control plots were selected based on Cerulean Warbler habitat preferences reported in regional studies (Wood et al. 2006, Hartman et al. 2009, Roth and

Treatment and control groups were evenly divided into higher quality and lower quality habitat conditions (Figure 1). The habitat characteristics selected to represent higher quality habitat were aspect, diameter at breast height (DBH), and floristics. Areas were deemed higher quality habitat if they were located on productive northeast facing slopes with more $\geq 38 \text{ cm DBH}$ trees and less $\geq 10 < 38 \text{ cm DBH}$ trees, as well as containing vegetation often associated with Cerulean Warbler territories, such as hickories ($Carya$ sp.), white oaks ($Quercus alba$), and grapevines ($Vitis$ sp.) (Table 1). Treatment and control plots were at least 200 m apart to help prevent the confounding effect of settlement occurring near treatment sites, yet within a control area.

Treatment and control conditions were selected $a \ priori$ and subsequently surveyed to quantify habitat quality. Within each treatment and control plot, a center tree was selected to serve as a) the center for vegetation surveys, b) the location for point counts surveys, and c) the tree from which songs were broadcast in treatment plots. Vegetation surveys were conducted by extending a meter-tape 30 m in four cardinal directions from the center. The sampling area was chosen because it roughly represents the average size of a male Cerulean Warbler territory found in the HEE (Dibala 2012). Within a 30-m radius of the center, the following variables were recorded: number of trees $\geq 38 \text{ cm DBH}$, number of trees $\geq 10 < 38 \text{ cm DBH}$, number of grapevines, and number of hickories and white oaks (high-use trees). To aid in surveying such a large area, the center tree was flagged, another meter tape was used to further section off quadrants, and a range finder was used to help determine if trees on the periphery of the sampling area were within the quadrant.

Aspect was determined in ESRI’s ArcMap and ArcCatalog v10.1 by creating a raster file from a light detection and ranging (lidar) dataset that was acquired from IndianaMap Framework.
through Open Topography (http://www.indianamap.org. http://dx.doi.org/10.5069/G9959FHZ). Lidar datasets are acquired through the use of a vehicle (i.e., plane), a Global Positioning System (GPS) and Inertial Measurement Unit, and a laser scanning system (Lefsky et al. 2002). The laser can record elevation data (z) at many coordinates (x,y), creating a point cloud of x,y,z vertices. Each laser pulse is emitted down to the earth and returns to the laser scanner; the amount of time recorded for each return is converted to a distance. Every pulse will record returns (i.e. elevation; z-value) for objects it encounters on the way down. For example, if the point makes contact with a tree, the first return will be the top of the tree and more returns will register as it travels through the tree’s vertical profile until it encounters a hard surface, such as the ground that will represent the last return. A las file that contains these data for my study area was downloaded from Open Topography. Points that were classified as ground points were used to create a 1 m x 1 m digital terrain model (DTM) raster using the 3D analyst tool LAS to Multipoint, the Terrain Wizard in ArcCatalog 10.1, and the 3D analyst tool Terrain to Raster. The DTM was resampled to a 3 m x 3 m DTM raster using the data management tool Resample, and was then converted to an aspect raster file using the spatial analyst tool Aspect. The aspect raster was then converted to a raster that transforms aspect to a number between zero and two (henceforth called Beers aspect) using the following equation:

\[ A' = \cos (45 + A) + 1 \] (Beers et al. 1966),

where \( A' \) is a value between zero and two, and \( A \) is the aspect (Beers et al. 1966). The value two represents productive northeast facing slopes and zero represented unproductive southwest facing slopes (Beers et al. 1966). The conversion was accomplished using Map Algebra in PythonWin. Map Algebra interprets inputs for cosine operations as radians; therefore, aspects were converted to radians prior to calculating Beers aspect. A 30 m buffer was created around
the center of each plot and the mean Beers aspect was calculated within these boundaries using the spatial analyst tool *Zonal Statistics*.

In 2014, three treatment and three control plots were selected (Figure 2). Plots were selected based on conditional requirements. Habitat characteristics used for site selection were canopy height and aspect. These variables were derived from lidar data. Plot selection requirements included mature trees near northeast facing aspect. Selected plots were required to have a mean canopy height $\geq 20$ m, a max height $\geq 30$ m, and a Beers’ aspect $\geq 1.1$ (Wood et al. 2006). Another requirement for plot selection was the absence of an established territory within 200 m of the center since 2010.

Plot centers were selected *a priori* and subsequently surveyed to see if they met the requirements. In treatment plots, three speakers were installed within 20-35 m of the plot center and 40-70 m apart. All point counts and habitat surveys were conducted from the plot centers.

Canopy height was derived and sampled using lidar data and ArcGIS. A canopy height model (CHM) was created by subtracting a digital terrain model (DTM) from a digital surface model (DSM) of first return lidar points. A three step process was used to create a DTM and DSM. A las file was first converted to multipoint files using the 3D analyst tool *Las to Multipoint*. Only filtered ground points were used to create the DTM, and all lidar points were used to create the DSMs. The multipoint files were then converted to terrain files using the *Terrain Wizard* in ArcCatalogue. Window size was selected as the pyramid type with a zmin point selection for the DTM, and a zmax point selection for the DSM. Pyramid properties were calculated and all default settings were accepted. Lastly, the terrain files were converted to raster files using the 3D analyst tool *Terrain to Raster*. The output data type was set to float, a linear sampling method was selected, and the output raster cell size was set to 1 m x 1 m.
The CHMs were analyzed for any height values that seemed invalid. These values could be due to laser pulses detecting objects in the atmosphere above the canopy. Researchers often replace or eliminate height values ≥ 35 m from digital models (i.e. Farrell et al. 2013) or go through a process of replacing these values with mean canopy height values if possible (i.e. Zhao et al. 2013). I used a conservative approach when correcting for errors in the canopy model, because high slopes in some areas could increase the canopy height. I first replaced any canopy height values ≥ 45 m with the mean canopy height for that cell, then re-processed the CHM and removed any canopy height values still ≥ 45 m from the model by setting the cell value to NoData.

Mean canopy height and Beers’ aspect were sampled within each plot (Table 2). Beers’ aspect was created from lidar data using the same method stated previously for Unit 1. Mean canopy height and Beers’ aspect were sampled within 30 meters of each plot center using the same method previously stated for Unit 1.

Social Attraction System

On 14 April 2013, a broadcast system was installed in the center of each treatment plot and was removed on 23 July 2013. The broadcast system design was adapted from Farrell and Campomizzi (2011). The system was mainly composed of two batteries, two digital timers, two power converters, mp3 player, amplifier, and waterproof-speaker (Figure 3). The system used two direct current (DC) batteries to supply power to the mp3 player and speaker separately. A 12 volt (V) 12 ampere hour (Ah) battery (Universal Battery, UB12120 12V 12Ah F2 terminals Sealed Lead Acid Battery, Universal Power Group, Inc.) powered the amplifier and speaker, and a 12V 8Ah battery (Universal Battery, UB1280 12V 8Ah F1 terminal, Universal Power Group,
Inc.) powered the mp3 player (SanDisk, Sansa Clip+ 4GB mp3 player, SanDisk Corporation). Battery specifications were chosen based on power requirements of their respective components. In addition, sealed lead acid batteries can operate in any orientation, allowing more versatility when arranging the electronic components within a container. The mp3 player was selected because it could shuffle and repeat through a selected list of tracks and was not prone to skipping when jostled like a cd player. Power to the system was controlled through digital timers (model Cn101A) that were attached to each battery. The timers could be programmed for weekly and daily schedules. Power was supplied to the speakers for six hours daily from 0430-1030 hrs. The pre-dawn start time was selected because many birds migrate at night (Gwinner 1996) and assess habitat at dawn (Amrhein et al. 2004); some research has suggested that producing vocalizations prior to dawn induces individuals to settle (Alessi et al. 2010). The stop time was selected based on personal observation of when Cerulean Warbler vocalizations start to decline each day during the breeding season (K. Barnes pers. obs.). The mp3 player remained continuously on and power was supplied to the mp3 player for varying durations throughout the study to charge the mp3 player’s internal battery and then allow the mp3 player to function off its own battery for a period of time. Intermittently supplying power to the mp3 player limited the power drawn from the external battery and prolonged the duration the system could function before the 12V batteries needed to be changed. The mp3 player’s internal battery was specified to last for up to 12 hours; however, by the end of the study most of the mp3 player batteries could no longer hold a charge. In the latter portion of the season, I changed the settings so that power was continuously supplied through the external battery, rendering the timer for the mp3 player useless.
Socket adapters (RoadPro, RPPSAPS 12V Clip-on Battery Cigarette Lighter Adaptor, DAS Company Inc.) and power converters were used to connect the amplifier and mp3 player to their respective timers. A power converter (MW 282 DC/DC Car Converter) with different voltage settings was used to regulate the voltage at 12V to power the amplifier. A power converter (Model 720006 5V 1A Car Charger Adapter) with a 5V setting and USB outlet was used to power and charge the mp3 player. The amplifier (Pyle PHA15 12V 15WX150 W 1 Channel output 3.5 mm input, PyleAudio) required 12V DC, had a 150 W one channel audio output, and a 3.5 mm audio input that connects to the mp3 player. Speaker wire extended from the amplifier, out the bottom of the container, to a waterproof speaker (Pyle Pro, PDWR30W 3.5” Indoor/Outdoor 300W Speaker Pair, PyleAudio) on top of the container. The speaker fit beneath the handle of the container by laying it on its side. It was duct-taped and connected to the handle using the wall mount attachment that came with it.

Female disconnects were used for connections to the battery, timer, and amplifier. Modifications were made to the 12v power converter and socket adapters. The socket adapter’s jumper leads were cut off, wire covering stripped, and disconnects were crimped on to allow attachment to the battery. The wires on the socket adaptor were then cut again, wire coverings stripped, and disconnects were crimped on to allow the attachment of the timer. The 12V power converter’s output plug was cut off, wire coverings stripped, and disconnects were crimped on to allow attachment to the amplifier.

Each speaker unit was placed in a 2.5 gallon bucket. The buckets had a handle and lid, and contained a layer of cat litter on the bottom to aid in keeping the electronics dry. A hole was punched in the bottom of the bucket to allow the speaker wire to extend outside the bucket to the waterproof speaker that was attached to the top of the bucket. Each bucket was suspended in a
tree from the bucket’s handle using rope that extended over a limb and was tied to the trunk of the tree. Rope was set in the tree using a tree climber’s sling-shot head on an 8-foot pole and 283 g weight. All speakers were suspended at a height of 10-11.4 m, which represents the lower to mid-canopy height range; a height that males will sing at, making it both logistically feasible and biologically relevant. The speakers were raised to a level just below the branch to decrease lateral movement; however, the buckets were still free to rotate (Figure 4).

Each speaker system broadcasted vocalizations from, at most, 27 unique males who were recorded locally (recordings from McKillip and Islam 2009). Each speaker system broadcast a 168 minute playlist playing random tracks on repeat. There were a total of nine tracks containing a total of 17 minutes of silence, and 27 tracks containing 151 minutes of male Cerulean Warbler recordings. McKillip and Islam (2009) and Robbins et al. (2009) suggested that male Cerulean Warbler pairing status could be determined through song rate; therefore, vocalization tracks were edited in the audio editing software program Audacity to control for the number of vocalizations per minute. Tracks had vocalizations ranging from 2.5-12.0 songs per minute, and contained 13 tracks with an average < 7 songs/min, and 14 tracks with an average ≥ 7 songs/min. Non-target heterospecific songs that were recorded in the tracks were removed by deleting segments of the recordings between Cerulean Warbler vocalizations. In addition, noise reduction (effects tool), amplification (effects tool), and gain (mixer board edit tool) were adjusted for each track to improve clarity and volume. Adjustments to track amplification were made during the first week of May, which increased broadcast distance. Gain adjustments and noise reduction were not made until 9 June 2013, and this greatly improved the broadcast distance. On 23 June 2013, ten tracks were added containing 26 minutes of fledgling begging and feeding vocalizations, as well as female chip notes. These recordings were locally recorded
by McKillip and Islam (2009) and also recorded during the 2013 field season using the microphone and recording option on the mp3 player to record vocalizations of three fledglings from three different broods. The purpose of using these tracks was to denote a successful territory to dispersing individuals.

In 2014, the same design for the broadcast systems and tracks were used; however, the timer for the mp3 player was removed and power was continuously supplied to the mp3 player. In addition, decoys were placed on each broadcast system and the buckets were spray painted brown. Decoys were made using a 3D printer (Stratasys, Dimension uPrint) and 3D printing software (Catalyst-EX). Decoys were plastic replicas of a wood carving of a Cerulean Warbler. The layer thickness of the decoy was set to 0.25 mm with sparse fill and built with soluble supports. A 1.27 cm wide hole was designed to be printed in the belly of the decoy using design software (Rhinoceros 5.0). The hole was designed for mounting the decoys on dowels, and was accomplished by creating a cylinder and performing a boolean subtraction with meshes. Decoys were first sprayed with Krylon Dual Superbond paint and primer (white flat), then hand painted using acrylic craft paint and finally sprayed with Krylon Colormaster Acrylic Crystal (clear flat) to prevent fading of the paint due to moisture. Each broadcast system had one male decoy, and for each aggregation of broadcast systems one speaker also had a female decoy. Decoys were attached to the broadcast systems by taping the dowels onto the buckets (See Figure 5 for photographs of the broadcast systems used in 2014). Speakers were deployed on 15 April and removed 10 May. All speakers were hung between 12-14.2 m high.

**Data Collection**
Point count surveys in the treatment and control plots were conducted every two to seven days to record the number of Cerulean Warbler territories established. The surveys were conducted from the center of each treatment and control plot. Prior to the point counts, the broadcast systems were temporarily turned off and batteries were replaced. At each point a surveyor listened for two minutes, broadcast a recording of a male Cerulean Warbler for one minute, and then listened for two minutes. Point counts were conducted between 0700–1100 hrs from 15 April - 23 July, 2013 and 15 April - 10 May, 2014, and any detection within 100 m was recorded. In 2014, all points were surveyed in Unit 1 and Unit 2. If a male was detected, then GPS points marking its location were collected to demarcate its territory. The male’s age and pairing status were also recorded following protocol in Dibala (2012); age was determined by plumage, and pairing status was determined by observing a female within the male’s territory. Target mist netting of individuals was implemented using conspecific song for the purposes of banding with aluminum and colored bands to facilitate re-sighting individuals.

Data Analysis

In 2013, habitat characteristics were compared between higher quality and lower quality conditions by conducting a two-tailed two-sample t-test with a 0.05 alpha value in Minitab v. 16.1.0 statistical software (Minitab Inc, 2012). Prior to analysis, all variables were checked to assess if assumptions of normality and equal variances were met. Territory density between treatment and control plots was not statistically analyzed due to the absence of settlement.

RESULTS
Site Selection

All variables to determine habitat condition in Unit 1 were normally distributed except for the number of grape within plots. The equal variance assumption was met for all variables except for grape, white oaks and hickories, and Beers aspect. A non-pooled two-sample t-test was performed for white oaks and hickories, and Beers aspect, and pooled t-tests were conducted on the remaining variables. Grape was not statistically analyzed (Table 1). There was no difference in the number of trees with $\geq 38$ cm DBH between higher and lower quality habitat ($t_{14} = 0.43, P = 0.672$). Both conditions were within a range that is often associated with Cerulean Warbler territories for this region, around 90 trees/ha with a DBH $\geq 38$ cm (Roth and Islam 2008). Higher quality habitat had less trees with a DBH $\geq 10 \leq 38$ cm ($t_{14} = -3.60, P = 0.003$) and an aspect at or near productive northeast facing slopes ($t_{8} = 8.12, P < 0.001$), which are representative of Cerulean Warbler habitat (Wood et al. 2006, Hartman et al. 2009, Roth and Islam 2008). There were more white oaks and hickories in higher quality habitat ($t_{8} = 3.10, P = 0.017$) and there was an average of $4.88 \pm 3.04$ grape in higher quality habitat, whereas the lower quality habitat did not contain any grape within the sampling area.

All requirements for control and treatment plots were met for Unit 2. Control areas had a mean canopy height of $24.7\pm3.4$ m, a mean maximum canopy height of $34.8\pm0.90$ m, and a mean Beers’ aspect of $1.7\pm0.14$. Treatment areas had a mean canopy height of $22.3\pm1.8$ m, a mean maximum canopy height of $33.2\pm1.7$ m, and a mean Beers’ aspect of $1.5\pm0.3$ (Table 2).

Social Attraction System
In 2013, the social attraction systems were operational 86% of the time. The component that most often failed was the mp3 player, which would turn off because its internal battery could not last the amount of time that had been designated through the timer. This problem ceased after the mp3 player was continuously powered through the external battery. However, three mp3 players did break during battery replacement; the reason for this is unclear. Two of the 5V power converters and one of the 12V power converters broke due to incorrect wire attachment to the battery. The speaker wires corroded and fell out of the speakers twice. In one instance, a wire fell out of a disconnect attached to the amplifier because it was not crimped on well. One of the male disconnects broke on a timer. There were no failures due to temperature, moisture, or impact related damage. The speaker systems persisted without problem through various weather conditions. From 15 April to 23 July 2013, the total accumulated precipitation was 44.5 cm, temperature ranged from 0.3°C to 33.7°C, and there were wind gusts up to 53.1 kph (weatherunderground.com, KINMARTI2 weather station, Martinsville, IN).

The distance the speakers could broadcast vocalizations varied based on track, direction the speaker was facing, and topography. In addition, modifications were made throughout the study to the tracks to improve the track quality and volume, such as amplification, noise reduction, and gain adjustments. Based on aural surveys of broadcast distance, vocalizations could be heard from roughly 30-100 m, which is comparable to the distance Cerulean Warblers can be heard in the field (K. Barnes pers. obs.).

In 2014, speakers were functional 100% of the time. However, when replacing batteries in one broadcast system a fuse was blown in the DC to DC power converter, which was then replaced. All decoys remained attached to the speakers and their paint did not fade.
**Cerulean Warbler Settlement**

In 2013, two Cerulean Warbler males were detected within 100 m of the speakers, but they did not establish territories. The first detection was on 1 May 2013, and the second was on 22 June 2013 and both were in the same high quality habitat plot. On both occasions, the male came within close proximity to the speaker and was counter singing with the broadcast vocalizations. The male on 1 May was identified through binoculars as an After Second Year (ASY) male. The male detected on 22 June was also heard on 23 June in the same area. On 22 June, an attempt was made to capture the male using a mistnet. The male flew down from the canopy to the mistnet, and although it was not captured, it was identified as an ASY male based on plumage. No Cerulean Warbler females or fledglings were observed in the area.

In 2014, no Cerulean Warblers established territories. Two detections were made in treatment areas; however, they did not establish territories. The first was on 19 April and the second was on 23 April. The male on 19 April was identified through binoculars as an ASY male. The other male was not aged. No females were observed in the area.

**DISCUSSION**

**Social Attraction System**

After operating the broadcast system for two field seasons, I would recommend several modifications to the design that would improve its reliability and decrease its cost. A timer should not be used to charge the mp3 player intermittently. Continuously charging the mp3 player limits the possibility of malfunctions and would also decrease the cost of the system. Another item that is not essential to purchase is the socket adapter that is used to transmit power...
from the battery/timer to the amplifier’s power converter. The power converter could be augmented by cutting off the male socket adapter plug and attaching disconnects to attach the converter directly to the timer; extra wire may be needed to connect the timer to the battery. It should be noted that the socket adapter did allow for quickly detaching components.

To save money, a different mp3 player could be used and the system could be powered by only one battery. There are less expensive mp3 players that were not considered for this study. Few companies give specifications on an mp3 player’s ability to randomly select tracks from a playlist and repeat the playlist endlessly. SansaClip mp3 players were purchased because of familiarity; however, if one has more time to experiment with other mp3 player models, it could save considerable amounts of money because these were the most expensive portions of the units. Money could be saved by powering the broadcast system with one battery. I did not know how much power the system would use to operate for ~ 1 week, so I decided to take a conservative approach and power the system with two batteries. However, the broadcast system had minimal power drawn after 5-6 days (~0.5 V) and could most likely function using one 12V 12Ah battery. It should be noted that having the speaker’s components connected to a battery and the mp3 player’s components connected to a different battery, made the broadcast system easier to take apart and put together.

