Predicting Olive-sided Flycatcher (*Contopus cooperi*) Breeding Habitats in Southwestern Nova Scotia Using LiDAR Metrics Informed by Drone Data.

by

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Abstract

The Olive-sided Flycatcher (OSFL) is a migratory species at risk bird, currently listed as "Threatened" in Nova Scotia, and "Special Concern" federally. The strategy to promote the recovery of OSFL population is expected to revolve around protecting existing breeding habitat as soon as these locations are found. Two studies have previously modeled OSFL habitat in Nova Scotia using tree-stand level input layers which makes it impossible to identify the within-stand characteristics used by the bird when choosing their habitat. These characteristics of fine-scale forest structure are closely tied to their foraging strategies and are the main driver determining OSFL occupancy rates in these habitats. The goal of this study is to use high-resolution drone imagery to inform LiDAR metrics as inputs for a model that predicts OSFL breeding habitat locations in Nova Scotia. The canopy height models (CHM) for the two data types were compared at 19 known OSFL habitat sites across the province by assessing tree spacing, canopy cover, and the vertical heterogeneity of the treetops to determine which LiDAR metrics can show the within-stand characteristics of OSFL habitat. A correlation test identified three metrics in the drone CHM that could be comparatively measured in the LiDAR CHM: canopy cover and the mean and standard deviation of tree heights. These metrics were then used as inputs for a Maximum Entropy (MaxEnt) model alongside other environmental layers important for characterizing OSFL habitat. MaxEnt created a predicted distribution of the species from occurrence data and the environmental input layers to identify where habitat with similar environmental characteristics could occur. After each run of the model, the performance of each input covariate was assessed, and the worst performing covariate was removed before the model ran again. This process was repeated until the best fit model was identified. The final model consisted of four environmental covariates used to predict OSFL habitat locations: proportion of canopy cover, distance to wetlands, mean canopy heights, and distance to spruce stands. The model performed comparatively well to previous predictive habitat models for the OSFL and identified 48.90% of the Kespukwitk area as being suitable habitat for the OSFL. The results showed the importance of capturing the variation within the OSFL's habitat for predicting habitat locations, evident by the LiDAR-derived covariate measuring the proportion of canopy cover performing better than all other covariate used in any model predicting OSFL habitat in Nova Scotia. Locating where these habitats occur throughout the province is crucial to inform where recovery strategies would be most effectively implemented to protect the OSFL Atlantic population.

Key Words: LiDAR Canopy Height Model; MaxEnt; Olive-sided Flycatcher; predictive habitat model; within-stand variability

List of Abbreviations

AC CDC	Atlantic Canada Conservation Data Centre
AIC	Akaike's Information Criterion
AUC	Area Under the Curve
BAM	Boreal Avian Modelling
BBS	Breeding Bird Survey
BMP	Beneficial Management Practices
CHM	Canopy Height Model
DSM	Digital Surface Model
DTM	Digital Terrain Model
FID	Forest Inventory Data
GIS	Geographic Information System
LiDAR	Light Detection and Ranging
MaxEnt	Maximum Entropy
MBCA	Migratory Birds Convention Act
OSFL	Olive-sided Flycatcher
SAR	Species at Risk
TPI	Topographic Position Index
TRI	Terrain Ruggedness Index
WAM	Wet Areas Mapping

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Introduction

Motivation

Aerial insectivores are experiencing the most drastic declines in population among land birds in Canada, primarily due to changing land use and decreasing insect populations (NABCI, 2019). With increased land-use changes in breeding and non-breeding habitat for bird species, continued declines in bird populations are to be expected (Zhao et al., 2019). One insectivore species in decline is the Olive-sided Flycatcher (OSFL), whose population has experienced a significant cumulative decline of 72% since 1970 (COSEWIC, 2019). Studies have shown habitat loss and degradation from anthropogenic impacts are the main threats to the OSFL (NSDLF, 2021). To effectively aid the recovery of the OSFL in Nova Scotia, a 2021 recovery plan emphasized the need to protect their current breeding and nonbreeding habitats (NSDLF, 2021). The identification of potential breeding habitats across the province is considered an essential component for the recovery of this species (NSDLF, 2021) yet, to date, attempts to identify OSFL breeding habitat in the province have been limited.