The system design was relatively simple which reduced the amount of time it took to train technicians. After 1-2 hours of training, technicians were able to independently lower and raise speaker systems (in buckets), replace batteries, and troubleshoot issues. All technicians that worked on the project helped assemble the systems, which ensured they understood how they worked.
Suspending the bucket from the tree was a successful technique. The bucket was heavy enough to not swing too much in the wind which limited jostling of the equipment within. It was also a fully waterproof system that could withstand heavy precipitation events. I did not test the system without a layer of cat litter on the bottom of the bucket; however, the litter likely helped maintain a dry interior. There were no issues with condensation or equipment being damaged due to increased humidity within the bucket. I also recommend that when suspending the bucket over a limb, a tree climber’s friction saver should be set. A friction-saver would make it easier to hoist the heavy system up, and limit damage to the rope and tree. These can be relatively expensive; however, old garden hose tubing could be considered over a tree-climber’s friction-saver.

The total cost of all speaker components for eight speakers, replacement components, housing, two sets of batteries, battery chargers, and tools was $2,580. Of this total, $165 was spent on replacing three mp3 players, two 5v power converters, one 12V power converter, and one timer, and $140 was spent on a forestry slingshot and weight. Although the slingshot expedites setting the line over a tree branch, a hand-toss method could also be used to set the line at lower heights. If one forgoes purchasing timers for the mp3 players and female socket adapters for the speaker’s battery, and power the system off of one 12v 12Ah battery, a total of ~$40 per system could be saved.

Cerulean Warblers and Social Information

Based on these results, it does not appear that Cerulean Warblers use social information during the pre- and post-breeding period to makes settlement decisions. Cerulean Warblers did not settle in response to locational cues in the pre-breeding season of 2013; in 2014, they did not
settle in response to locational cues/public information broadcasted during the post-breeding season of 2013; and they did not settle in response to aggregated locational cues, or mock breeding aggregations, in the settlement period of 2014. However, it is impossible to know how many male Cerulean Warblers were actually exposed to these signals and given the opportunity to make a settlement decision. In addition, the effect of these signals on female Cerulean Warbler behavior is also unknown due to the difficulty in determining their presence. To my knowledge, only one male was exposed to a broadcast system during the settlement period in 2013, one male was exposed to the broadcast system in the post-breeding period in 2013, and two males were exposed to the broadcast systems in 2014. Perhaps these individuals were not prone to social information because they were experienced breeders. In addition, during the first three weeks of broadcasting vocalizations in 2013, improvements were being made to the tracks to increase the distance the speakers could be heard. This, coupled with the fact that the speakers were not aggregated could limit the signal strength and decrease the amount of individuals exposed to the settlement cue.

It should be noted that many studies that test if locational cues induce settlement, use an aggregated speaker arrangement, which confounds the interpretation of an individual’s settlement response. It is impossible to know if individuals are responding because of a locational cue or because they interpret these signals as a breeding aggregation or hidden lek with a reproductive advantage. For example, Farrell et al. (2012) tested the response of warblers to locational and public information cues; however, in each treatment area they placed three speakers 20-30 meters apart. Betts et al. (2008) tested the response of warblers to locational cues late in the season by placing two speakers 20 m apart in each treatment area.
Researchers rarely reported if there were non-target species recorded on the tracks they broadcast. Non-target species vocalizations are often present in the “background” of recordings and could influence settlement decisions of certain species, creating a confounding effect when interpreting a settlement response. Researchers have found that the presence of resident species, such as Great Tits (*Parus major*) in Europe and Black-capped Chickadees (*Poecile atricapillus*) in North America, is used by heterospecific migratory species as settlement cues, and these species could be used as keystone information providers (see review, Syzmkowiak 2013). All of the audio recorded between Cerulean Warbler songs in the tracks were deleted to limit a possible settlement response due to heterospecific cues. Future research is needed to assess if Cerulean Warblers use heterospecific resident species presence as a settlement cue. One study did note that Cerulean Warbler presence was associated with higher avian species richness, diversity, and abundance (Carpenter et al. 2011).

There has been some concern about the effect of conspecific attraction studies on other breeding birds. Betts et al. (2010) found that as Black-throated Blue Warblers were attracted to new habitat through social attraction, other birds responded negatively by leaving the area. I did not measure the response of other breeding birds in the area, and I am uncertain of their response to my broadcast systems. However, it was noted that two mature forest bird species, the Red-eyed Vireo (*Vireo olivaceus*) and Ovenbird (*Seiurus aurocapilla*), nested within 5-20 m of a broadcast system. Northern Parulas (*Setophaga americana*), Hooded Warblers (*Setophaga citrina*), and Worm-eating Warblers (*Helmitheros vermivorum*) were often heard and these species counter sang or approached the broadcast systems.

*Site Selection and Habitat Condition*
It is paradoxical that Cerulean Warbler relative abundance is low in Unit 1 given its suitable habitat features. Two landscape level features that could have an adverse effect on settlement within the unit are harvest treatment and distance to forest tract edge. However, another unit that has received the same harvest treatment as Unit 1 has the highest relative abundance of all nine units. In addition, other researchers have reported that canopy openness, such as single tree removal, and patch cuts, may be useful treatments for increasing Cerulean Warbler abundance (Boves et al. 2013, Sheehan et al. 2013). Unit 1 is also the furthest north of all units. It is ~1000 m from the edge of the forest tract, which may decrease settlement; however, Wood et al. (2006) found that edge effects on Cerulean Warbler settlement were only evident up to 340 m.

If Cerulean Warbler settlement is not influenced through social cues, then their clustered distribution could be a factor of habitat quality (Fretwell and Lucas 1969). Habitat features that elicit such a distribution must stem beyond general habitat features that are often reported, such as DBH and aspect (i.e. Hartman et al. 2009, Wood et al. 2006), but there has not been a consensus when reporting a preferred microhabitat structure. However, many researchers do suggest that settlement is associated with some kind of heterogeneous canopy structure (Harrison 1984, Oliarnyk 1996, Oliarnyk and Robertson 1996, Rodewald 2004, Stoleson 2004, Weakland et al. 2005, Wood et al. 2005, Wood et al. 2006, Bakermans and Rodewald 2009, Bakermans et al. 2012, Wood and Perkins 2012, Boves et al. 2013, Sheehan et al. 2013), which is often hard to measure.

Cerulean Warblers are a canopy dwelling species, and habitat features that researchers report as being associated with Cerulean Warbler territories are most often those that can be easily measured from the ground. As a result, these habitat variables may only be associated with
the true structural cues that elicit a settlement response. Perhaps the habitat variables that are actually being selected for are hard to measure from the ground, such as horizontal and vertical canopy structure. If aspect, DBH, and floristics are not strongly influential in Cerulean Warbler settlement then the distinction between higher and lower quality conditions that were made in this study may be irrelevant.

Perhaps a more robust method for testing Cerulean Warbler response to social cues in lower and higher quality habitat would have been to select lower quality habitat that is extremely unsuitable habitat, such as within a patch cut; however, from a conservation management standpoint this information may be less useful. My intent was to test if settlement could be induced in habitat that is not ideal but is available for use, without decreasing reproductive success. This information would provide conservation managers with more confidence in using social broadcast systems to attract individuals to protected areas, especially if habitat quality is unknown in these areas.

The Importance of Understanding the Effect of Social Information

It is important to use a holistic approach when considering the cues that elicit Cerulean Warbler settlement. A conservation management approach based on Cerulean Warbler behavioral traits and preferred habitat structure could reverse declining population trends. The implications of conspecific attraction could extend beyond the ability of managers to “seed” forests using social broadcast systems. The use of social information by Cerulean Warblers could help us understand how quality habitat becomes vacant, how ecological sinks occur, the implications of fragmentation, or how to best conduct habitat selection studies.
For example, areas of habitat that are seemingly appropriate breeding habitat could become empty due to site fidelity and conspecific attraction. If experienced breeders show conditional site fidelity and only return to areas where they were reproductively successful, then consecutive poor nesting years could limit return rates of experienced breeders, and inexperienced breeders would not know that these areas were appropriate nesting habitat because they lack a conspecific cue. Conversely, if experienced breeders have unconditional site fidelity and return to areas despite their reproductive success, then temporal changes that decrease habitat quality in these areas could create aggregations within poor habitat. Experienced breeders would return to poor quality breeding habitat and attract inexperienced breeders through conspecific attraction.

Social cues could also help us understand how fragmentation may limit reproductive success and survival. If males aggregate as a way to attract females, and similarly, if females are attracted to aggregations, then forest fragmentation would limit space for these clusters to occur, and ultimately decrease mate attraction and reproductive success. In addition, if aggregations occur due to predator deterrence or avoidance, then fragmentation could again limit space for aggregations to occur and decrease survival.

Lastly, future research would need to address the confounding effects that conspecific attraction may have on habitat preference studies; if males choose to settle in sub-quality habitat near a conspecific over high-quality habitat that is isolated, then studies that examine preferred habitat characteristics will be less reliable. To combat this issue, researchers could only sample habitats that were settled first, presumably by experienced males. This would decrease the likelihood that an individual sacrificed habitat quality over proximity to conspecifics and better represent habitat preference.


Figure 1. Experimental design and study plots within Morgan-Monroe State Forest, southern Indiana, 2013.
Figure 2. Experimental design and study plots within Morgan-Monroe State Forest, southern Indiana, 2014.
Figure 3. Broadcast system design. Speaker components are all within a bucket that contains a lid and a layer of cat litter on the bottom. A waterproof speaker sits outside and on top of the bucket (Adapted from Farrell and Camponizzi 2011).
Figure 4. Photographs of broadcast system installation: A.) setting the line over a low tree limb using a slingshot and weight; B.) tying the line to the system; C.) hoisting the system; D.) Broadcast system suspended in tree.
Figure 5. Photographs of social attraction system used in 2014: A.) three speakers that were aggregated per plot—note decoys of both males and females; B.) equipment organized in bucket; C.) 12V 8Ah batter, socket adapter with USB charger, and mp3 player; D.) 12V 12Ah, timer, socket adapter, power converter, amplifier, and speaker; E.) equipment in pictures C and D connected via 3.5 mm input from amplifier and mp3 player; F.) hole and cat litter in bottom of bucket, note speaker wire from amplifier extending through bottom of bucket.
Table 1. Pooled and non-pooled two-tailed two-sample t-tests conducted on higher vs. lower habitat quality variables within treatment and control plots in Unit 1 of Morgan-Monroe State Forest, Indiana.

<table>
<thead>
<tr>
<th>Habitat Condition</th>
<th>Higher Quality Mean ± SD</th>
<th>Lower Quality Mean ± SD</th>
<th>df</th>
<th>T-Value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$ Grape</td>
<td>4.9 ± 3.0</td>
<td>0 ± 0</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>$N$ Trees ≥ 38 cm DBH/ha</td>
<td>94.6 ± 29.8</td>
<td>88.4 ± 27.9</td>
<td>14</td>
<td>0.43</td>
<td>0.672</td>
</tr>
<tr>
<td>$N$ Trees ≥ 10&lt;38 cm DBH/ha</td>
<td>246.4 ± 67.7</td>
<td>364.7 ± 68.6</td>
<td>14</td>
<td>-3.6</td>
<td>0.003</td>
</tr>
<tr>
<td>$N$ High Use Trees/ha</td>
<td>49.1 ± 32.7</td>
<td>12.9 ± 9.5</td>
<td>8</td>
<td>3.1</td>
<td>0.017</td>
</tr>
<tr>
<td>Beers’ Aspect</td>
<td>1.6 ± 0.4</td>
<td>0.3 ± 0.1</td>
<td>8</td>
<td>8.12</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Table 2. Mean Beers’ aspect, mean canopy height, and max canopy height within 30 m of treatment and control plot centers in Unit 2 of Morgan-Monroe State Forest, Indiana. All plots were required to have a Beers’ aspect ≥ 1.1, a mean canopy height ≥ 20 m, and a max canopy height ≥ 30 m.

<table>
<thead>
<tr>
<th>Plot</th>
<th>Treatment</th>
<th>Mean Beers’ Aspect</th>
<th>Mean Canopy Height (m)</th>
<th>Max Canopy Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Song</td>
<td>1.9</td>
<td>22.3</td>
<td>35.5</td>
</tr>
<tr>
<td>2</td>
<td>Song</td>
<td>1.5</td>
<td>20.1</td>
<td>32.3</td>
</tr>
<tr>
<td>3</td>
<td>Song</td>
<td>1.2</td>
<td>24.5</td>
<td>31.7</td>
</tr>
<tr>
<td>4</td>
<td>No Song</td>
<td>1.6</td>
<td>20.1</td>
<td>33.8</td>
</tr>
<tr>
<td>5</td>
<td>No Song</td>
<td>1.9</td>
<td>25.6</td>
<td>34.7</td>
</tr>
<tr>
<td>6</td>
<td>No Song</td>
<td>1.6</td>
<td>28.4</td>
<td>36.0</td>
</tr>
</tbody>
</table>
INTEGRATING LIDAR-DERIVED CANOPY STRUCTURE INTO CERULEAN WARBLER HABITAT MODELS

ABSTRACT

Many researchers have suggested that Cerulean Warblers (*Setophaga cerulea*) are attracted to a heterogeneous canopy structure; however, measuring the canopy structure of mature deciduous forests from the ground can be laborious and subjective. I used light detection and ranging (lidar) data to create canopy height models that provide accurate objective data on the vertical and horizontal canopy structure throughout the entire extent of our study area in south-central Indiana’s Morgan-Monroe state forest. In addition I used these data to construct digital terrain models to derive topographic metrics. I used these data and ground-level surveys in habitat models to determine which explanatory variables were associated with Cerulean Warbler occurrence and density (high-use areas). The top model examining the relationship of habitat variables to Cerulean Warbler occurrence indicated that occurrence was more likely on northeast facing slopes, lower elevations, steeper slopes, and in areas with greater hickory (*Carya* sp.) basal area (m$^2$/ha). Other influential variables were a tall canopy and greater total basal area (m$^2$/ha), and tuliptree (*Liriodendron tulipifera*) basal area (m$^2$/ha). The top models examining the relationship of habitat variables to Cerulean Warbler density indicated that high-use areas are more likely to exist on steeper slopes, with less total basal area (m$^2$/ha) and large trees (≥ 53 cm DBH), more white oak (*Quercus alba*) basal area (m$^2$/ha), and contain a homogeneous horizontal and vertical canopy structure. Other influential variables were areas lower in elevation with more small shrubs and saplings ≥ 3 < 10 cm DBH per ha.
INTRODUCTION

Breeding bird habitat selection is the behavioral response of avifauna to external cues, resulting in the preference for environmental components that increase survival and fitness (Block and Brennan 1993). External cues that elicit avian habitat selection exist on a continuum of spatial scales, from broad-scale macrohabitat, such as an appropriate geographic region, to fine-scale microhabitat, such as an area containing a specific foraging substrate (Block and Brennan 1993). Researchers have historically defined settlement cues by correlating a species’ occupancy to climate, geology, and vegetative characteristics (Grinnell 1917, Kendeigh 1945, MacArthur et al. 1962). However, bird territories are often found to be aggregated even within large tracts of seemingly suitable habitat (Darling 1952). These aggregations could be due to environmental structures or microhabitat features that increase habitat quality (Fretwell and Lucas 1969).

Horizontal and vertical canopy structure can be an important predictor of avian species composition (MacArthur et al. 1962, Goetz et al. 2007, Culbert et al. 2013, Goetz et al. 2014). Canopy structures, such as gaps or a dense vertical vegetation strata, create favorable conditions for certain avifauna. Smith and Dallman (1996) reported the frequent use of canopy gaps by the Black-throated Green Warbler (*Setophaga virens*). Hooded Warbler (*Setophaga citrina*) abundance was found to increase in response to small openings in the canopy (Robinson and Robinson 2001), while Yellow-breasted Chat (*Icteria virens*) and Blue-winged Warbler (*Vermivora cyanoptera*) abundance was found to increase in response to larger clearcuts (Annand and Thompson III 1997). Black-throated Blue Warbler (*Setophaga caerulescens*) and
Swainson’s Thrush (*Catharus ustulatus*) prefer an intact upper canopy with a predominant shrub layer in the lower strata (Doyon et al. 2005).

The predominant changes that occur in response to canopy openings are increased light penetration and foliage growth in the lower vegetation strata (e.g., saplings, herbaceous cover; Runkle 1982). This increased growth can create structural features in which certain species prefer to nest (e.g., shrub nesting species). An increase in vertical vegetation density and diversity can increase availability of arthropods for foliage-gleaning species (Blake and Hoppes 1986, Martin and Karr 1986, Gorham et al. 2002, Marshall and Cooper 2004, Moorman et al. 2007). Stenger (1958) indicated that smaller territories are indicative of greater food availability, and Marshall and Cooper (2004) reported results that further confirmed this hypothesis by showing that vegetation density and arthropod abundance were inversely proportional to territory size. Goetz et al. (2007) found that vertical density and canopy height were the best predictors for avian species richness in forested habitats.

Areas of empty space within a forest may be structurally appealing to some bird species for social reasons. Canopy gaps may allow for more effective signaling because they contain less vegetation that acts as an acoustic impediment, thus allowing male vocalizations to project farther (Barg et al. 2006). In addition, canopy gaps may serve as a way to define the edge of a territory from nearby nesting individuals (Rail et al. 1997).

The Cerulean Warbler is a small, Neotropical migratory wood warbler that breeds high in the canopy of large mature deciduous forests of central and eastern North America (Buehler et al. 2013). Although it was once abundant, it is now considered one of the fastest declining Neotropical wood warblers in North America (Sauer et al. 2011). Its population declined 70% from 1966 to 2006 (Sauer et al. 2011) and it is listed as a “Species of Concern” by the U.S. Fish and Wildlife Service (2012) and endangered in the state of Indiana (Indiana Department of Natural Resources 2012). Territory distributions of Cerulean Warblers have been described as loosely clustered (Roth and Islam 2007) and aggregations can occur due to habitat quality (Fretwell and Lucas 1969); however, habitat selection studies across the Cerulean Warbler’s range have been largely inconsistent, especially when describing microhabitat features (Rosenberg et al. 2000, Boves et al. 2013a).

A microhabitat feature that has been considered a Cerulean Warbler research priority is canopy structure (Hamel 2000); however, results from many studies are contradictory and it is still unclear what type of canopy structure Cerulean Warblers prefer. For example, Stoleson (2004), Bakersman and Rodewald (2009), Bakersman et al. (2012), Boves et al. (2013a, 2013b), and Sheehan et al. (2013) all found that Cerulean Warbler abundance increased to some extent with canopy openness. Conversely, Newell and Rodewald (2012) and Register and Islam (2008) found no difference in Cerulean Warbler abundance between harvested and unharvested forests, and Roth and Islam (2008) and Carpenter et al. (2011) found that the Cerulean Warbler selects for a more closed canopy.

Barg et al. (2006) found no significant difference between the distances of high use areas of Cerulean Warbler territories to the nearest canopy gaps, versus the distance of random points to the nearest canopy gap. In contrast, Rodewald (2004), Weakland et al. (2005), and Wood et al.
(2005, 2006) found that Cerulean Warblers territories were often found near small canopy gaps, canopy disturbances, and snags.

Oliarnyk and Robertson (1996) compared the distance of Cerulean Warbler nests to canopy gaps and found that they were closer to canopy gaps than random points within the territory to the nearest canopy gap. Conversely, Hamel et al. (2005) compared the distance of nests to canopy gaps and random points to canopy gaps and found that there was no statistical difference. Barg et al. (2006) stated that nest success decreased with proximity to gaps, and Boves et al. (2013b) found that reproductive success was negatively associated with canopy openness. Contrary to these claims, Bakersman and Rodewald (2009) reported increased nest survival with canopy openness.

Jones and Robertson (2001) reported that territories often have dense canopy cover between 12-18 m in height. Opposite to their claim, Weakland and Wood (2005) found territory density positively associated with canopy cover between 6-12 m and >24 m. Jones and Robertson (2001) reported that nesting habitat had dense vegetation from the midstory to upper canopy (i.e. >12 m), while Boves et al. (2013a) reported that nesting habitat had greater understory cover and less mid-story cover.

Rosenberg et al. (2000) suggested that Cerulean Warblers prefer a complex upper canopy created by an emergent layer of tall scattered trees that project above the canopy, and much like a canopy gap, this would also create a canopy edge. Other researchers have suggested that Cerulean Warbler territories may often be on slopes because it provides this same heterogeneous canopy structure (Bakersman et al. 2012, Newell and Rodewald 2012) and would perhaps provide increased sunlight reaching the canopy and cause an increase in prey abundance and size (Newell and Rodewald 2012).
Collecting data on canopy structure variables is often laborious and subjective at the ground level; however, light detection and ranging (lidar) technology provides an objective and accurate method for obtaining data on the vertical and horizontal extent of a forest canopy that can improve habitat selection models (Farrell et al. 2013, Merrick et al. 2013). Lidar datasets are acquired through the use of a vehicle (i.e., plane), a Global Positioning System (GPS) and Inertial Measurement Unit, and a laser scanning system (Lefsky et al. 2002). The laser can record elevation data \((z)\) at many coordinates \((x,y)\), creating a point cloud of \(x,y,z\) vertices. Each laser pulse is emitted down to the earth and returns to the laser scanner; the amount of time recorded for each return is converted to a distance. Every pulse will record returns for objects it encounters on the way down. For example, if the point makes contact with a tree, the first return will be the top of the tree and more returns will register as it travels through the tree’s vertical profile until it encounters a hard surface, such as the ground that will represent the last return. A canopy height model (CHM) can be created by subtracting the last returns from the first returns, or in other words, by subtracting a digital terrain model of the ground from a digital surface model of the canopy (Dees et al. 2012). The CHM can then be examined for certain selected canopy attributes (e.g., Goetz et al. 2010, Palminteri et al. 2012).

My overall research objective was to determine the most important predictors of Cerulean Warbler occurrence and inter-annual density (i.e. breeding hotspots) using variables from ground level surveys and lidar data made available through IndianaMap Framework Data.

**METHODS**

*Data Overview and Study Sites*
To examine the effects of habitat features on male Cerulean Warbler settlement, three data sets were concurrently examined: locational point data of male Cerulean Warbler territories collected from 2009-2013 within nine 225 ha study plots, vegetation survey data collected from 2010-2013 in used and unused areas within the nine study plots, and corresponding lidar data collected in 2009-2011 and obtained from the IndianaMap Framework Data. The study plots were established in 2006 as part of the Hardwood Ecosystem Experiment (HEE; Swihart et al. 2013) and are composed of mature deciduous forest (Homoya et al. 1985). The HEE is a long term landscape level study that is designed to assess the effects of different silvicultural treatments on various taxa. The HEE has nine 225 ha research units within Morgan-Monroe and Yellowwood state forests in Indiana’s Morgan, Monroe, and Brown counties (Figure 1). The units were defined based on tree harvest methods that were conducted in fall 2008. There are three control units that contain no harvests, and six treatment units. Treatment units consist of three “uneven-aged” treatment units and three “even-aged” treatment units. Uneven-aged units received group cuts and single tree removal. Group cuts consisted of eight small cuts; four 0.4 ha cuts, two 1.2 ha cuts, and two 2 ha cuts. Single tree removal consisted of a target basal area of 16.1-23.0 m²/ha and was implemented throughout the remainder of the uneven-aged units but not within 15.2 m of the group cuts. Even-aged units received clearcuts and shelterwood cuts. Clearcuts consisted of two 4 ha cuts. At the time of this study, shelterwood cuts have only received phase 1 removal of understory and small diameter trees in two 4 ha areas.

Locational point data of male Cerulean Warblers were collected with a GPS unit to map male territories. Playback was used to elicit a male’s vocal response and defense of a territory, and then the coordinates of 5-12 song perches per individual were recorded (Falls et al. 1992). The spatial extents of territories were estimated by creating minimum convex polygons from
each individual’s point data (Mohr 1947) using ESRI’s ArcGIS 10.1 data management tool *Minimum Bounding Geometry* (ESRI 2014). Male Cerulean Warbler point data from 2009-2013 were chosen because these data are from post-harvest years and annual Cerulean Warbler distributions will be representative of settlement cues that currently exist on the landscape and during the time lidar data were collected.

Vegetation data were obtained from annual surveys conducted within Cerulean Warbler territories and at random non-use areas. Survey methods were adapted from James and Shugart (1970). A meter tape was extended 11.3 m in each cardinal direction from either the territory’s centroid or from a random point in an unused area at least 50 m from a Cerulean Warbler territory. Centroids and random points were generated in ArcGIS using the data management tools *Feature to Point* and *Create Random Points*, respectively. Tree species and diameter at breast height (DBH) for all trees ≥ 10 cm DBH were recorded within 11.3 m of the plot center. Species and abundance were recorded for all trees and shrubs > 3 < 10 cm DBH and ≤ 3 cm DBH within a 5 m of the plot center. The species and height of the tallest tree was recorded within the northeast, northwest, southeast, and southwest quadrants of the plot. Tree height was estimated using a Nikon rangefinder (Nikon, Forestry Pro Laser Rangefinder 8381, Nikon INC). Ground cover and canopy cover were estimated by recording the presence or absence of vegetation at 2, 4, 6, 8, and 10 m in each cardinal direction with a densiometer. Ground cover was estimated at each 2 m interval by placing a flag in the ground and recording the flag’s visibility where it entered the soil. Aspect was recorded using a compass, and slope was measured with a clinometer. Ground cover was not used for analyses. Canopy cover, aspect, and slope were not used from these surveys for my analyses; instead these were calculated using lidar data, and averages were derived for the extent of the entire territory.
At the time of this study, the state of Indiana was acquiring lidar data for all of Indiana’s 92 counties (OpenTopography 2014). By 2011, 22 counties had already acquired lidar datasets through different vendors. Woolpert Inc. was contracted to obtain lidar data for the remaining 70 counties from 2011-2013. These data are compiled with an average post spacing of 1.5 meters and integrated with pre-2011 lidar data, and all are made available as las files by IndianaMap Framework Data. Lidar data were collected in 2009 for Morgan County by Kucera International Inc., in 2010 for Monroe County by MJ Harden, and in 2011 for Brown County by Woolpert Inc. After reviewing these data I found that the point density at which each county was sampled differed, and based on a visual interpretation, the digital representation of the canopy structure differed for each county. For example, three HEE units in Brown County had an average of 3,617,648 points per research unit, an average point spacing of 0.870 m, and an average point density of 1.28 points/m². Three research units in Monroe County had an average of 7,811,184 points per unit, an average point spacing of 0.608 m, and an average point density of 2.69 points/m². In addition, Monroe County had more returns throughout the vertical canopy, with an average of 18.5% third and fourth returns, versus an average 4.49% third and fourth returns in Brown county units. Given this disparity in sampling intensity, I chose to restrict all analyses to Monroe County (Figure 1). Monroe County was sampled on 11 and 12 April with an Optech Gemini system with a root mean square error vertical accuracy value of 10.58 cm, a scan angle of 52° and a maximum of four returns per laser pulse.

I constructed digital terrain models (DTM) and canopy height models (CHM) from lidar data and these were used to obtain data on canopy structure and landscape level variables within Cerulean Warbler territories and areas of non-use. All manipulations of lidar data and sampling of rasters were conducted in ESRI’s ArcGIS v. 10.1 and python script was written in PythonWin
to expedite these processes. Python script is included in the appendix for a more detailed description of GIS analyses.

DTMs, CHMs, and mean CHMs were created in ArcGIS from las files. These rasters represent an elevation model of the bare earth, a digital model of the maximum canopy height measured in distance from bare earth, and a digital model of the mean canopy height measured in distance from bare earth, respectively. To create CHMs and mean CHMs, a DTM is subtracted from a digital surface model (DSM) of lidar first return elevation values (i.e. top of vegetation) and mean lidar return elevation values, respectively (Figures 2a & 2b; See Appendix Code 1). A three step process was used to create DTMs and DSMs (Figure 2a). The las files were first converted to multipoint files using the 3D analyst tool Las to Multipoint. Only filtered ground points were used to create the DTM, and all lidar points were used to create the DSMs. The multipoint files were then converted to terrain files using the Terrain Wizard in ArcCatalogue. Window size was selected as the pyramid type with a zmin point selection for the DTM, a zmax point selection for the DSM, and a zmean point selection for the mean DSM. Pyramid properties were calculated and all default settings were accepted. Lastly, the terrain files were converted to raster files using the 3D analyst tool Terrain to Raster. The output data type was set to float, a linear sampling method was selected, and the output raster cell size was set to 1 m x 1 m.

The CHMs were analyzed for any height values that seemed invalid (See Appendix Code 1). These values could be due to laser pulses detecting objects in the atmosphere above the canopy. Researchers often replace or eliminate height values $\geq 35$ m from digital models (i.e. Farrell et al. 2013) or go through a process of replacing these values with mean canopy height values if possible (i.e. Zhao et al. 2013). I used a conservative approach when correcting for errors in the canopy model, because steep slopes in some areas could increase the canopy height.
I first replaced any canopy height values ≥ 45 m with the mean canopy height for that cell, then re-processed the CHM and removed any canopy height values still ≥ 45 m from the model by setting the cell value to NoData.

**Model Response Variable**

Generalized linear models were used to determine habitat characteristics that are associated with Cerulean Warbler occurrence and density. A logistic regression analysis was used to examine habitat characteristics in Cerulean Warbler territories versus non-use areas. A negative binomial generalized linear model was used to determine which characteristics are associated with high use areas, represented as the number of territory centroids from 2009-2013 that are within 100 m of each selected territory’s centroid. As recommended by Zuur et al. (2009), this model was selected because it works well when the response variable has an overdispersed poisson distribution. Density was quantified for sample territories by using the management tools *Select Layer by Attribute* and *Select Layer by Location* (See Appendix Code 2).

I sampled the same number and area of Cerulean Warbler territories and random non-use areas for logistic regression analyses. Within Monroe County, a total of 72 vegetation surveys were conducted in random non-use areas from 2010-2013. Random vegetation surveys that fell within 50 meters of a Cerulean Warbler territory from 2009-2013 were removed using the analysis tool *Select by Location*. In addition, random vegetation surveys that happened to overlap were also deleted randomly using the analysis tool *Polygon Neighbor* to identify overlapping territories and the Python *choice()* method to randomly select which overlapping areas to delete (See Appendix Code 3). This reduced the number of random vegetation surveys to 64.
The process of randomly deleting over-lapping areas was also conducted on all 2010-2013 Cerulean Warbler territories within Monroe County, which reduced a total of 155 mapped territories to 83 non-overlapping territories that also had associated vegetation survey data. Data from these territories were used in the negative binomial generalized linear model.

From the 83 non-overlapping territories, 64 territories were randomly selected using a random number generator, and these territories were essentially copied and created around each random non-use vegetation point. This was accomplished by calculating the difference between a territory centroid’s coordinates and a random vegetation point’s coordinates and then applying that difference to the vertices of the territory polygon, which shifts its position around the random vegetation point. To implement this approach, I used the management tools Feature to Point, Vertices to Points, Calculate Field, and Minimum Bounding Geometry (See Appendix Code 4). Random non-use areas that overlapped and could be moved apart slightly while still keeping the boundary of the vegetation survey within the extent of the random non-use areas were kept; however, if a random non-use area extended into a Cerulean Warbler territory from 2009-2013 or overlapped another random non-use area and could not be adjusted, it was deleted, and the Cerulean Warbler territory that was used to build it was also deleted. This reduced the total sample size for the logistic regression analysis to 58 random non-use areas to 58 Cerulean Warbler territories.

Explanatory Variables: Creating and sampling Canopy Structure and Landscape Feature Rasters

Using the DTMs, CHMs, and mean CHMs, the following raster files were created: canopy gaps ≥ 20 m², canopy ≤ 12 m tall (i.e. canopy openness), canopy > 24 m tall (i.e. above
average height trees), vertical density ratio (VDR), VDR ≤ 0.33 (i.e. open understory), VDR > 0.66 (i.e. dense understory), slope, aspect, and Beers aspect. From the canopy gaps raster, the following data were obtained for territories and identical non-use random areas (collectively referred to as “an extent”): the number of gaps that intersect an extent, the number of gaps that have their centroid in an extent, the average size of gaps that intersect an extent, the average size of gaps that have their centroid in an extent, the distance from the centroid of an extent to the nearest gap, the amount of gap edge within an extent (Figures 2b-2e; See Appendix Code 1).

The binary raster files for canopy height ≤ 12 m, canopy height > 24 m, VDR ≤ 0.33, and VDR > 0.66 were created using map algebra in PythonWin. By using map algebra, each cell in a CHM was analyzed with a binary function: if z of a cell (x,y) is less than, greater than, or equal to a certain number, then 1, otherwise 0 (Vepakomma et al. 2008). Canopy gaps were calculated from the canopy height ≤ 12 m raster. This was accomplished using the spatial analyst tools Region Group, and Extract by Attribute. Canopy gaps were then converted to a vector format using the conversion tool Raster to Polygon, and all polygons with an ID of zero (i.e. non gaps) were deleted. Slope, aspect, and Beers aspect rasters were created by resampling the DTM to a 3 m x 3 m DTM raster using the data management tool Resample. This was then converted to slope and aspect raster files using the spatial analyst tool Slope and Aspect, respectively. The aspect raster was then converted to a Beers aspect raster that transforms aspect to a number between zero and two using the following equation:

\[ A' = \cos (45 + A) + 1 \] (Beers et al. 1966),

where \( A' \) is a value between zero and two, and \( A \) is the aspect (Beers et al. 1966). The value two represents productive northeast facing slopes and zero represents unproductive southwest facing slopes (Beers et al. 1966). Cerulean Warblers tend to settle on productive northeast facing slopes.
(Wood et al. 2006, Hartman et al. 2009, Newell and Rodewald 2012, Boves et al. 2013a). The conversion was accomplished using map algebra that interprets inputs for cosine operations as radians; therefore, aspects were converted to radians prior to calculating Beers aspect.

Variables associated with canopy gap rasters were calculated using the data management tools Select Layer by Attribute and Select Layer by Location. The variables calculated were the number of gaps that intersect an extent, the number of gaps that have their centroid in an extent, the average size of gaps that intersect an extent, and the average size of gaps that have their centroid in an extent. The distance from an extent to the nearest gap was collected using the analysis tool Generate Near Table. The amount of gap edge within an extent was determined by converting gaps to polylines using the data management tool Polygon to Line, then clipping the polylines with the extent of the territory or non-use area using the analysis tool Clip, and then using the data management tools Select Layer by Attribute and Select Layer by Location (See Appendix Code 2).

The spatial extent of all random non-use areas and Cerulean Warbler territories selected for analyses was used to sample raster files using the spatial analyst tool Zonal Statistics as Table. Means were calculated within the extent of these areas for the following variables: canopy height, canopy height ≤ 12 m, canopy height > 24 m, VDR, VDR ≤ 0.33, VDR > 0.66, elevation, aspect, Beers aspect, and slope. In addition, standard deviations were calculated for canopy height and VDR to represent vertical and horizontal heterogeneity (See Appendix Code 1).

Gaulton and Malthus (2010) stated that the definition of a gap should vary by study as different forests and questions will require different standards. For the purpose of this study, canopy gaps were defined as any empty area greater than or equal to 20 m² and extending down vertically at least 12 m above the ground. The horizontal distance was chosen to minimize the
inclusion of small gaps that could result from interstitial space within a single tree’s canopy (Vepakomma et al. 2008, Gaulton and Malthus 2010). The vertical parameter was chosen based on habitat type and Cerulean Warbler ecology. The study plots were composed of mostly mature deciduous forest and regional studies examining the same plots have reported an average canopy height of ~ 24 m for both Cerulean Warbler territories and unused areas (Dibala 2012). Cerulean Warblers prefer mature deciduous forests (Hamel 2000) and sing in the upper canopy of large trees (Barg et al. 2006, Jones and Islam 2006, Wood and Perkins 2012) and forage from the lower to mid-canopy (Barg et al. 2006, Wood and Perkins 2012). Considering their preferred placement in the vertical canopy strata, the vertical threshold would not have to be very low to create a gap that is relevant to the species. Therefore, a vertical threshold of 12 m was chosen to represent a gap with 50% of the vertical canopy strata missing.

Vertical Density Ratio

Researchers have found that the vegetation density on a vertical axis may have an influence on Cerulean Warbler settlement and nest placement (Jones and Robertson 2001, Weakland and Wood 2005, Boves et al. 2013a). Goetz et al. (2007) determined that the vertical density ratio derived from lidar data is a good predictor of species richness in forested landscapes, and Goetz et al. (2010) determined that VDR can be used to predict occupancy of Black-throated Blue Warblers, a species that prefers a dense understory (Doyon et al. 2005). The VDR is calculated from the maximum canopy height (X) minus the median canopy height (Y) divided by the maximum canopy height (VDR=(X-Y)/X; Goetz et al. 2007). Values closer to 1 will have a more dense vertical vegetation stratum, while values closer to 0 will have a more open vertical vegetation stratum. I used a variation of this equation by substituting the median
canopy height with the mean canopy height. In addition, I used lidar data from a discrete lidar system that records a maximum of four returns per laser pulse, while Goetz et al. (2007) used a full waveform lidar system that records a full waveform spectrum for the entire vertical vegetation stratum per laser pulse. Due to these differences, I wanted to determine how well the calculated VDR from our dataset describes the canopy structure. Vertical canopy density was measured from the ground using a 17.5 meter stratification pole and was then correlated to the calculated VDR from the lidar dataset.

I wanted to assess VDR within Cerulean Warbler habitat and therefore, restricted analyses to deciduous forest with an overstory layer. These areas were selected using canopy height models and aerial photographs, where areas with a canopy height ≥ 20 m were selected and pine forests, delineated from aerial photographs, were excluded. To ensure that sampling of areas that had a range of vertical density ratios, I restricted sampling to 10 areas that had a VDR ≤ 0.33 (low VDR), 10 areas with a VDR > 0.33 ≤ 0.66 (medium VDR), and 10 areas that had a VDR > 0.66 (high VDR). I selected areas ≥ 0.03 ha (10 meter radius) to ensure that I sampled within an area that met these criteria despite the inaccuracy associated with handheld GPS unit (accuracy ± 2-5 m). In addition, the sampling area was large enough to allow for multiple samples. Areas in which the canopy were > 20 m tall and met the designated VDR levels were sorted by size in ArcGIS, and sampling points were then placed in the centers of the top 10 largest defined extents per VDR level. The mean VDR was calculated for a radius of 10 m around each center sampling point using spatial analyst tools Buffer and Zonal Statistics as Table.

Within the center of each sampling extent I raised a 17.5 m stratification pole and counted the number of branches that touched the pole from 0 - 20 m (hence forth referred to as
hits); the last 2.5 meters were assessed by envisioning the pole extending vertically 2.5 m beyond its terminus. I determined that extending beyond 2.5 m was too subjective; therefore, upper canopies were not sampled. Quantifying the number of branches that pass through a specified area is similar to the way that lidar pulses register objects they hit as traveling through the canopy. I sampled each area three times by sampling in the center and 5 m from the center in two randomly selected directions. An azimuth was selected using a list of randomly generated numbers from 0-360.

Normality for mean VDR and mean number of hits was determined using a Shapiro-Wilk Normality Test. A Spearman rank correlation was conducted to assess the association between VDR and the mean number of hits within each extent. An ANOVA was conducted to determine differences between the mean number of hits per VDR level, and a Tukey’s post-hoc test was conducted to determine differences per VDR level. All statistical analyses had a significance level of $\alpha = 0.05$.