Using provincial LiDAR data, informed by proprietary drone data, I aim to create a model to identify the desirable characteristics of the known OSFL breeding habitats, and to predict additional potential breeding habitat locations in the Kespukwitk area of southwestern Nova Scotia. Previous OSFL habitat models in the province have not considered the bird's foraging ecology, and I anticipate that this fine spatial resolution data will help to identify within-stand features that are important to the species. The resulting identification of potential breeding habitat locations throughout the province can then be used to inform conservation techniques and prevent habitat degradation caused by anthropogenic activities.

Background

The OSFL is a medium-sized migratory bird that breeds primarily in forested Canada and overwinters in South America (COSEWIC, 2019). The species has faced substantial long-term population decline (COSEWIC, 2019; Altman & Sallabanks, 2020); however, the rate of decline has slowed in Canada over the past decade, which has resulted in a recent downgrade of their national Species at Risk (SAR) status to "Special Concern", based on recommendations in the COSEWIC 2018 report (Government of Canada, 2023; Parks Canada, 2023). Nova Scotia represents only a small portion of the OSFL's breeding range, where their breeding season extends from mid-May to mid-August (COSEWIC, 2019), and where their provincial SAR status remains as "Threatened" (Government of Nova Scotia, n.d.-b).

With the OSFL population on decline, the conservation of their habitat is vital to promote the recovery of the species (NSDLF, 2021), especially in areas where large portions of habitat are at risk of being lost or degraded (NSDLF, 2021). In general, conifer swamps are considered good habitat in the eastern portion of the OSFL's range (Westwood, 2016), but these are understudied habitats in Nova Scotia (Government of Nova Scotia, 2011).

Two published models have attempted to locate OSFL breeding habitat in Nova Scotia by mapping environmental characteristics of the bird's preferred habitat (Westwood et al., 2019; Bale et al., 2020). Neither of these studies considered the variability of fine-scale forest structures within habitats, although, these characteristics are believed to be the driving factor for determining occupancy rates for OSFL habitat (Hack et al., 2023). The development of the fine spatial resolution remote sensing technology, Light Detection and Ranging (LiDAR), has revitalized studies of forest inventory and ecological research, and is especially useful for habitat studies of flying vertebrates (Jaime-González et al. 2017).

Summary of Literature and Knowledge Gaps

In 2021, a 5-year recovery plan was adopted for the OSFL in Nova Scotia (NSDLF, 2021). The only recovery technique identified was to implement the Precautionary Principle; however, the report acknowledged gaps in existing OSFL habitat data in the province that prevented the implementation of more specific recovery strategies (NSDLF, 2021). The report suggested that the main recovery techniques in the future would revolve around protecting existing breeding habitat essential for OSFL survival once it was known where these habitats occur (NSDLF, 2021).

Several habitat studies have characterized OSFL breeding habitat in Nova Scotia (Westwood, 2016; Staicer, 2017; Simai, 2019; McBeath, 2023). These studies identified the environmental features such as wetness, topography, and specific tree-species that are characteristic of OSFL habitat (Westwood, 2016), alongside crucial within-stand features that show the fine-scale forest structures such as spacing between trees and emergent perches above the surrounding canopy (McBeath, 2023).

The results from the Westwood 2016 study informed two models that previously sought to identify OSFL habitat within the province. Westwood et al. (2019) predicted population density and distribution of the OSFL by comparing occurrence points to wetness and forest cover variables derived from remote sensing data to characterize OSFL habitat. In the second model, Bale et al. (2020) used maximum entropy modeling (MaxEnt 3.3 software) to predict OSFL habitat in Nova Scotia based on the Forest Inventory Data (FID) that provides single measurements for stand attributes.