**Explanatory Variables: Compiling Vegetation Data**

Data from 2010-2013 vegetation surveys within Cerulean Warbler territories and random non-use areas were used to calculate the following variables: average DBH of trees $\geq 10$ cm DBH, total basal area ($m^2/ha$) of trees $\geq 10$ cm DBH, number of trees per ha $\geq 10$ cm DBH, total basal area ($m^2/ha$) of hickories (*Carya* spp.) $\geq 10$ cm DBH, total basal area ($m^2/ha$) of white oak (*Quercus alba*), total basal area ($m^2/ha$) of tuliptree (*Liriodendron tulipifera*) $\geq 10$ cm DBH, number of trees $\geq 10 < 23$ cm DBH per ha, number of trees $\geq 23 < 38$ cm DBH per ha, number of trees $\geq 38 < 53$ cm DBH per ha, number of trees $> 53$ cm DBH per ha, number of saplings and shrubs $< 3$ cm DBH per ha, and number of small trees and shrubs $\geq 3 < 10$ cm DBH per ha.
Hickories were selected because Cerulean Warblers commonly forage in these trees (Gabbe et al. 2002, Barg et al. 2006, George 2009, MacNeil 2010), they are a productive source of prey items (Barg et al. 2006, Wagner 2012), and are commonly used as song perches (Barg et al. 2006, Jones and Islam 2006). White oaks were selected because Cerulean Warblers commonly nest in these trees (Roth and Islam 2008, Boves et al. 2013a) and they are often used as song perches (Jones and Islam 2006). Tuliptrees were selected because these are commonly used as song perches (Jones and Islam 2006) and reported as a preferred tree in other regions (Boves et al. 2013a).

Data Analysis

All statistical analyses were performed in statistical software program R v. 3.0.2 (R 2013). Two sample statistical tests with an alpha value of 0.05 were conducted to compare used plots to unused plots, and low-use areas (density ≤ 2 territories within 100 m of sample territory’s center) to high-use areas (density > 2 territories within 100 m of sample territory’s center). Normality and equal variance was determined using Shapiro-Wilk Normality Test, and F-test or Levene’s Test, respectively. Transformations were applied when possible to correct for skewed distributions. Pooled or non-pooled two sample t-test were used when distributions were normal or approximately normal when applying the central limit theorem, and Mann-Whitney-Wilcoxon Tests were used when distributions were not normal and variances were equal.

General habitat characteristics that are associated with Cerulean Warbler breeding habitat were determined by conducting a logistic regression (LR) with presence and absence as the response variable and data from ground and lidar surveys as explanatory variables. A total of 58 non-use areas and 58 territories were sampled.
Assuming breeding aggregations are a response to habitat quality (Fretwell and Lucas 1969), the most preferred habitat characteristics were determined by conducting a negative binomial generalized linear model (\(NB\)) with the number of territory centroids from 2009-2013 within 100 m of a sample territory as the response variable and data from ground and lidar surveys as explanatory variables. This model was selected because the response variable had an overdispersed poisson distribution. A total of 83 territories were sampled.

Explanatory variables were selected based on variables reported in Cerulean Warbler habitat selection studies and personal observations (See Table 1 for variables included in generalized linear models). The following 26 explanatory variables were considered for inclusion in the model: average DBH of trees \(\geq\) 10 cm DBH, total basal area \(\text{(m}^2/\text{ha})\) of trees \(\geq\) 10 cm DBH, number of trees \(\geq\) 10 cm DBH per ha, total basal area \(\text{(m}^2/\text{ha})\) of hickories \(\geq\) 10 cm DBH, total basal area \(\text{(m}^2/\text{ha})\) of white oak \(\geq\) 10 cm DBH, total basal area \(\text{(m}^2/\text{ha})\) of tuliptree \(\geq\) 10 cm DBH, number of trees \(\geq\) 10 < 23 cm DBH per ha, number of trees \(\geq\) 23 < 38 cm DBH per ha, number of trees \(\geq\) 38 < 53 cm DBH per ha, number of trees > 53 cm DBH per ha, number of saplings and shrubs < 3 cm DBH per ha, number of small trees and shrubs \(\geq\) 3 < 10 cm DBH per ha, mean canopy height, standard deviation of mean canopy height, percent canopy \(\leq\) 12 m tall, percent canopy > 24 m tall, mean VDR, standard deviation of mean VDR, percent VDR \(\leq\) 0.33, percent VDR > 0.66, number of canopy gaps \(\geq\) 20 m\(^2\) that have their centroid within an extent, mean size of canopy gaps \(\geq\) 20 m\(^2\) that have their centroid within an extent, distance from an extent to the nearest canopy gap, the sum of canopy gaps \(\geq\) 20 m\(^2\) edge within an extent, mean elevation, mean slope, and mean Beers aspect.

An information theoretic approach was conducted using \textit{a priori} models, and model quality was assessed using Akaike Information Criteria (AICc). The top models with \(\Delta\text{AICc} \leq 2\)
are presented as the most parsimonious models and Akaike weights ($w_i$) are given as a more intuitive indication of the relative support of each model in the set of models considered (Burnham and Andersen 2002). Model averaging was conducted on top models if necessary, and estimates of beta, standard errors, and 85% confidence intervals are reported for each variables within top models; 85% CI are presented to assess if any model parameters are uninformative (i.e. zero contained within the interval; Arnold 2010). A second order correction (AICc) was used to prevent overfitting the model due to low sample size and high number of parameters (Burnham and Andersen 2002). Three full models were selected for both occurrence and density analyses to assess which variables best explain the general habitat characteristics that are selected by Cerulean Warblers and the more specific habitat characteristics that are representative of breeding hotspots. Furthermore, the three full models will help assess the predictive capabilities of lidar derived variables versus variables derived from vegetation surveys. The three full models selected represent the following data types: 1) variables derived only from vegetation surveys ($V$), 2) variables derived only from lidar data ($L$), and 3) variables derived from both vegetation and lidar surveys ($VL$). Variables were examined for outliers using dotcharts and those that had large outliers were squared or square root transformed. Variables were examined for colinearity by constructing a Pearson’s correlation matrix and calculating variance inflation factors (VIF). All covariates within full models were required to have a VIF of < 3 (Zuur et al. 2009). The following considerations were used when selecting which covariates to drop from the full model to prevent overfitting: 1) variables that had a general representation of habitat characteristics were included over more specific variables, 2) if one of two similar variables had large outliers it was dropped from the model, and 3) variables that were more practical from a conservation standpoint were included.
The full models for LR analyses contained the following variables: 1) LR_V - the number of trees >53 cm DBH per ha, total basal area (m²/ha) of trees ≥ 10 cm DBH, number of trees ≥ 10 cm DBH per ha, total basal area (m²/ha) of hickories ≥ 10 cm DBH, total basal area (m²/ha) of white oak ≥ 10 cm DBH, total basal area (m²/ha) of tuliptree ≥ 10 cm DBH, number of saplings and shrubs < 3 cm DBH per ha, number of small trees and shrubs ≥ 3 < 10 cm DBH per ha, 2) LR_L - mean canopy height, mean VDR, standard deviation of mean VDR, number of canopy gaps ≥ 20 m² that have their centroid within an extent, distance from an extent to the nearest gap, mean elevation, mean slope, and mean Beers aspect, and 3) LR_VL - all of the variables in LR_V and LR_L models except for the number of trees ≥ 10 cm DBH per ha, and the number of trees >53 cm DBH per ha, because they had a VIF > 3. LR_V models included 10 a priori models each containing three covariates, and the null and full models. LR_L models included 10 a priori models containing two to three covariates, and null and full models. LR_VL models included 25 a priori models containing three to four covariates, and the null and full models.

The full models for NB analyses contained the following variables: 1) NB_V - the number of trees >53 cm DBH per ha, total basal area (m²/ha) of trees ≥ 10 cm DBH, number of trees ≥ 10 cm DBH per ha, total basal area (m²/ha) of hickories ≥ 10 cm DBH, total basal area (m²/ha) of white oak ≥ 10 cm DBH, total basal area (m²/ha) of tuliptree ≥ 10 cm DBH, number of saplings and shrubs < 3 cm DBH per ha, number of small trees and shrubs ≥ 3 < 10 cm DBH per ha, 2) NB_L - mean canopy height, mean VDR, standard deviation of VDR, number of canopy gaps ≥ 20 m² that have their centroid within an extent, distance from an extent to the nearest gap, mean elevation, mean slope, and mean Beers aspect, and 3) LR_VL - all of the variables in NB_V and NB_L models except for the number of trees ≥ 10 cm DBH per ha, and mean canopy height,
because they had a VIF > 3. \( NB_v \) models included 10 \textit{a priori} models containing two to three covariates, and the null and full models. \( NB_L \) models included 10 \textit{a priori} models containing two to three covariates, and the null and full models. \( NB_{VL} \) models included 25 \textit{a priori} models containing three to four covariates, and the null and full models.

**RESULTS**

\textit{Vertical Density Ratio}

There was a positive association between mean number of hits per extent and the calculated VDR \((R^2 = 0.80, P = <0.001; \text{Figure 3})\). Mean return differed per VDR level \((F = 34.57, P = <0.001)\), and a post-hoc comparison showed the mean return for low VDR differed from both medium and high VDRs (mean return ± S.D: low VDR = 2.60 ± 0.95, medium VDR = 4.87 ± 0.61, high VDR = 5.70 ± 0.97).

\textit{Occurrence Habitat Models}

There was one top model with \( \Delta \text{AICc} \leq 2 \) for \( LR \) analyses (i.e. \( LR_v + LR_L + LR_{VL} \)). This model had a \( W_i \) of 0.42, and contained the variables total basal area \((\text{m}^2/\text{ha})\) of hickories > 10 cm DBH, mean Beers’ aspect, mean slope, and mean elevation (Figure 4, Table 2). Cerulean Warbler occurrence was positively associated with the total basal area of hickories and a more north east facing aspect, and negatively associated with slope and elevation (Table 3). The variables contained in the model were derived from both lidar and vegetation data, and the \( W_i \) of the model within the smaller \( LR_{VL} \) subset was 0.64 (Table 4).
There was one top model with a $\Delta AIC_c \leq 2$ for $LR_V$ model subset. This model had a $W_i$ of 0.86, and contained the variables total basal area ($m^2/ha$) of hickories $> 10$ cm DBH, total basal area ($m^2/ha$) of tuliptrees $> 10$ cm DBH, and total basal area ($m^2/ha$) of white oaks $> 10$ cm DBH (Table 4). In this model Cerulean Warbler occurrence was positively associated with the total basal area of hickories, tuliptrees, and white oaks; however, zero was contained within the 85% confidence interval (CI) for white oak total basal area, which indicates a weak effect. When the $LR_V$ model subset is grouped with $LR_L$ and $LR_{VL}$ model subsets, its $\Delta AIC_c$ increases to 16.35 and its $W_i$ decreases to <0.001, which indicates a poor overall predictor of Cerulean Warbler occurrence (Table 2).

There were two top models with $\Delta AIC_c \leq 2$ for $LR_L$ model subset. The top model was the full model containing all lidar variables, and it had a $W_i$ of 0.57. The second model had a $\Delta AIC_c$ of 0.91, a $W_i$ of 0.37, and contained the variables mean Beers’ aspect, mean slope, and mean elevation (Table 4). Model averaging was conducted on these models and Cerulean Warbler occurrence was positively associated with a taller canopy, a denser and more variable vertical vegetative stratum, and more northeast facing aspect, and negatively associated with slope and elevation. It also indicated a positive association with both the distance to the nearest canopy gap, and the number of canopy gaps; however, zero was contained within the 85% CI for these variables, which indicates a weak effect. When the $LR_L$ model subset is grouped with $LR_{VL}$ and $LR_V$ model subsets, the $\Delta AIC_c$ of the top two models increased to 4.70 and 5.61, and their $W_i$ decreased to 0.13, and 0.08, respectively (Table 2).

When comparing used and unused plots with two sample statistical tests, used plots had a more northeast facing aspect (Two sample T-test; $t = -4.30, P = <0.001$). Used and unused plots had mean Beer’s aspect 1.28 and 0.85, respectively, and 72% of used plots were located on north.
to southeast facing slopes (337.5-360 and 0-157.5 degrees; Figure 5). Used plots had a taller average canopy height (Two Sample T-test; $t = -2.82$, $P = 0.006$), and a higher percentage of canopy with a height > 24 m (Two Sample T-test; $t = -2.07$, $P = 0.040$). Used plots had a greater total basal area (m$^2$/ha) (Two Sample T-test; $t = -2.04$, $P = 0.043$), and greater total basal area (m$^2$/ha) of hickories (Two Sample T-test; $t = -3.38$, $P = 0.001$) and tuliptrees (Two Sample T-test; $t = -2.77$, $P = 0.007$). Used plots were at lower elevations (T-test; $D = 0.28$, $P = 0.024$), had more trees and shrubs ≥ 3 < 10 cm DBH per ha (Two Sample T-test; $t = 1.69$, $P = 0.095$), more trees ≥ 53 cm DBH (Two Sample T-test; $t = -1.71$, $P = 0.090$; however, these differences were only marginally significant (Table 5).

Density Habitat Models

There were four models from NB analyses (i.e. $NB_V + NB_L + NB_{VL}$) with $\Delta$ AICc ≤ 2. The top model had a $W_i$ of 0.21, and contained the variables total basal area (m$^2$/ha) of trees > 10 DBH, standard deviation of mean VDR, and the number of gaps within a territory. The second top model had a $\Delta$ AICc of 0.04, a $W_i$ of 0.21, and contained the variables mean slope, total basal area (m$^2$/ha) of trees > 10 cm DBH, and the number of trees > 53 cm DBH per ha. The third top model had a $\Delta$ AICc of 0.32, a $W_i$ of 0.18 and contained the variables same variables as the second top model with the addition of the total basal area (m$^2$/ha) of white oaks > 10 cm DBH. The fourth top model had a $\Delta$ AICc of 0.72, a $W_i$ of 0.15, and contained the variables mean slope, standard deviation of mean VDR, and the number of trees > 53 cm DBH per ha (Table 6). Model averaging was conducted on these top models and Cerulean Warbler high-use areas were positively associated with slope and white oak basal area, and negatively associated with total basal area, large trees, the number of gaps, and variation in the density of the vertical vegetative
stratum (Figure 6 and Table 7). The variables contained in the model were derived from both lidar and vegetation data, and the $W_i$ of the models within the smaller $NB_{VL}$ subset were 0.24, 0.23, 0.20, and 0.16 (Table 8).

There were two top models with a $\Delta$AICc ≤ 2 for $NB_{V}$ models. The top model had a $W_i$ of 0.46 and contained the variables total basal area ($m^2/ha$) of white oaks > 10 cm DBH, and the number of trees > 53 cm DBH per ha. The second top model had a $\Delta$AICc of 1.46, a $W_i$ of 0.22, and contained the variables total basal area ($m^2/ha$) of tuliptrees > 10 cm DBH, and the number of trees > 53 cm DBH per ha (Table 8). Model averaging was conducted on these models and Cerulean Warbler high use areas were positively associated with the total basal area ($m^2/ha$) of white oaks and tuliptrees, and negatively associated with large trees. When the $LR_{V}$ model subset is grouped with $LR_{L}$ and $LR_{VL}$ model subsets, the $\Delta$AICc of the two top models increased 9.30 and 10.76 and their $W_i$ decreased to 0.002 and 0.001, which indicates a poor overall predictor of Cerulean Warbler occurrence (Table 5).

There were two top models with $\Delta$AICc ≤ 2 for $NB_{L}$ models. The top model had a $W_i$ of 0.40 and contained the variables mean slope, mean elevation, and standard deviation of mean VDR. The second model had a $\Delta$AICc of 0.53, and $W_i$ of 0.31 and contained the variables mean slope, number of gaps within a territory, and standard deviation of mean VDR (Table 8). Model averaging was conducted on these models and Cerulean Warbler high-use areas were positively associated with slope, and negatively associated with variation within the vertical vegetative stratum. High-use areas were also negatively associated with the number of canopy gaps, and elevation; however, zero was contained within the 85% CI for these variables, which indicates a weak effect. When the $NB_{L}$ model subset is grouped with $NB_{VL}$ and $NB_{V}$ model subsets, the
\( \Delta AICc \) of the top two models increased to 3.40 and 3.93, and their \( W_i \) decreased to 0.03, and 0.04, respectively (Table 5).

When comparing high-use to low-use areas with two sample statistical tests, high-use areas were associated with lower elevations (Two Sample T-test; \( t = 2.94, P = 0.004 \)) and more shrubs and trees \( \geq 3 \times 10 \) cm DBH per ha (Two Sample T-test; \( t = -2.02, P = 0.047 \)). They also had less percent canopy with open vertical vegetative stratum (Two Sample T-test; \( t = 1.71, P = 0.090 \)), less canopy gap edge (i.e. polyline) within the territory (Two Sample T-test; \( t = 1.87, P = 0.065 \)), and a higher vertical vegetative density (Two Sample T-test; \( t = -1.75, P = 0.084 \)); however, these differences were only marginally significant (Table 9).

**DISCUSSION**

*Vertical Density Ratio Ground-truthing*

Although there was a strong correlation between the mean number of hits per sampling area and the calculated VDR per sampling area, the differences between medium and high VDR in the lower 20 m of the canopy were insignificant. My analyses did show that in the lower 20 m of the vegetation stratum, low VDR does represent less vegetation, and medium and high VDR represent a greater amount of vegetation. Perhaps if the entire vertical vegetation stratum could be quantified from the ground using our sampling method, a difference between medium and high VDR levels would be seen based on differences quantified in the upper canopy. From my analyses I can only affirm that VDR, calculated from discrete lidar and the mean canopy height, will provide a coarse representation of the vegetation density in the lower 20 m of the canopy.
Habitat Models

Occurrence and density analyses had top models that contained both lidar and vegetation variables. These models had the most empirical support for predicting Cerulean Warbler occurrence and density ($\Delta$AICc ≤ 2); models that contained only lidar variables had less support for predicting occurrence and density ($4 \leq \Delta$AICc ≤ 7), and those that contained only variables derived from vegetation sampling had essentially no support for predicting occurrence and density in comparison to other candidate models ($\Delta$AICc > 10) (Burnham and Anderson 2002). It is not recommended that vegetation surveys be eliminated from habitat selection studies; however, surveys can be time consuming, laborious, and expensive to complete. Supplementing available lidar data with a few important vegetation metrics could be a more parsimonious approach. For example, identifying the floristics or total basal area for a plot could supplement important lidar metrics, such as, canopy height and aspect. Equipment such as wedge prisms could be an effective tool for quickly quantifying important variables from the ground.

The top LR model had considerable support, with a $W_i$ of 0.58, and it indicated that Cerulean Warbler occurrence was positively associated with slope, northeast facing slopes, lower elevations, and hickory basal area. Other influential variables that have a positive association with Cerulean Warbler occurrence are areas with greater tuliptree basal area, and a tall dense canopy with increased stratification. This is indicated by used areas having more large trees ($\geq 53$ cm DBH), more small trees and shrubs ($\geq 3 < 10$ cm DBH), greater total basal area, less and a mean VDR of 0.6 (Table 5). The difference between the mean slope and elevation for used and unused areas is slight and most likely not biologically relevant; however, it should be noted that the variance between random unused areas and used areas was not equal (Slope F-test F = 0.42, $p = 0.001$; elevation Levene’s Test F = 23.61, $p = <0.001$; Figure 3); there is greater variation in
the mean slope and elevation within Cerulean Warblers territories than in unused areas, suggesting that perhaps Cerulean Warblers are selecting areas more than what is commonly available. For example, their selection of bottomlands and ridges could explain why territories have a wider range in elevations. In addition, ridgetops and drainages have gentle slopes, but drainages and ridges also have steep slopes extending down to or away from these areas, which could explain why there is greater variation in the slope that Cerulean Warblers select.

There was less support for NB models than LR models, with four top models having $W_i \leq 0.21$. These models indicated that high-use areas are associated with a more closed canopy on steeper slopes that have greater white oak basal area, less large trees and less total basal area. Other influential variables that have a positive association with high-use areas are a dense vertical vegetative stratum, less canopy gap edge, and more small trees and shrubs ≥ 3 < 10 cm DBH per ha, perhaps indicating greater stratification and a homogeneous canopy structure. Most of the coefficients in the NB models are slight and lack strong support; however, these patterns are supported by other similar research which found clustered areas to have greater stratification and smaller trees (Roth and Islam 2007). Differences in vertical vegetation density and heterogeneity could be a function of territory size often being smaller in these clustered areas (Dibala 2012); however, other research suggests that territory size is smaller because of greater vegetation density (Marshall and Cooper 2004). It should be noted though, that the differences that were detected for VDR and its standard deviation in relation to density are slight and VDR at our scale is a coarse measurement, suggesting that these differences are inconsequential beyond knowing that the vertical vegetation stratum is denser in the lower 20 m of its stratum.

Mean elevation was not included in the top models; however, two sample statistics suggested that high-use areas were at lower elevations, and elevation was included in models
with considerable support (Table 6 and Table 9). Cerulean Warblers often select territories near streams in our research plots (Dibala 2012) and I have observed that high-use areas tend to occur near wide drainages (~150 m wide; also suggested in Roth and Islam 2007), which may explain why territories were at lower elevations than non-use areas. Large drainages may be important for hatch year wood warblers that can travel down these corridors during the post-breeding season, perhaps due to increased cover that provides protection from predators, cooler temperatures, and greater food abundance (Mitchell et al. 2010a, Mitchell et al. 2010b).

Many researchers suggest that Cerulean Warblers select areas that have, or are near, canopy gaps; however, our models do not support this claim. Out of the 83 territories that were sampled for density analyses, 38 did not have a canopy gap as defined by this study. The remaining 54% of territories had canopy gaps with a mean size that ranged from 20-480 m² and a total mean of 103 m², which is near the average size of a single tree-fall gap (70-100 m²; Canham et al. 1990); a common natural disturbance in mature forest systems (Seymour et al. 2002). However, it should be noted that having an emergent canopy layer on steep slopes does create a canopy edge similar to that of a gap, which would provide conditions that are favorable for projecting song over the landscape (Ex: Figure 7). This structure would be especially pronounced on ridgetops and on steep slopes near wide drainages.

Some researchers have reported Cerulean Warbler breeding distributions to occur frequently on northeast facing slopes (Wood et al. 2006, Hartman et al. 2009, Boves et al. 2013a); however, other research has not (Carpenter et al. 2011). There are many variables included in my models that are created by abiotic conditions that occur on northeast facing slopes, which tend to be more productive due to less solar radiation, cooler temperatures, and increased soil moisture; such abiotic conditions produce a taller canopy, influence species
composition, and create higher vegetative stratification (Doolittle 1958, Rosenberg et al. 1983, Tajchman and Wiant 1983, Frank et al. 1984, Hicks and Frank 1984, Werling and Tajchman 1984, McNab 1989, Fekeldulegn et al. 2002, Lopez et al. 2008). A northeast facing aspect (Marquis and Le Corff 1997, Jeffries et al. 2006) and a dense vertical vegetative stratum (Marshall and Cooper 2004) can also increase herbivorous prey abundance, such as lepidopteran larvae, which are an important food source for many songbirds (Cramp 1998). In addition, hickories, white oaks, and tuliptrees, which are often used for foraging, nesting, and song perches (Gabbe et al. 2002, Barg et al. 2006, Jones and Islam 2006, Roth and Islam 2008, George 2009, Macneil 2010, Wagner 2012, Boves et al. 2013a), were associated with Cerulean Warbler settlement, further suggesting that their settlement may be resource based to optimize nesting habitat.

Settlement may be a behavioral response to structural cues that optimize nesting habitat; however, settlement could also be a behavioral response to a much simpler settlement cue. Cerulean Warbler’s arrival to their breeding grounds occurs during a period when trees are in the process of leafing out, and based on research (Lopez et al. 2008) and aerial photographs of our research units during mid-April, northeast aspects leaf-out first. Leaf out occurring first on shady slopes is counter intuitive because leaf-out is temperature dependent. However, slope aspect can influence tree species composition and contain species that generally leaf out earlier, such as, American hornbeam (*Carpinus caroliniana*) in the understory, sugar maples (*Acer saccharum*) and beech (*Fagus grandifolia*) in the mid-story, and shagbark hickories (*Carya ovata*) and tuliptrees in the upper canopy (Fekedulegn et al. 2002, Lopez et al. 2008). In addition, these areas leaf out sooner because they are generally more productive than southwest facing slopes and have more energy reserves to produce leaves earlier, while southwest facing species have a
more conservative approach to leaf production due to water limitations (Lopez et al. 2008). Certainly northeast facing slopes that have early leaf-out would be a more suitable location for a foliage gleaning species to settle, especially when they are under temporal constraint to establish a territory prior to the arrival of females. Such an external cue could lead to a clustered distribution in areas where northeast facing slopes are limited.

Variables that are often associated with Cerulean Warbler presence and density are also associated with northeast facing slopes, such as canopy height and vertical vegetation density, making it difficult to know what cue is inducing their settlement. Is settlement a behavioral response to multiple variables that will optimize nesting habitat, or is settlement simply the behavioral response to areas in mature forests that have leaves at the time of their arrival? In Alabama, Carpenter et al. (2011) did not find any association with Cerulean Warbler settlement and aspect, and this could be due to lower latitudes leafing out sooner and thus, not influencing breeding distributions. However, in this study many of the same variables that were associated with Cerulean Warbler presence were also included in our habitat models, suggesting that they are more attracted to a certain vegetation structure than simply settling in what habitat is currently available. In addition, our research units in 2012 leafed out much earlier than usual and Cerulean Warbler settlement was still more common on northeast facing slopes.

In Indiana, West Virginia, Kentucky, Ohio, and Tennessee (Wood et al. 2006, Hartman et al. 2009, Newell and Rodewald 2012, and Boves et al. 2013a), northeast facing slopes can be a strong predictor of Cerulean Warbler presence. This may be due to an associated vegetation structure that optimizes nesting habitat. When prioritizing habitat to protect or restore for Cerulean Warblers, or when determining which areas of a landscape to include in a research study, northeast facing aspects should be given strong consideration (i.e. McDermott et al. 2013).
It was surprising to find that increased canopy heterogeneity did not influence occurrence or density in the model candidate set. This could be due to there being a lack of more intermediate to severe silvicultural disturbance in the research units contained in Monroe County. Monroe County units are either control units or even-age units, which have larger clear cuts (two 4 ha openings; i.e. regeneration cuts), or first phase shelterwood cuts (i.e. removing the lower canopy within two 4 ha areas) that have little perturbation to the canopy. In addition, the buffers around these areas could have some single tree selection.

Many researchers have found that Cerulean Warblers are attracted to canopy disturbances, suggesting that single tree removal with a large target basal area (thinning), group selection (patch cuts > 0.4 ha and < 2 ha), or second phase shelterwood cuts could be beneficial for promoting Cerulean Warbler populations. However, Boves et al. (2013b) found reproductive success was lower in disturbed areas (areas that have been thinned) than non-disturbed areas (control areas), suggesting that timber harvest methods can create an ecological sink. It is then important to understand habitat selection in a more natural setting, and emulate the habitat in these areas to better promote population growth, especially if these natural settings have areas with high breeding densities and also exhibit better reproductive success. I would suggest from my results to protect steeper northeast facing slopes adjacent to ridge tops and wide drainages, and emulate only single tree fall canopy openings up to ~ 100 $m^2/0.3$ ha (i.e. one large tree removed per average Cerulean Warbler territory size). This type of harvest management will also increase vegetation in the lower strata, further increasing the vertical vegetation density. However, this is not a long term management approach to habitat conservation because oaks and hickories will not be retained; these species need more sunlight to germinate and out-compete more shade tolerant species. Therefore, regeneration cuts on northeast slopes should be
conducted every 100+ years. This will temporarily remove prime habitat, but will not create an ecological sink like thinning may do, nor change the floristics of a stand solely through single tree removal. This type of harvest method should promote the growth of tuliptrees, oaks, and hickories (Runkle 1982). This is perhaps the best long term management approach, as long as enough prime habitat is retained for displaced birds to settle in. Other timber harvest methods should be conducted on northwest to southwest facing slopes, but timber harvest methods should not include thinning at a large target basal area, instead regeneration cuts or patch cuts should be implemented.
LITERATURE CITED


FIGURES
Figure 1. Hardwood Ecosystem Experiment (HEE) research units in relation to Monroe County study extent. Purple areas indicate buffer areas, yellow areas indicate control units that have not received any harvest treatments, green areas indicate uneven-aged harvest practices (i.e. single tree removal and patch cuts), and orange area indicate even-aged harvest practices (i.e. currently first phase shelterwood cuts and larger clear cuts). Lidar data was only used from Monroe County so habitat models are restricted to, and representative of, conditions present in control and even-aged units.
Figure 2a. Flow chart representing how lidar data (las files) were sampled and processed to create raster and vector files that were sampled for habitat models. Text in boxes indicate what the file created represents, the image is a depiction of this file, and the italicized text indicates which ArcGIS tools were used to create these layers and other pertinent information. In this figure, las files are being converted to digital terrain and digital surface models (max and mean) by converting las files to multipoint files, multipoint files to terrain files, and terrain files to raster files.
Figure 2b. Flow chart representing how lidar data (las files) were sampled and processed to create raster and vector files that were sampled for habitat models. Text in boxes indicate what the file created represents and the image is a depiction of this file. In this figure, digital terrain and surface models are being converted to canopy height models (max and mean) by subtracting the digital terrain model from both the max and mean digital surface model. Map algebra in PythonWin was used to process these surface models. See Appendix Code 1.
Figure 2c. Flow chart representing how lidar data (las files) were sampled and processed to create raster and vector files that were sampled for habitat models. Text in boxes indicate what the file created represents and the image is a depiction of this file. In this figure, a digital terrain model is converted to rasters representing slope, aspect, and Beers’ aspect. These files were created using ArcGIS spatial analyst tools Slope and Aspect, and using Map Algebra in PythonWin to convert aspect to Beers’ Aspect (i.e. Cos(45-Aspect)+1. See Appendix Code 1.
Figure 2d. Flow chart representing how lidar data (las files) were sampled and processed to create raster and vector files that were sampled for habitat models. Text in boxes indicate what the file created represents and the image is a depiction of this file. In this figure, a max canopy height model is sampled to create rasters representing canopy percent openness, and percent tall canopy. These files were created using Map Algebra to sample canopy areas < 12 m and > 24 m. The canopy openness file is then sampled to create a vector file depicting canopy gaps > 20 m² using ArcGIS spatial analyst tool Region Group and the conversion tool Raster to Polygon. See Appendix Code 1.
Figure 2e. Flow chart representing how lidar data (las files) were sampled and processed to create raster and vector files that were sampled for habitat models. Text in boxes indicate what the file created represents and the image is a depiction of this file. In this figure, max and mean canopy height models are used to create a raster representing vertical vegetation density (i.e. VDR=[max canopy height – mean canopy height]/max canopy height). This file was then sampled to create rasters representing the percent low VDR (i.e. areas ≤ 0.33) and percent high VDR (i.e. areas > 0.66 VDR). These files were created using Map Algebra in PythonWin. See Appendix Code 1.
Figure 3. Correlation between VDR and mean number of hits (i.e. the number of branches that touched a stratification pole from 0 - 20 m; Spearman Rank Correlation $R^2=0.80$, $P<0.001$). Mean VDR was calculated for an area with a 10 m radius and classified as: $VDR \leq 0.33$ (low VDR), $0.33 < VDR \leq 0.66$ (medium VDR), and $VDR > 0.66$ (high VDR).
Figure 4. Fitted line for variables in the top logistic regression model. Dots indicate observed values.
Figure 5. Real mean azimuth using Zar (1999) transformation ($\arctan^2(\sum\cos(A)), \sum\sin(A)$) for use and non-use areas. Each blue point indicates the mean azimuth for an extent. The dotted line and arrow help indicate total mean azimuth. The length of the arrow indicates strength of estimate.
Figure 6. Fitted line (red) and 95% confidence intervals (blue dotted line) for variables in the top negative binomial models. Dots indicate observed values.
Figure 7. Crosssection of LAS dataset to show how canopy edge is formed on steep slopes near wide drainages. Note the light red region having a canopy edge created by the steep slope extending down to the drainage.
TABLES
Table 1. Variables used in candidate model sets for logistic regression and negative binomial generalized linear models. Variable code used in candidate models, its description, the Cerulean Warbler habitat association that is described and the research that suggests this variable may be important to include in candidate models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Code</th>
<th>Description</th>
<th>CERW association</th>
<th>Research that suggests variable settlement association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total basal area (m²/ha)</td>
<td>TB.HA</td>
<td>The total basal area (m²/ha) of trees ≥ 10 cm DBH</td>
<td>Tree size and abundance</td>
<td>see above</td>
</tr>
<tr>
<td>Large Trees</td>
<td>53.HA</td>
<td>The number of trees per ha with ≥ 53 cm DBH</td>
<td>Tree size and abundance</td>
<td>see above</td>
</tr>
<tr>
<td><em>Carya</em> sp. basal area (m²/ha)</td>
<td>CBA.HA</td>
<td>The total basal area (m²/ha) of <em>Carya</em> sp. ≥ 10 cm DBH</td>
<td>Foraging and song perch species</td>
<td>Gabbe et al. 2002, Barg et al. 2006, Jones and Islam 2006, George 2009, MacNeil 2010, Wagner 2012</td>
</tr>
<tr>
<td><em>Quercus alba</em> basal area (m²/ha)</td>
<td>QBA.HA</td>
<td>The total basal area (m²/ha) of <em>Quercus alba</em> ≥ 10 cm DBH</td>
<td>Nesting and song perch species</td>
<td>Jones and Islam 2006, Roth and Islam 2008, Boves et al. 2013a</td>
</tr>
<tr>
<td><em>Liriodendron tulipifera</em> basal area (m²/ha)</td>
<td>LBA.HA</td>
<td>The total basal area (m²/ha) of <em>Liriodendron tulipifera</em> ≥ 10 cm DBH</td>
<td>Song perch species</td>
<td>Jones and Islam 2006, Boves et al. 2013a</td>
</tr>
<tr>
<td>Variable</td>
<td>Code</td>
<td>Description</td>
<td>CERW association</td>
<td>Research that suggests variable settlement association</td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>-------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Canopy height (m)</td>
<td>Avg.CH</td>
<td>The mean canopy height (m)</td>
<td>Tall canopy</td>
<td>Jones and Robertson 2001, Roth and Islam 2008, Carpenter et al. 2011, Boves et al. 2013a</td>
</tr>
<tr>
<td>Vertical density ratio</td>
<td>Avg.Vdr</td>
<td>The mean vertical density ratio (VDR=[max canopy height/mean can Ht]/max can Ht)</td>
<td>Structure of the vertical vegetative stratum</td>
<td>Jones and Robertson 2001, Weakland and Wood 2005, Roth and Islam 2007, Boves et al. 2013a</td>
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<td>Number of shrubs &lt; 3 cm DBH</td>
<td>S3.HA</td>
<td>The number of shrubs and trees &lt; 3 cm DBH per ha</td>
<td>Shrub layer</td>
<td>Wood et al. 2006, Roth and Islam 2007, Hartman et al. 2009, Bakersman et al. 2012, Boves et al. 2013a</td>
</tr>
<tr>
<td>Number of shrubs ≥ 3 &lt; 10 cm DBH</td>
<td>S310.HA</td>
<td>The number of shrubs and trees ≥ 3 &lt; 10 cm DBH per ha</td>
<td>Shrub layer</td>
<td>see above</td>
</tr>
<tr>
<td>Horizontal vegetative heterogeneity</td>
<td>Std.CH</td>
<td>The standard deviation of the mean canopy height</td>
<td>Heterogeneous vegetative structure</td>
<td>see above</td>
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<tr>
<td>Number of canopy gap</td>
<td>N.Gaps</td>
<td>The number of canopy gaps ≥ 20 m² that have their centroid within the territory or non-use area</td>
<td>Heterogeneous vegetative structure</td>
<td>see above</td>
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<tr>
<td>Distance to nearest canopy gap (m)</td>
<td>Near.Gap</td>
<td>The distance (m) to the nearest canopy gap from the centroid of territories and nonuse areas</td>
<td>Heterogeneous vegetative structure</td>
<td>see above</td>
</tr>
</tbody>
</table>
Table 2. All candidate logistic regression (LR) models. LR_v indicates models only containing variables derived from vegetation surveys, LR_l indicates models only containing lidar derived variables, and LR_vl indicates models containing variables derived from both vegetation surveys and lidar data. K is the number of parameters in a model, L is the log-likelihood value, \( \Delta AICc \) is the difference between each model’s AICc value and the smallest AICc value in the candidate set, and \( W_i \) is the Akaike weight of each model in relation to the entire candidate set.

<table>
<thead>
<tr>
<th>Model</th>
<th>K</th>
<th>L</th>
<th>( \Delta AICc )</th>
<th>( W_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( LR_{vl}(\text{Avg.Beers, Avg.Elev, Avg.Slope+CBA.HA})^{a,b} )</td>
<td>5</td>
<td>-62.75</td>
<td>0.00</td>
<td>0.576</td>
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<tr>
<td>( LR_{vl}(\text{Avg.Beers, Avg.Elev, Avg.Slope, TB.HA}) )</td>
<td>5</td>
<td>-63.92</td>
<td>2.34</td>
<td>0.178</td>
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<tr>
<td>( LR_{l}(\text{full})^{c} )</td>
<td>9</td>
<td>-60.52</td>
<td>4.70</td>
<td>0.055</td>
</tr>
<tr>
<td>( LR_{vl}(\text{Avg.Beers, Avg.Elev, Avg.Slope, TB.HA}) )</td>
<td>5</td>
<td>-66.27</td>
<td>7.06</td>
<td>0.017</td>
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<tr>
<td>( LR_{vl}(\text{Avg.Beers, Avg.Elev, Avg.Slope, QBA.HA}) )</td>
<td>5</td>
<td>-66.58</td>
<td>7.66</td>
<td>0.012</td>
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<tr>
<td>( LR_{vl}(\text{CBA.HA, LBA.HA, Avg.Beers}) )</td>
<td>5</td>
<td>-66.11</td>
<td>7.72</td>
<td>0.012</td>
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<tr>
<td>( LR_{vl}(\text{Avg.Beers, CBA.HA, TB.HA, SRT.S310.HA}) )</td>
<td>5</td>
<td>-66.85</td>
<td>8.21</td>
<td>0.009</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SRT.Near.Gap, Avg.Vdr, SRT.S310.HA, SRT.S310.HA}) )</td>
<td>5</td>
<td>-67.08</td>
<td>8.67</td>
<td>0.0005</td>
</tr>
<tr>
<td>( LR_{vl}(\text{TB.HA, CBA.HA, Avg.Beers, SQ.Avg.CH}) )</td>
<td>5</td>
<td>-68.64</td>
<td>9.59</td>
<td>0.0005</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SQ.Avg.CH, Avg.Vdr, Avg.Beers}) )</td>
<td>3</td>
<td>-70.86</td>
<td>11.89</td>
<td>0.002</td>
</tr>
<tr>
<td>( LR_{vl}(\text{full}) )</td>
<td>15</td>
<td>-56.96</td>
<td>12.69</td>
<td>0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SQ.Avg.CH, SRT.Near.Gap, Avg.Beers}) )</td>
<td>4</td>
<td>-70.82</td>
<td>13.97</td>
<td>0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SQ.Avg.CH, Avg.Slope, CBA.HA, LBA.HA}) )</td>
<td>5</td>
<td>-70.14</td>
<td>14.79</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SRT.N.Gaps, Std.Vdr, Avg.Beers, SRT.S310.HA}) )</td>
<td>5</td>
<td>-70.88</td>
<td>16.27</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{CBA.HA, LBA.HA, QBA.HA}) )</td>
<td>4</td>
<td>-72.01</td>
<td>16.35</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SRT.N.Gaps, Std.Vdr, CBA.HA, LBA.HA}) )</td>
<td>5</td>
<td>-71.83</td>
<td>18.18</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{TB.HA, LBA.HA, Avg.Elev, SQ.Avg.CH}) )</td>
<td>5</td>
<td>-71.87</td>
<td>18.26</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SQ.Avg.CH, SRT.N.Gaps, LBA.HA}) )</td>
<td>4</td>
<td>-73.67</td>
<td>19.67</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{Avg.Slope, SQ.Avg.CH}) )</td>
<td>3</td>
<td>-75.03</td>
<td>20.23</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{SQ.Avg.CH, Avg.Vdr, SRT.S310.HA}) )</td>
<td>4</td>
<td>-73.95</td>
<td>20.23</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{Avg.Slope, SQ.Avg.CH, Avg.Vdr}) )</td>
<td>4</td>
<td>-74.40</td>
<td>21.13</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{Std.Vdr, SRT.N.Gaps, SQ.Avg.CH}) )</td>
<td>4</td>
<td>-74.59</td>
<td>21.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{Avg.Vdr, SQ.Avg.CH, TB.HA}) )</td>
<td>4</td>
<td>-74.63</td>
<td>21.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( LR_{vl}(\text{CBA.HA, Trees.HA, TB.HA})^{d} )</td>
<td>4</td>
<td>-74.83</td>
<td>21.99</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Table 2 Continued

<table>
<thead>
<tr>
<th>Model</th>
<th>K</th>
<th>L</th>
<th>ΔAICc</th>
<th>$W_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LR_k$(Avg.Slope, SRT.N.Gaps, SQ.Avg.CH)</td>
<td>4</td>
<td>-74.89</td>
<td>22.10</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(LBA.HA, Trees.HA, TB.HA)</td>
<td>4</td>
<td>-75.46</td>
<td>23.24</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(full)</td>
<td>9</td>
<td>-69.82</td>
<td>23.29</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(TB.HA, QBA.HA, Avg.Slope, SQ.Avg.CH)</td>
<td>5</td>
<td>-74.70</td>
<td>23.90</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(Avg.Elev, Avg.Slope, QBA.HA, LBA.HA)</td>
<td>5</td>
<td>-74.83</td>
<td>24.17</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(Avg.Vdr, SRT.S3.HA, SRT.S310.HA, TB.HA)</td>
<td>5</td>
<td>-75.11</td>
<td>24.73</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(SRT.S3.HA, SRT.S310.HA, TB.HA)</td>
<td>4</td>
<td>-76.50</td>
<td>25.31</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(Trees.HA, TB.HA, SRT.S310.HA)</td>
<td>4</td>
<td>-76.81</td>
<td>25.94</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(SRT.S310.HA, 53.HA, TB.HA)</td>
<td>4</td>
<td>-76.90</td>
<td>26.12</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR$(null)</td>
<td>1</td>
<td>-80.41</td>
<td>26.81</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(SRT.S3.HA, SRT.S310.HA, 53.HA)</td>
<td>4</td>
<td>-77.31</td>
<td>26.94</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(TB.HA, Avg.Vdr, SRT.Near.Gap)</td>
<td>4</td>
<td>-77.62</td>
<td>27.55</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(TB.HA, SRT.N.Gaps, Std.Vdr)</td>
<td>4</td>
<td>-77.62</td>
<td>27.56</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(SRT.S3.HA, SRT.S310.HA, Avg.Vdr, SRT.Near.Gap)</td>
<td>5</td>
<td>-76.76</td>
<td>28.03</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(SRT.S3.HA, TB.HA, 53.HA)</td>
<td>4</td>
<td>-78.07</td>
<td>28.45</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(QBA.HA, Trees.HA, 53.HA)</td>
<td>4</td>
<td>-78.13</td>
<td>28.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(Trees.HA, TB.HA, 53.HA)</td>
<td>4</td>
<td>-78.27</td>
<td>28.86</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(Avg.Vdr, Std.Vdr, SRT.Near.Gap)</td>
<td>4</td>
<td>-78.41</td>
<td>29.15</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_k$(SRT.N.Gaps, Std.Vdr)</td>
<td>3</td>
<td>-79.66</td>
<td>29.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>$LR_{12}$(SRT.S3.HA, SRT.S310.HA, SRT.N.Gaps+Std.Vdr)</td>
<td>5</td>
<td>-78.22</td>
<td>30.94</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Note: Bolded models indicate top models for each model subset. *Top $LR$ model. **Top $LR_{12}$ model. ***Top $LR_k$ models. ****Top $LR_{12}$ model.
Table 3. Estimated coefficients for each variables in the top logistic regression ($LR$) model, with their standard error and 85% confidence interval.

<table>
<thead>
<tr>
<th>LR Top Model Variables</th>
<th>Estimated Coefficient</th>
<th>SE</th>
<th>Lower 85% CI</th>
<th>Upper 85% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg.Beers</td>
<td>1.96</td>
<td>0.47</td>
<td>1.31</td>
<td>2.67</td>
</tr>
<tr>
<td>Avg.Slope</td>
<td>-0.10</td>
<td>0.04</td>
<td>-0.16</td>
<td>-0.04</td>
</tr>
<tr>
<td>Avg.Elev</td>
<td>-0.03</td>
<td>0.01</td>
<td>-0.05</td>
<td>-0.02</td>
</tr>
<tr>
<td>CBA.HA</td>
<td>0.18</td>
<td>0.07</td>
<td>0.08</td>
<td>0.29</td>
</tr>
</tbody>
</table>
Table 4. Top models for each logistic regression (LR) subset. \( LR_v \) indicates models only containing variables derived from vegetation surveys, \( LR_l \) indicates models only containing lidar derived variables, and \( LR_{vl} \) indicates models containing variables derived from both vegetation surveys and lidar data. K is the number of parameters in a model, L is the log-likelihood value, \( \Delta \text{AICc} \) is the difference between each model’s AICc value and the smallest AICc value in the candidate subset, and \( W_i \) is the Akaike weight of each model in relation to the the candidate subset. (+) indicates a positive association, and (-) indicates a negative association.

<table>
<thead>
<tr>
<th>Subset Top Models</th>
<th>K</th>
<th>L</th>
<th>( \Delta \text{AICc} )</th>
<th>( W_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( LR_{vl} ) subset---</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg.Beers(+), Avg.Elev(-), Avg.Slope(-), CBA.HA(+)</td>
<td>5</td>
<td>-62.75</td>
<td>0.00</td>
<td>0.637</td>
</tr>
<tr>
<td>( LR_l ) subset---</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ.Avg.CH(+), Avg.Vdr(+), Std.Vdr(+), SRT.N.Gaps(+), SRT.Near.Gap(+), Avg.Beers(+), Avg.Slope(-), Avg.Elev(-)</td>
<td>9</td>
<td>-60.52</td>
<td>0.00</td>
<td>0.568</td>
</tr>
<tr>
<td>( LR_v ) subset---</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBA.HA(+), LBA.HA(+), QBA.HA(+)</td>
<td>4</td>
<td>-72.01</td>
<td>0.00</td>
<td>0.857</td>
</tr>
</tbody>
</table>
Table 5. Two sample statistics for all considered variables between used and unused area, with variable code and description. Mean±SE, t value, and p value are given for pooled and non-pooled two sample two tailed t-tests. All tests had an alpha value of 0.05. Those p values that are significant and marginally significant (p <0.1) are bolded.

<table>
<thead>
<tr>
<th>Variable Code</th>
<th>Variable Description</th>
<th>Used</th>
<th>Unused</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg.Gap.IN c</td>
<td>Average canopy gap size within used and unused areas</td>
<td>1.8±0.3</td>
<td>2.3±0.3</td>
<td>1.2</td>
<td>0.233</td>
</tr>
<tr>
<td>N.Gaps.IN a</td>
<td>Number of canopy gaps within used and unused areas</td>
<td>0.6±0.1</td>
<td>0.7±0.1</td>
<td>1.08</td>
<td>0.284</td>
</tr>
<tr>
<td>Near.Gap</td>
<td>Distance to nearest canopy gap from the center of used and unused areas</td>
<td>20.2±2.4</td>
<td>16.9±1.9</td>
<td>-1.48</td>
<td>0.140</td>
</tr>
<tr>
<td>Polylne c</td>
<td>The sum length of all canopy gap edge within used and unused areas</td>
<td>1.0±0.1</td>
<td>1.2±0.1</td>
<td>1.03</td>
<td>0.304</td>
</tr>
<tr>
<td>Std.CH</td>
<td>The standard deviation of canopy height within used and unused areas</td>
<td>5.0±0.2</td>
<td>4.9±0.3</td>
<td>-0.44</td>
<td>0.659</td>
</tr>
<tr>
<td>Avg.CH12 b</td>
<td>Percent of used and unused areas that have a canopy heights &lt; 12 m</td>
<td>0.18±0.02</td>
<td>0.23±0.02</td>
<td>1.75</td>
<td>0.084</td>
</tr>
<tr>
<td>Avg.CH24</td>
<td>Average canopy height within used and unused areas</td>
<td>0.63±0.03</td>
<td>0.53±0.04</td>
<td>-2.07</td>
<td><strong>0.040</strong></td>
</tr>
<tr>
<td>Avg.CH</td>
<td>Percent of used and unused areas that have canopy heights &gt; 24 m</td>
<td>24.9±0.6</td>
<td>22.4±0.7</td>
<td>-2.82</td>
<td><strong>0.006</strong></td>
</tr>
<tr>
<td>Avg.Vdr</td>
<td>Average vertical density ratio within used and unused areas (VDR=[max canopy height/mean can Ht]/max can Ht)</td>
<td>0.6±0.007</td>
<td>0.6±0.007</td>
<td>-0.77</td>
<td>0.445</td>
</tr>
<tr>
<td>Avg.Highvdr</td>
<td>Percent of used and unused areas that have a dense vertical vegetative stratum (VDR &gt;0.66)</td>
<td>0.3±0.02</td>
<td>0.3±0.02</td>
<td>-1.26</td>
<td>0.21</td>
</tr>
<tr>
<td>Avg.Lowvdr a</td>
<td>Percent of used and unused areas that have a sparse vertical vegetative stratum (VDR ≤ 0.33)</td>
<td>0.21±0.01</td>
<td>0.21±0.01</td>
<td>0.09</td>
<td>0.932</td>
</tr>
<tr>
<td>Std.Vdr a</td>
<td>The standard deviation of mean VDR within used and unused areas</td>
<td>0.16±0.003</td>
<td>0.15±0.006</td>
<td>-0.4</td>
<td>0.536</td>
</tr>
<tr>
<td>Avg.Beers</td>
<td>Mean Beers' aspect within used and unused areas, where NE aspect=2 and SW aspect=0 (Beers' Aspect=cos(45-A)+1)</td>
<td>1.28±0.08</td>
<td>0.85±0.07</td>
<td>-4.3</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Avg.Elev</td>
<td>Mean elevation within used and unused areas</td>
<td>236.5±3.7</td>
<td>243.9±2.1</td>
<td>1.74</td>
<td><strong>0.086</strong></td>
</tr>
<tr>
<td>Avg.Slope</td>
<td>Mean slope (degrees) within used and unused areas</td>
<td>15.5±1.0</td>
<td>15.4±0.6</td>
<td>-0.16</td>
<td>0.872</td>
</tr>
</tbody>
</table>
Table 5 Continued.

<table>
<thead>
<tr>
<th>Variable Code</th>
<th>Variable Description</th>
<th>Used</th>
<th>Unused</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg.DBH</td>
<td>Mean DBH per ha of trees ≥ 10 cm DBH within used and unused areas</td>
<td>26.8±0.6</td>
<td>25.8±0.9</td>
<td>-0.365</td>
<td>0.365</td>
</tr>
<tr>
<td>TB.HA</td>
<td>The total basal area (m²/ha) of trees ≥ 10 cm DBH within used and unused areas</td>
<td>27.4±1.52</td>
<td>23.3±1.6</td>
<td>-2.04</td>
<td><strong>0.043</strong></td>
</tr>
<tr>
<td>Trees.HA</td>
<td>Number of trees ≥ 10 cm DBH per ha within used and unused areas</td>
<td>376.3±15.9</td>
<td>352.2±22.8</td>
<td>-0.87</td>
<td>0.387</td>
</tr>
<tr>
<td>S3.HA</td>
<td>Number of trees/shrubs &lt; 3 cm DBH per ha within used and unused areas</td>
<td>4243.5±584.9</td>
<td>3709.1±509.8</td>
<td>-0.69</td>
<td>0.492</td>
</tr>
<tr>
<td>S310.HA a</td>
<td>Number of trees/shrubs ≥ 3 &lt;10 cm DBH per ha within used and unused areas</td>
<td>21.2±1.3</td>
<td>25.1±1.9</td>
<td>1.69</td>
<td><strong>0.095</strong></td>
</tr>
<tr>
<td>1023.HA</td>
<td>Number of trees ≥ 10 &lt; 23 cm DBH per ha within used and unused areas</td>
<td>198.3±10.6</td>
<td>193.5±22.1</td>
<td>-0.19</td>
<td>0.847</td>
</tr>
<tr>
<td>2338.HA</td>
<td>Number of trees ≥ 23 &lt; 38 cm DBH per ha within used and unused areas</td>
<td>101.7±8.6</td>
<td>90.5±9.3</td>
<td>-0.88</td>
<td>0.378</td>
</tr>
<tr>
<td>3853.HA</td>
<td>Number of trees ≥ 38 &lt; 53 cm DBH per ha within used and unused areas</td>
<td>48.7±5.1</td>
<td>49.1±6.0</td>
<td>0.05</td>
<td>0.956</td>
</tr>
<tr>
<td>53.HA a</td>
<td>Number of trees ≥ 53 cm DBH per ha within used and unused areas</td>
<td>3.9±0.5</td>
<td>2.8±0.4</td>
<td>-1.71</td>
<td><strong>0.090</strong></td>
</tr>
<tr>
<td>CBA.HA c</td>
<td>The total basal area (m²/ha) of all hickories ≥ 10 cm DBH within used and unused areas</td>
<td>1.1±0.1</td>
<td>0.6±0.1</td>
<td>-3.38</td>
<td><strong>0.001</strong></td>
</tr>
<tr>
<td>LBA.HA b</td>
<td>The total basal area (m²/ha) of all tuliptrees ≥ 10 cm DBH within used and unused areas</td>
<td>0.94±0.1</td>
<td>0.48±0.1</td>
<td>-2.77</td>
<td><strong>0.007</strong></td>
</tr>
<tr>
<td>QBA.HA a</td>
<td>The total basal area (m²/ha) of all white oaks ≥ 10 cm DBH within used and unused areas</td>
<td>1.0±0.2</td>
<td>1.1±0.2</td>
<td>0.35</td>
<td>0.725</td>
</tr>
</tbody>
</table>

Note: Transformed variables are indicated in superscript: * square root transformed; † cube root transformed; ‡ log transformed. Mean±SE are not back transformed for these variables.
Table 6. All candidate negative binomial (NB) models. NB_V indicates models only containing variables derived from vegetation surveys, NB_L indicates models only containing lidar derived variables, and NB_VL indicates models containing variables derived from both vegetation surveys and lidar data. K is the number of parameters in a model, L is the log-likelihood value, ∆AICc is the difference between each model’s AICc value and the smallest AICc value in the candidate set, and W_i is the Akaike weight of each model in relation to the entire candidate set.

<table>
<thead>
<tr>
<th>Model</th>
<th>K</th>
<th>L</th>
<th>∆AICc</th>
<th>W_i</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB_VL(TB.HA, SRT.N.Gaps, Std.Vdr)(^{a,b})</td>
<td>5</td>
<td>-194.92</td>
<td>0.00</td>
<td>0.214</td>
</tr>
<tr>
<td>NB_VL(Avg.Slope, 53.HA, TB.HA)(^{a,b})</td>
<td>5</td>
<td>-194.94</td>
<td>0.04</td>
<td>0.210</td>
</tr>
<tr>
<td>NB_VL(53.HA, SRT.QBA.HA, Avg.Slope, Std.Vdr)(^{a,b})</td>
<td>6</td>
<td>-193.92</td>
<td>0.32</td>
<td>0.183</td>
</tr>
<tr>
<td>NB_VL(Std.Vdr, 53.HA, Avg.Slope)(^{a,b})</td>
<td>5</td>
<td>-195.28</td>
<td>0.72</td>
<td>0.149</td>
</tr>
<tr>
<td>NB_VL(TB.HA, LBA.HA, Avg.Elev, SRT.N.Gaps)</td>
<td>6</td>
<td>-195.20</td>
<td>2.88</td>
<td>0.051</td>
</tr>
<tr>
<td>NB_L(Std.Vdr, Avg.Elev, Avg.Slope)(^{c})</td>
<td>5</td>
<td>-196.62</td>
<td>3.39</td>
<td>0.039</td>
</tr>
<tr>
<td>NB_L(Std.Vdr, SRT.N.Gaps, Avg.Slope)(^{c})</td>
<td>5</td>
<td>-196.89</td>
<td>3.93</td>
<td>0.030</td>
</tr>
<tr>
<td>NB_L(Avg.Slope, Avg.Elev, 53.HA)</td>
<td>5</td>
<td>-196.93</td>
<td>4.02</td>
<td>0.029</td>
</tr>
<tr>
<td>NB_VL(Avg.Slope, Avg.Elev, TB.HA)</td>
<td>5</td>
<td>-197.23</td>
<td>4.61</td>
<td>0.021</td>
</tr>
<tr>
<td>NB_VL(Avg.Elev, Std.Vdr, 53.HA)</td>
<td>5</td>
<td>-197.50</td>
<td>5.15</td>
<td>0.016</td>
</tr>
<tr>
<td>NB_L(Avg.Beers, Avg.Elev, Avg.Slope)</td>
<td>5</td>
<td>-197.94</td>
<td>6.03</td>
<td>0.010</td>
</tr>
<tr>
<td>NB_VL(Avg.Elev, Avg.Slope, SRT.QBA.HA, LBA)</td>
<td>6</td>
<td>-197.21</td>
<td>6.90</td>
<td>0.007</td>
</tr>
<tr>
<td>NB_L(Avg.Slope, Avg.Elev, SQ.Avg.CH)</td>
<td>5</td>
<td>-198.48</td>
<td>7.12</td>
<td>0.006</td>
</tr>
<tr>
<td>NB_L(SRT.Near.Gap, Std.Vdr)</td>
<td>4</td>
<td>-199.95</td>
<td>7.80</td>
<td>0.004</td>
</tr>
<tr>
<td>NB_L(full)</td>
<td>10</td>
<td>-192.83</td>
<td>8.10</td>
<td>0.004</td>
</tr>
<tr>
<td>NB_VL(Avg.Beers, Avg.Elev, SRT.CBA.HA, SRT.QBA.HA)</td>
<td>6</td>
<td>-197.81</td>
<td>8.10</td>
<td>0.004</td>
</tr>
<tr>
<td>NB_VL(53.HA, LBA.HA, Avg.Elev, SRT.Near.Gap)</td>
<td>6</td>
<td>-198.24</td>
<td>8.97</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_VL(TB.HA, SRT.QBA.HA, Avg.Slope, SRT.Near.Gap)</td>
<td>6</td>
<td>-198.35</td>
<td>9.18</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_V(SRT.QBA.HA, 53.HA)(^{d})</td>
<td>4</td>
<td>-200.70</td>
<td>9.30</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_VL(TB.HA, Avg.Beers, Avg.Slope)</td>
<td>5</td>
<td>-199.57</td>
<td>9.30</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_VL(SRT.S3.HA, SRT.S310.HA, SRT.N.Gaps, Std.Vdr)</td>
<td>6</td>
<td>-198.43</td>
<td>9.35</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_L(Avg.Vdr, Std.Vdr, Avg.Near.Gap)</td>
<td>5</td>
<td>-199.80</td>
<td>9.75</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_L(SQ.Avg.CH, Avg.Vdr, Std.Vdr)</td>
<td>5</td>
<td>-199.93</td>
<td>10.01</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB_VL(SRT.Near.Gap, Avg.Slope, SRT.QBA.HA)</td>
<td>5</td>
<td>-200.03</td>
<td>10.22</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB_VL(full)</td>
<td>16</td>
<td>-185.41</td>
<td>10.45</td>
<td>0.002</td>
</tr>
<tr>
<td>NB_V(LBA.HA, 53.HA)(^{d})</td>
<td>4</td>
<td>-201.44</td>
<td>10.76</td>
<td>0.001</td>
</tr>
<tr>
<td>NB_VL(Avg.Beers, 53.HA, Avg.Vdr)</td>
<td>5</td>
<td>-200.79</td>
<td>11.73</td>
<td>0.001</td>
</tr>
<tr>
<td>NB_L(Avg.Beers, Avg.Slope, SQ.Avg.CH)</td>
<td>5</td>
<td>-201.07</td>
<td>12.29</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB_VL(Avg.Slope, Avg.Beers, LBA.HA, SRT.CBA.HA)</td>
<td>6</td>
<td>-200.30</td>
<td>13.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB_L(SRT.N.Gaps, SRT.Near.Gap)</td>
<td>4</td>
<td>-202.60</td>
<td>13.10</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Table 4: Two sample statistics for high vs. low-use areas.
Table 6 Continued.

<table>
<thead>
<tr>
<th>Model</th>
<th>K</th>
<th>L</th>
<th>ΔAICc</th>
<th>Wi</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(SRT.S3.HA, SRT.N.Gaps, Avg.Beers)</td>
<td>5</td>
<td>-201.69</td>
<td>13.54</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;V&lt;/sub&gt;(null)</td>
<td>2</td>
<td>-205.12</td>
<td>13.76</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(53.HA, SRT.CBA.HA, Avg.Beers, Avg.Vdr)</td>
<td>6</td>
<td>-200.74</td>
<td>13.97</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.S3.HA, SRT.S310.HA, 53.HA)</td>
<td>5</td>
<td>-201.94</td>
<td>14.03</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(TB.HA, 53.HA)</td>
<td>4</td>
<td>-203.08</td>
<td>14.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.S3.HA, TB.HA, 53.HA)</td>
<td>5</td>
<td>-202.00</td>
<td>14.16</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(CBA.HA, 53.HA)</td>
<td>4</td>
<td>-203.14</td>
<td>14.17</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(full)</td>
<td>9</td>
<td>-197.37</td>
<td>14.58</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.CBA.HA, LBA.HA, SRT.QBA.HA)</td>
<td>5</td>
<td>-202.31</td>
<td>14.77</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(SRT.S3.HA, SRT.S310.HA, SRT.Near.Gap, SRT.N.Gaps)</td>
<td>6</td>
<td>-201.47</td>
<td>15.42</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(Avg.Vdr, SRT.N.Gaps, SQ.Avg.CH)</td>
<td>5</td>
<td>-202.67</td>
<td>15.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.S3.HA, SRT.S310.HA, TB.HA)</td>
<td>5</td>
<td>-202.82</td>
<td>15.80</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(TB.HA, Avg.Vdr, SRT.Near.Gap)</td>
<td>5</td>
<td>-202.83</td>
<td>15.81</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.S3.HA, SRT.S310.HA)</td>
<td>4</td>
<td>-203.98</td>
<td>15.84</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(SRT.S310.HA, 53.HA, Avg.Vdr)</td>
<td>5</td>
<td>-202.99</td>
<td>16.13</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;T&lt;/sub&gt;(SRT.S310.HA, TB.HA, 53.HA)</td>
<td>5</td>
<td>203.04</td>
<td>16.24</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(TB.HA, SRT.CBA.HA, Avg.Beers, Avg.Vdr)</td>
<td>6</td>
<td>-203.21</td>
<td>17.09</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(SRT.Near.Gap, Avg.Vdr, SRT.S3.HA)</td>
<td>5</td>
<td>-203.75</td>
<td>17.66</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>NB&lt;sub&gt;TV&lt;/sub&gt;(SRT.S3.HA, SRT.S310.HA, Avg.Vdr, SRT.Near.Gap)</td>
<td>6</td>
<td>-203.53</td>
<td>19.53</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Note: Bolded models indicate top models for each model subset. "Top NB models." "Top NB<sub>TV</sub> model." "Top NB<sub>T</sub> models." "Top NB<sub>TV</sub> model."
Table 7. Estimated coefficients derived from model averaging for each variable in the top negative binomial (NB) models, with their conditional standard error and 85% confidence interval.

<table>
<thead>
<tr>
<th>NB Top Model Variables</th>
<th>Estimated Coefficient</th>
<th>Conditional SE</th>
<th>Lower 85% CI</th>
<th>Upper 85% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std.Vdr</td>
<td>-9.60</td>
<td>3.36</td>
<td>-14.49</td>
<td>-4.72</td>
</tr>
<tr>
<td>SRT.QBA.HA</td>
<td>0.11</td>
<td>0.06</td>
<td>0.02</td>
<td>0.20</td>
</tr>
<tr>
<td>Avg.Slope</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>53.HA</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.002</td>
</tr>
<tr>
<td>SRT.N.Gaps</td>
<td>-0.31</td>
<td>0.13</td>
<td>-0.50</td>
<td>-0.12</td>
</tr>
<tr>
<td>TB.HA</td>
<td>-0.02</td>
<td>0.01</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
</tbody>
</table>
Table 8. Top models for each negative binomial (NB) subset. \(NB_V\) indicates models only containing variables derived from vegetation surveys, \(NB_L\) indicates models only containing lidar derived variables, and \(NB_{VL}\) indicates models containing variables derived from both vegetation surveys and lidar data. \(K\) is the number of parameters in a model, \(L\) is the log-likelihood value, \(\Delta AICc\) is the difference between each model’s AICc value and the smallest AICc value in the candidate subset, and \(W_i\) is the Akaike weight of each model in relation to the candidate subset. (+) indicates a positive association, and (-) indicates a negative association.

<table>
<thead>
<tr>
<th>Subset Top Models</th>
<th>K</th>
<th>L</th>
<th>(\Delta AICc)</th>
<th>(W_i)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(NB_{VL}) subset—</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TB.HA(-), SRT.N.Gaps(-), Std.Vdr(-)</td>
<td>5</td>
<td>-194.92</td>
<td>0.00</td>
<td>0.238</td>
</tr>
<tr>
<td>Avg.Slope(+), 53.HA(-), TB.HA(-)</td>
<td>5</td>
<td>-194.94</td>
<td>0.04</td>
<td>0.234</td>
</tr>
<tr>
<td>53.HA(-), SRT.QBA.HA(+), Avg.Slope(+), Std.Vdr(-)</td>
<td>6</td>
<td>-193.92</td>
<td>0.32</td>
<td>0.203</td>
</tr>
<tr>
<td>Std.Vdr(-), 53.HA(-), Avg.Slope(+)</td>
<td>5</td>
<td>-195.28</td>
<td>0.72</td>
<td>0.166</td>
</tr>
<tr>
<td>(NB_L) subset—</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Vdr(-), Avg.Elev(-), Avg.Slope(+)</td>
<td>5</td>
<td>-196.62</td>
<td>0.00</td>
<td>0.398</td>
</tr>
<tr>
<td>Std.Vdr(-), SRT.N.Gaps(-), Avg.Slope(+)</td>
<td>5</td>
<td>-196.89</td>
<td>0.53</td>
<td>0.305</td>
</tr>
<tr>
<td>(NB_V) subset—</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRT.QBA.HA(+), 53.HA(-)</td>
<td>4</td>
<td>-200.70</td>
<td>0.00</td>
<td>0.456</td>
</tr>
<tr>
<td>LBA.HA(+), 53.HA(-)</td>
<td>4</td>
<td>-201.44</td>
<td>1.46</td>
<td>0.219</td>
</tr>
</tbody>
</table>
Table 9. Two sample statistics between Cerulean Warbler low- and high-use areas for all considered variables, with variable code and description. Mean±SE, t value, and p value are given for pooled and non-pooled two sample two tailed t-tests, and median±interquartile range, Z value, and p value are given for Mann-Whitney U-tests. All tests had an alpha value of 0.05. Those p values that are significant and marginally significant (p <0.1) are bolded.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable Description</th>
<th>Low Density</th>
<th>High Density</th>
<th>t/Z</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg.Gap.IN</td>
<td>Average canopy gap size within a territory</td>
<td>1.9±0.4</td>
<td>1.3±0.3</td>
<td>1.13</td>
<td>0.263</td>
</tr>
<tr>
<td>N.Gaps.IN</td>
<td>Number of canopy gaps within a territory</td>
<td>0.5±0.1</td>
<td>0.4±0.1</td>
<td>1.24</td>
<td>0.217</td>
</tr>
<tr>
<td>Near.Gap</td>
<td>Distance to nearest canopy gap from the center of a territory</td>
<td>20.7±2.7</td>
<td>26.8±19.8</td>
<td>-1.12</td>
<td>0.267</td>
</tr>
<tr>
<td>Polyline a</td>
<td>The sum length of all canopy gap edge within a territory</td>
<td>5.9±1.1</td>
<td>3.4±0.7</td>
<td>1.87</td>
<td>0.065</td>
</tr>
<tr>
<td>Std.CH</td>
<td>The standard deviation of canopy height within a territory</td>
<td>5.0±0.3</td>
<td>4.8±0.3</td>
<td>0.42</td>
<td>0.679</td>
</tr>
<tr>
<td>Avg.CH12</td>
<td>Percent of a territory that has a canopy heights &lt; 12 m</td>
<td>0.02±0.11</td>
<td>0.01±0.06</td>
<td>0.94(Z)</td>
<td>0.353</td>
</tr>
<tr>
<td>Avg.CH</td>
<td>Average canopy height within a territory</td>
<td>25.0±0.7</td>
<td>26.1±0.5</td>
<td>-1.19</td>
<td>0.239</td>
</tr>
<tr>
<td>Avg.CH24</td>
<td>Percent of a territory that has a canopy heights &gt; 24 m</td>
<td>0.6±0.04</td>
<td>0.7±0.03</td>
<td>-1.16</td>
<td>0.249</td>
</tr>
<tr>
<td>Avg.Vdr</td>
<td>Average vertical density ratio within a territory (VDR=[max canopy height/mean can Ht]/max can Ht)</td>
<td>0.57±0.008</td>
<td>0.59±0.008</td>
<td>-1.75</td>
<td>0.084</td>
</tr>
<tr>
<td>Avg.Highvdr</td>
<td>Percent of a territory that has a dense vertical vegetative stratum (VDR &gt; 0.66)</td>
<td>0.3±0.02</td>
<td>0.3±0.02</td>
<td>-1.35</td>
<td>0.182</td>
</tr>
<tr>
<td>Avg.Lowvdr b</td>
<td>Percent of a territory that has a sparse vertical vegetative stratum (VDR ≤ 0.33)</td>
<td>0.4±0.02</td>
<td>0.3±0.02</td>
<td>1.71</td>
<td>0.090</td>
</tr>
<tr>
<td>Std.Vdr</td>
<td>The standard deviation of mean VDR within a territory</td>
<td>0.16±0.005</td>
<td>0.15±0.004</td>
<td>1.53</td>
<td>0.130</td>
</tr>
<tr>
<td>Avg.Beers</td>
<td>Mean Beers' aspect within a territory, where NE aspect=2 and SW aspect=0 (Beers' Aspect=\cos(45\cdot A)+1)</td>
<td>1.3±0.08</td>
<td>1.3±0.09</td>
<td>-0.2</td>
<td>0.839</td>
</tr>
<tr>
<td>Variable</td>
<td>Variable Description</td>
<td>Low Density</td>
<td>High Density</td>
<td>t/Z</td>
<td>p</td>
</tr>
<tr>
<td>---------------</td>
<td>---------------------------------------------------------------------------------------</td>
<td>-------------</td>
<td>--------------</td>
<td>-------</td>
<td>------</td>
</tr>
<tr>
<td>Avg.Elev</td>
<td>Mean elevation within a territory</td>
<td>244.5±3.9</td>
<td>228.3±3.8</td>
<td>2.94</td>
<td><strong>0.004</strong></td>
</tr>
<tr>
<td>Avg.Slope</td>
<td>Mean slope (degrees) within a territory</td>
<td>15.6±1.1</td>
<td>16.9±1.0</td>
<td>-0.87</td>
<td>0.388</td>
</tr>
<tr>
<td>Avg.DBH</td>
<td>Mean DBH per ha of trees ≥ 10 cm DBH within a territory</td>
<td>27.6±0.8</td>
<td>27.4±0.7</td>
<td>0.20</td>
<td>0.841</td>
</tr>
<tr>
<td>TB.HA</td>
<td>The total basal area (m²/ha) of trees ≥ 10 cm DBH within a territory</td>
<td>30.2±1.8</td>
<td>26.9±1.6</td>
<td>1.29</td>
<td>0.199</td>
</tr>
<tr>
<td>Trees.HA</td>
<td>Number of trees ≥ 10 cm DBH per ha within a territory</td>
<td>388±19</td>
<td>358±20</td>
<td>1.25</td>
<td>0.215</td>
</tr>
<tr>
<td>S3.HA</td>
<td>Number of trees/shrubs &lt; 3 cm DBH per ha within a territory</td>
<td>5066±820</td>
<td>3843±449</td>
<td>1.31</td>
<td>0.196</td>
</tr>
<tr>
<td>S310.HA</td>
<td>Number of trees/shrubs ≥ 3 &lt;10 cm DBH per ha within a territory</td>
<td>453±61</td>
<td>645±72</td>
<td>-2.02</td>
<td><strong>0.047</strong></td>
</tr>
<tr>
<td>1023.HA</td>
<td>Number of trees ≥ 10 &lt; 23 cm DBH per ha within a territory</td>
<td>199±15</td>
<td>186±14</td>
<td>0.64</td>
<td>0.528</td>
</tr>
<tr>
<td>2338.HA</td>
<td>Number of trees ≥ 23 &lt; 38 cm DBH per ha within a territory</td>
<td>105±10</td>
<td>95±9</td>
<td>0.71</td>
<td>0.478</td>
</tr>
<tr>
<td>3853.HA</td>
<td>Number of trees ≥ 38 &lt; 53 cm DBH per ha within a territory</td>
<td>52±7</td>
<td>53±7</td>
<td>-0.11</td>
<td>0.912</td>
</tr>
<tr>
<td>53.HA</td>
<td>Number of trees ≥ 53 cm DBH per ha within a territory</td>
<td>33±5</td>
<td>23±4</td>
<td>1.54</td>
<td>0.128</td>
</tr>
<tr>
<td>CBA.HA</td>
<td>The total basal area (m²/ha) of all hickories ≥ 10 cm DBH within a territory</td>
<td>3.4±0.6</td>
<td>3.7±0.8</td>
<td>-0.31</td>
<td>0.759</td>
</tr>
<tr>
<td>LBA.HA&lt;sup&gt;a&lt;/sup&gt;</td>
<td>The total basal area (m²/ha) of all tuliptrees ≥ 10 cm DBH within a territory</td>
<td>1.1±0.2</td>
<td>1.3±0.2</td>
<td>-0.74</td>
<td>0.463</td>
</tr>
<tr>
<td>QBA.HA&lt;sup&gt;a&lt;/sup&gt;</td>
<td>The total basal area (m²/ha) of all white oaks ≥ 10 cm DBH within a territory</td>
<td>0.7±0.2</td>
<td>1.1±0.2</td>
<td>-1.18</td>
<td>0.243</td>
</tr>
</tbody>
</table>

Note: Transformed variables are indicated in superscript: * square root transformed; * cube root transformed; * log transformed. Mean±SE are not back transformed for these variable.
APPENDIX

CODE 1

# Create raster and vector files to sample habitat in CERW territories
import arcpy
import math
from arcpy.sa import *
arcpy.CheckOutExtension("spatial")
arcpy.env.workspace="H:/LiDAR/Rasters.gdb"
arcpy.env.overwriteOutput=True

UnitID=range(1,10)

# 45 degrees to radians
Best=(45*math.pi)/180

for i in UnitID:
    # DTM=zmin_2, DSM=zmax, mean DSM=_zmean
    R1=arcpy.Raster("unit"+str(i)+"_zmin_2")
    R2=arcpy.Raster("unit"+str(i)+"_zmax")
    R3=arcpy.Raster("unit"+str(i)+"_zmean")
    # CHM
    OutR1=(R2) - (R1)
    # Mean CHM
    OutR2=(R3) - (R1)
    # Correct negative values for CHM and mean CHM = MaxCHcon1, MeanCHcon1.
    OutR3=arcpy.sa.Con(OutR1<0, 0, OutR1)
    OutR4=arcpy.sa.Con(OutR2<0, 0, OutR2)
    # Replace heights >45 with mean height = MaxCHfix1.
    OutR5=arcpy.sa.Con(OutR3>45, OutR4, OutR3)
    # Replace heights still greater than 45 with "NoData" = Final max CHM.MaxCHfix2
    OutR6=arcpy.sa.Con(OutR5<45, OutR5)
    # If mean height is greater than max height then replace with max height.
    # = Final mean CHM. MeanCon2.
    OutR7=arcpy.sa.Con(OutR4>OutR6, OutR6, OutR4)
    # MaxCH-MeanCH=MaxCH = Vertical Density Ratio (VDR)
    OutR8=((OutR6)-(OutR7))/(OutR6)
    OutR9=Con(IsNull(OutR8), 0, OutR8)

# Save raster outputs
OutR1=save("unit"+str(i)+"_MaxCH")
OutR2=save("unit"+str(i)+"_MeanCH")
OutR3=save("unit"+str(i)+"_MaxCHcon1")
OutR4=save("unit"+str(i)+"_MeanCHcon1")
OutR5=save("unit"+str(i)+"_MaxCHfix1")
OutR6=save("unit"+str(i)+"_MaxCHfix2")
OutR7=save("unit"+str(i)+"_MeanCHcon2")
OutR9=save("unit"+str(i)+"_VDR")

# Resample raster to 3m x 3m.
# This shows change in value between cells better
# and will have less "flat areas"
OutR10=arcpy.Resample_management(R1, "unit"+str(i)+"_zmin3", "3", "NEAREST")
# Aspect raster
OutR11 = Aspect(OutR10)

# Convert Aspect raster in degrees to aspect raster in radians
OutR12 = (OutR11 * math.pi) / 180

# Convert aspect raster to Beers aspect. NE=2, SW=0,
# continuous decline from NE to SW.
OutR13 = Cos(Best - OutR12) + 1

# Slope raster
OutR14 = Slope(OutR10)

# Save output rasters
OutR11.save("unit" + str(i) + ", Aspect")
OutR13.save("unit" + str(i) + ", Beers")
OutR14.save("unit" + str(i) + ", Slope")

# Create canopy gaps raster and vector file,
# Canopy under 12 m raster, Canopy over 24 m raster,
# HighVDR raster, and lowVDR raster.
OutR15 = OutR6 <= 12
OutR16 = OutR6 > 24

# Use canopy openness raster to create gaps. Region group will group like cells.
# Clumped areas of 1 will be turned into gaps.
OutR17 = RegionGroup(OutR15, "FOUR", ", ", ", ", 0)

# Only selecting larger gaps. 20=20 square meters gap. Gap big enough to
# not be just interstitial space between the leaves of one tree.
OutR18 = ExtractByAttributes(OutR17, "COUNT>=20")

# Convert raster gaps to polygons so we can use "select layer by" tools. Final gap.
OutR19 = arcpy.RasterToPolygon_conversion(OutR18, "Unit" + str(i) + ", CH12Gaps", "NO_SIMPLIFY", "VALUE")

# Areas of low VDR. Open vegetation.
OutR20 = OutR9 <= 0.3333

# Areas of high VDR. Dense vegetation.
OutR23 = OutR9 > 0.6666

OutR1.save("unit" + str(i) + ", CH12")
OutR2.save("unit" + str(i) + ", CH24")
OutR3.save("unit" + str(i) + ", CH12Region")
OutR4.save("unit" + str(i) + ", CH12Reg20")

OutR6.save("unit" + str(i) + ", lowVDR")
OutR7.save("unit" + str(i) + ", highVDR")

# Get rid of polygons outlining canopy greater than 12 m (i.e. non-gaps).
for i in UnitID:
x = "Unit" + str(i) + ", CH12Gaps"
up_curs = arcpy.UpdateCursor(x)
for row in up_curs:
    if row.grid_code == 0:
        up_curs.deleteRow(row)
del row
del up_curs

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CODE 2
# Record the number and average size of gaps that intersect polygons.
# Record the number and average size of gaps that have their center in polygons.
# Record the sum amount of gap edge within an extent
# Record the number of territory centroids from 2009-2013 within 100m of sample territory
import arcpy
```python
arcpy.env.workspace="H:/LiDAR/New File Geodatabase.gdb"
arcpy.env.overwriteOutput=True

#Make layers. I merged all used and unused extents, and all gaps.
A="H:/LiDAR/New File Geodatabase.gdb/Territory_Polygons_2010_2013_randter_withveg"
B=arcpy.MakeFeatureLayer_management(A, "Territory_Polygons_2010_2013_randter_withveg_lyr")
C="H:/LiDAR/New File Geodatabase.gdb/ALL_GAPS"
D=arcpy.MakeFeatureLayer_management(C, "ALL_GAPS_lyr")

#Create list of extents by name
Count=arcpy.GetCount_management(B)
for i in Count:
    values=set()
    X=arcpy.SearchCursor(B)
    for row in X:
        values.add(row.getValue("NAME_YR"))
        values.add(row.getValue("NAME_YR"))
    valuesList=list(values)

#Select territory by names in list. Select all gaps that intersect extent. Get count and mean values.
for i in valuesList:
    arcpy.SelectLayerByAttribute_management(B, "NEW_SELECTION", '"NAME_YR" =\"' + i + '\"')
    E=arcpy.MakeFeatureLayer_management(B, "Territory_selectatt")
    arcpy.SelectLayerByLocation_management(D, "INTERSECT", E)
    F=arcpy.MakeFeatureLayer_management(D, "ALL_GAPS_selloc")
    G=arcpy.Statistics_analysis(F, "Stats_Table", [['Shape_Area', 'MEAN']])
    H=arcpy.SearchCursor(G)
    for rows in H:
        I=rows.getValue("FREQUENCY")
        J=rows.getValue("MEAN_Shape_Area")
        R=arcpy.UpdateCursor(B)
        for rowss in R:
            if rowss.NAME_YR == i:
                rowss.setValue("N_Gaps", I)
                K.updateRow(rowss)
                rowss.setValue("Avg_Gap", J)
                K.updateRow(rowss)
    del rowss, K

#Select territory by names in list (need field with names). Select all gaps that have their centers
#within the extent.
#Get count and mean values. Need to have empty fields to add these data (i.e. "Avg_Gap_IN")
for i in valuesList:
    arcpy.SelectLayerByAttribute_management(B, "NEW_SELECTION", '"NAME_YR" =\"' + i + '\"')
    L=arcpy.MakeFeatureLayer_management(B, "Territory_selectatt")
    arcpy.SelectLayerByLocation_management(D, "HAVE_THEIR_CENTER_IN", L)
    M=arcpy.MakeFeatureLayer_management(D, "ALL_GAPS_selloc")
    N=arcpy.Statistics_analysis(M, "Stats_Table", [['Shape_Area', 'MEAN']])
    O=arcpy.SearchCursor(N)
    for rows in O:
        P=rows.getValue("FREQUENCY")
        Q=rows.getValue("MEAN_Shape_Area")
        R=arcpy.UpdateCursor(B)
        for rowss in R:
            if rowss.NAME_YR == i:
                rowss.setValue("N_Gaps_IN", P)
```
R.updateRow(rowss)
  rowss.setValue("Avg_Gap_IN", Q)
R.updateRow(rowss)
del rowss, R

# Turn gap polygons to polylines and clip them with extents.
PolygonToLine_management("ALL_GAPS", "ALL_GAPS_POLYLINE")
Clip_analysis("ALL_GAPS_POLYLINE", "Territory_Polygons_2010_2013_randter_withveg", 
"ALL_GAPS_POLYLINE_IN")

S="H:/LiDAR/New File Geodatabase.gdb/ALL_GAPS_POLYLINE_IN"
T=arcpy.MakeFeatureLayer_management(C, "ALL_GAPS_POLYLINE_IN_lyr")

# Select territory by names in list. Select all gaps that intersect extent. Get count and mean values.
for i in valuesList:
arcpy.SelectLayerByAttribute_management(B, "NEW_SELECTION", "NAME_YR" ='+""+ i+'"')
U=arcpy.MakeFeatureLayer_management(B, "Territory_selectatt")
arcpy.SelectLayerByLocation_management(T, "INTERSECT", U)
V=arcpy.MakeFeatureLayer_management(T, "ALL_GAPS_POLYLINE_IN_selloc")
W=arcpy.Statistics_analysis(V, "Stats_Table", [['Shape_Length', 'SUM']])
XX=arcpy.SearchCursor(W)
for rows in XX:
  Y=rows.getValue("MEAN_Shape_Length")
Z=arcpy.UpdateCursor(B)
  for rowss in Z:
    if rowss.NAME_YR == i:
      rowss.setValue("Polyline", Y)
 Z.updateRow(rowss)
del rowss, Z

# Record the number territories within 100 m of sample territory
# make layers
AA="H:/LiDAR/New File Geodatabase.gdb/Ter_withVg_2010_2013"
BB=arcpy.MakeFeatureLayer_management(A, "Ter_withVg_2010_2013_lyr")
CC="H:/LiDAR/New File Geodatabase.gdb/Ter_2009_2013"
DD=arcpy.MakeFeatureLayer_management(C, "Ter_2009_2013_lyr")

# Make a list of territories by name
Count=arcpy.GetCount_management(BB)
for i in Count:
  values=set()
  X=arcpy.SearchCursor(BB)
  for row in X:
    values.add(row.getValue("NAME_YR"))
  values.add(row.getValue("NAME_YR"))
  valuesList=list(values)

# Select each territory by attribute (name) and then use that selection to determine the
# number of territory centroids from 2009-2013 within 100 m
# Then get statistics for those selections
for i in valuesList:
arcpy.SelectLayerByAttribute_management(BB, "NEW_SELECTION", "NAME_YR" ='+""+ i+'"')
EE=arcpy.MakeFeatureLayer_management(BB, "Territory_selectatt")
arcpy.SelectLayerByLocation_management/DD, "WITHIN_A_DISTANCE", EE, "100 Meters")
FF=arcpy.MakeFeatureLayer_management/DD, "ALL_Centroids_selloc")
GG=arcpy.Statistics_analysis(FF, "Stats_Table", [["NAME_YR", "COUNT"]])
# Add statistics to each territory. Need to make a new field named Density.
HH=arcpy.SearchCursor(GG)
for rows in HH:
   II=rows.getValue("FREQUENCY")
   JJ=arcpy.UpdateCursor(BB)
   for rowss in JJ:
      if rowss.NAME_YR == i:
         rowss.setValue("Density", II)
         JJ.updateRow(rowss)
   del rowss, JJ

CODE 3
#Method for unbiased deletion of overlapping polygons.
import arcpy
from random import choice
arcpy.env.workspace="H:/LiDAR/New File Geodatabase.gdb"
arcpy.env.overwriteOutput=True

#File with polygons that overlap. ID these. Make list of overlapping polygons.
x="H:/LiDAR/New File Geodatabase.gdb/Units_5_9_rand_withveg"
y=arcpy.PolygonNeighbors_analysis (x, "Polygon_Neighbors_All", "NAME_YR", "NO_AREA_OVERLAP", "BOTH_SIDES")
Count=arcpy.GetCount_management(y)
print Count
#Until you have zero overlapping polygons, randomly select an overlapping polygons and delete it.
#Repeat overlap analysis and deletion.
while Count > 0:
   values = set()
   rows = arcpy.SearchCursor(y)
   for row in rows:
      values.add(row.getValue("src_NAME_YR"))
   valuesList=list(values)
   z=choice(valuesList)
   print z
   up_curs = arcpy.UpdateCursor(x)
   for row in up_curs:
      if row.NAME_YR == z:
         up_curs.deleteRow(row)
   del row
   del up_curs
   y=arcpy.PolygonNeighbors_analysis (x, "Polygon_Neighbors_All", "NAME_YR", "NO_AREA_OVERLAP", "BOTH_SIDES")
   Count=arcpy.GetCount_management(y)
   print Count

CODE 4
#Create Random Polygons...copy/paste

import arcpy
InputWorkspace="H:/LiDAR/New File Geodatabase.gdb"
arcpy.env.workspace=InputWorkspace
# get rid of feature classes

if arcpy.Exists("intCentroid"): 
    arcpy.Delete_management("intCentroid")

if arcpy.Exists("intVert"): 
    arcpy.Delete_management("intVert")

# Territories to copy and place where random points are. N territories = N points
InputTerritory="Units_5_9_ter_buil"

# Create new fields for random points
Random="Units_5_9_withveg"
arcpy.AddXY_management(Random) 
check=arcpy.GetCount_management(Random) 
print check
arcpy.AddField_management(Random, "Random_X", "DOUBLE")
arcpy.AddField_management(Random, "Random_Y", "DOUBLE")
arcpy.CalculateField_management(Random, "Random_X", 
"[POINT_X]"
) 
arcpy.CalculateField_management(Random, "Random_Y", 
"[POINT_Y]"
)

# Create centroid for each territory
Center=arcpy.FeatureToPoint_management(InputTerritory, "intCentroid", "CENTROID")
arcpy.AddXY_management(Center)
check2=arcpy.GetCount_management(Center) 
print check2
arcpy.AddField_management(Center, "Center_X", "DOUBLE")
arcpy.AddField_management(Center, "Center_Y", "DOUBLE")
arcpy.CalculateField_management(Center, "Center_X", 
"[POINT_X]"
) 
arcpy.CalculateField_management(Center, "Center_Y", 
"[POINT_Y]"
)

# Join fields Center and Random
arcpy.JoinField_management(Center, "OBJECTID", Random, "OBJECTID")

# Add Fields center table
arcpy.AddField_management(Center, "Diff_X", "DOUBLE")
arcpy.AddField_management(Center, "Diff_Y", "DOUBLE")

# Subtract random xy from center xy
arcpy.CalculateField_management(Center, "Diff_X", 
"[Center_X]-[Random_X]"
) 
arcpy.CalculateField_management(Center, "Diff_Y", 
"[Center_Y]-[Random_Y]"
)

# Territory vertices to points
Vert=arcpy.FeatureVerticesToPoints_management(InputTerritory, "intVert")
arcpy.AddXY_management(Vert)

# Join diff xy fields to vert
arcpy.JoinField_management(Vert, "ORIG_FID", Center, "OBJECTID", ["Diff_X", "Diff_Y")

# Subtract Diff xy to Vert XY
arcpy.CalculateField_management(Vert, "POINT_X", 
"[POINT_X]-[Diff_X]"
) 
arcpy.CalculateField_management(Vert, "POINT_Y", 
"[POINT_Y]-[Diff_Y]"
)
#Create xy event layer using vert table xy
RandomVert=arcpy.MakeXYEventLayer_management(Vert, "POINT_X", "POINT_Y", "intRVert", r"Coordinate Systems\Projected Coordinate Systems\Utm\Nad 1983\NAD 1983 UTM Zone 16N.prj")

#Create random polygons
OutputRandomPoly="Units_5_9_rand_withveg"
check3=arcpy.MinimumBoundingGeometry_management(RandomVert, OutputRandomPoly, "CONVEX_HULL", "LIST", "ORIG_FID")
check3=arcpy.GetCount_management(check3)
print check3

#Get rid of intermediate feature classes
if arcpy.Exists("intCentroid"):
arcpy.Delete_management("intCentroid")
if arcpy.Exists("intVert"):
arcpy.Delete_management("intVert")

#Get back random veg name
A="H:/LiDAR/New File Geodatabase.gdb/Units_5_9_rand_withveg"
arcpy.AddField_management(A, "Orig_Name", "TEXT")
B=arcpy.MakeFeatureLayer_management(A, "Units_5_9_rand_withveg_lyr")
C="H:/LiDAR/New File Geodatabase.gdb/RandomVeg_2010_2012_buf11_2"
D=arcpy.MakeFeatureLayer_management(C, "RandomVeg_2010_2012_buf11_2_lyr")
Count=arcpy.GetCount_management(B)
for i in Count:
    values=set()
    X=arcpy.SearchCursor(B)
    for row in X:
        values.add(row.getValue("NAME_YR"))
    valuesList=list(values)
    for i in valuesList:
        arcpy.SelectLayerByAttribute_management(B, "NEW_SELECTION", '"NAME_YR" ="'+i+'"")
        E=arcpy.MakeFeatureLayer_management(B, "Territory_selectatt")
        arcpy.SelectLayerByLocation_management(D, "HAVE_THEIR_CENTER_IN", E,)
        F=arcpy.MakeFeatureLayer_management(D, "RandomVeg_buf_selloc")
        H=arcpy.SearchCursor(F)
        for rows in H:
            I=rows.getValue("NAME_YR")
            J=arcpy.UpdateCursor(B)
            for rowss in J:
                if rowss.NAME_YR == i:
                    rowss.setValue("Orig_Name", I)
                    J.updateRow(rowss)
        del rowss, J

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CODE 5
#Get data from rasters based on extent of used and unused Cerulean Warbler extents.
import arcpy
arcpy.env.extent="MAXOF"
from arcpy.sa import *

arcpy.CheckOutExtension("spatial")
arcpy.env.workspace="H:/LiDAR/Rasters.gdb"
arcpy.env.overwriteOutput=True

UnitID=range(1,11)

#Add extents and rasters
for i in UnitID:
    Zones1="H:/LiDAR/New File Geodatabase.gdb/Territory_Polygons_2010_2013_ter_withveg"
    Zones2="H:/LiDAR/New File Geodatabase.gdb/Territory_Polygons_2010_2013_rand_withveg"
    R1=arcpy.Raster("unit"+str(i)+"_VDR")
    R2=arcpy.Raster("unit"+str(i)+"_CH12")
    R3=arcpy.Raster("unit"+str(i)+"_CH24")
    R4=arcpy.Raster("unit"+str(i)+"_KDE_30")
    R5=arcpy.Raster("unit"+str(i)+"_highVDR")
    R6=arcpy.Raster("unit"+str(i)+"_lowVDR")
    R7=arcpy.Raster("unit"+str(i)+"_MaxCHfix2")
    R8=arcpy.Raster("unit"+str(i)+"_zmin3")
    R9=arcpy.Raster("unit"+str(i)+"_Slope")
    R10=arcpy.Raster("unit"+str(i)+"_Beers")
    R11=arcpy.Raster("unit"+str(i)+"_Aspect")

#Get data using extents
Table1=ZonalStatisticsAsTable(Zones1, "NAME_YR", R1, "unit"+str(i)+"_VDRTable")
Table2=ZonalStatisticsAsTable(Zones1, "NAME_YR", R2, "unit"+str(i)+"_CH12Table")
Table3=ZonalStatisticsAsTable(Zones1, "NAME_YR", R3, "unit"+str(i)+"_CH24Table")
Table4=ZonalStatisticsAsTable(Zones1, "NAME_YR", R4, "unit"+str(i)+"_KDE_30")
Table5=ZonalStatisticsAsTable(Zones1, "NAME_YR", R5, "unit"+str(i)+"_highVDR")
Table6=ZonalStatisticsAsTable(Zones1, "NAME_YR", R6, "unit"+str(i)+"_lowVDR")
Table7=ZonalStatisticsAsTable(Zones1, "NAME_YR", R7, "unit"+str(i)+"_MaxCHfix2")
Table8=ZonalStatisticsAsTable(Zones1, "NAME_YR", R8, "unit"+str(i)+"_zmin3")
Table9=ZonalStatisticsAsTable(Zones1, "NAME_YR", R9, "unit"+str(i)+"_Slope")
Table10=ZonalStatisticsAsTable(Zones1, "NAME_YR", R10, "unit"+str(i)+"_Beers")
Table11=ZonalStatisticsAsTable(Zones1, "NAME_YR", R11, "unit"+str(i)+"_Aspect")

Table12=ZonalStatisticsAsTable(Zones2, "NAME_YR", R1, "unit"+str(i)+"_VDRTable_Rand")
Table13=ZonalStatisticsAsTable(Zones2, "NAME_YR", R2, "unit"+str(i)+"_CH12Table_Rand")
Table14=ZonalStatisticsAsTable(Zones2, "NAME_YR", R3, "unit"+str(i)+"_CH24Table_Rand")
Table15=ZonalStatisticsAsTable(Zones2, "NAME_YR", R4, "unit"+str(i)+"_KDE_30")
Table16=ZonalStatisticsAsTable(Zones2, "NAME_YR", R5, "unit"+str(i)+"_DensityTable_Rand")
Table17=ZonalStatisticsAsTable(Zones2, "NAME_YR", R6, "unit"+str(i)+"_DensityTable_Rand")
Table18=ZonalStatisticsAsTable(Zones2, "NAME_YR", R7, "unit"+str(i)+"_MaxCHfix2")
Table19=ZonalStatisticsAsTable(Zones2, "NAME_YR", R8, "unit"+str(i)+"_DensityTable_Rand")
Table20=ZonalStatisticsAsTable(Zones2, "NAME_YR", R9, "unit"+str(i)+"_DensityTable_Rand")
Table21=ZonalStatisticsAsTable(Zones2, "NAME_YR", R10, "unit"+str(i)+"_DensityTable_Rand")
Table22=ZonalStatisticsAsTable(Zones2, "NAME_YR", R11, "unit"+str(i)+"_DensityTable_Rand")

A=[
B=[
C=[
D=[
E=[
F=[
G=[
H=[
I=[
J=[
K=[

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#Append use and non-use tables for each unit into one table then merge all units' tables together.

for i in range (1, 10):
    A.append("unit"+str(i)+"_AspectTable")
    A.append("unit"+str(i)+"_AspectTable_Rand")
    B.append("unit"+str(i)+"_BeersTable")
    B.append("unit"+str(i)+"_BeersTable_Rand")
    C.append("unit"+str(i)+"_CH12Table")
    C.append("unit"+str(i)+"_CH12Table_Rand")
    D.append("unit"+str(i)+"_CH24Table")
    D.append("unit"+str(i)+"_CH24Table_Rand")
    E.append("unit"+str(i)+"_DensityTable")
    E.append("unit"+str(i)+"_DensityTable_Rand")
    F.append("unit"+str(i)+"_ElevationTable")
    F.append("unit"+str(i)+"_ElevationTable_Rand")
    G.append("unit"+str(i)+"_highVDRTable")
    G.append("unit"+str(i)+"_highVDRTable_Rand")
    H.append("unit"+str(i)+"_lowVDRTable")
    H.append("unit"+str(i)+"_lowVDRTable_Rand")
    I.append("unit"+str(i)+"_SlopeTable")
    I.append("unit"+str(i)+"_SlopeTable_Rand")
    J.append("unit"+str(i)+"_VDRTable")
    J.append("unit"+str(i)+"_VDRTable_Rand")
    K.append("unit"+str(i)+"_CHTable")
    K.append("unit"+str(i)+"_CHTable_Rand")

arcpy.Merge_management(A, "H:/LiDAR/New File Geodatabase.gdb/AAll_AspectTable")
arcpy.Merge_management(B, "H:/LiDAR/New File Geodatabase.gdb/AAll_BeersTable")
arcpy.Merge_management(C, "H:/LiDAR/New File Geodatabase.gdb/AAll_CH12Table")
arcpy.Merge_management(D, "H:/LiDAR/New File Geodatabase.gdb/AAll_CH24Table")
arcpy.Merge_management(E, "H:/LiDAR/New File Geodatabase.gdb/AAll_DensityTable")
arcpy.Merge_management(F, "H:/LiDAR/New File Geodatabase.gdb/AAll_ElevationTable")
arcpy.Merge_management(G, "H:/LiDAR/New File Geodatabase.gdb/AAll_highVDRTable")
arcpy.Merge_management(H, "H:/LiDAR/New File Geodatabase.gdb/AAll_lowVDRTable")
arcpy.Merge_management(I, "H:/LiDAR/New File Geodatabase.gdb/AAll_SlopeTable")
arcpy.Merge_management(J, "H:/LiDAR/New File Geodatabase.gdb/AAll_VDRTable")
arcpy.Merge_management(K, "H:/LiDAR/New File Geodatabase.gdb/AAll_CHTable")

arcpy.ResetEnvironments()