A general critique of OSFL habitat models is that they do not use input data that can show the within-stand variability of forest habitats that are important for the species, causing these models to be less effective than species distribution models for other species (Betts et al., 2022). Both the Westwood et al. (2019) and Bale et al. (2020) models were limited in this regard due to the data that could show the finer-scale variability being unavailable at the time.

Introduction to the Study

The goal of my study is to create a model that can more effectively predict OSFL breeding habitat in Nova Scotia. The identification of potential breeding habitat in the province will be essential for the recovery of the species (NSDLF, 2021) since it will inform where to apply conservation techniques and prevent habitat degradation caused by anthropogenic activities. This study will differ from previous OSFL habitat models by using LiDAR data to characterize the variability within these habitats. Habitat characteristics measured with drone data will inform the selection of LiDAR metrics that are used as inputs. It is expected that using drone imagery to analyze breeding habitat characteristics will allow for the inclusion of within-stand features, such as the spacing of trees and diverse canopy structures as inputs for the model to create a more accurate prediction of OSFL breeding habitat in Nova Scotia. However, the use of the 1m spatial resolution LiDAR data required a large amount of storage space to create the input layers; therefore, my final predictive model was restricted to the Kespukwitk area of southwestern Nova Scotia.

Summary of Approach

A two-step approach was used in this study to first identify which fine-scale forest structure metrics could be identified using provincial LiDAR data, and then using those metrics alongside other environmental data as inputs for a species distribution model to characterize OSFL habitat and predict additional potential locations. The project involved analysis of known OSFL breeding habitats in order to predict the location of additional breeding areas, focusing on 19 OSFL breeding sites around Nova Scotia where high-resolution drone imagery was collected. The use of drone data provided sub-meter spatial resolution data that allowed us to quantify variation within the territories to identify specific tree metrics such as density, canopy cover, height, and canopy surface roughness (i.e., rugosity), while also providing elevation measurements for which a canopy height model (CHM) can be produced. The observations from the drone data were then compared to features in the provincial LiDAR data for the same sites to determine to what extent the LiDAR data can detect metrics of within-stand forest features, irrespective of stand boundaries. The identified metrics were then used as inputs for a species distribution model.

This Geographic Information System (GIS)-based model used LiDAR data from the Nova Scotia government's opensource data catalogue (Government of Nova Scotia, 2023). The benefit of using LiDAR data is that it allows for measurements of canopy height and density which are important features of OSFL habitat (Westwood, 2016). It also provides information that the Forest Inventory Data (FID) does not have, such as more current measurements and the data to calculate within-stand variability of forest stands. LiDAR data was used for the model because it provided fine spatial resolution data already available for the model area, where drone imagery is not available at larger scales.

Literature Review

Context

This literature review will explore the current state of research related to the OSFL within its breeding range across Canada and into western United States (Altman & Sallabanks 2020) and its relevance to predicting breeding habitat in Nova Scotia. Although OSFL habitat is generally similar, the climate and disturbance regimes differ across its range (Kotliar and Melcher, 1998; Westwood, 2016). I will discuss the status and conservation of the OSFL in Nova Scotia, including the anthropogenic impact to the species and how we can minimize adverse affects. I will then review the various habitat studies done for the eastern population of OSFL. Lastly, I will discuss the use of habitat models to help identify breeding habitat locations around the province, and how new approaches to modeling can further conservation.

Status and Conservation

Conservation Status and Protection

The OSFL is a migratory bird, inhabiting Nova Scotia during its breeding season from mid-May to mid-August (COSEWIC, 2019). The species has faced long-term population decline at a significant rate of 2.8% mean annual decline from 1989 to 2016, and a cumulative decline of 72% since 1970 (COSEWIC 2019). However, the rate of decline has slowed in Canada over the past decade, causing their national Species at Risk (SAR) status to recently be downgraded from "Threatened" to "Special Concern" (Government of Canda, 2023; Parks Canada, 2023), but the species still retains their "Threatened" SAR status in Nova Scotia (Government of Nova Scotia, n.d.-b). With this downgrade in status, the OSFL is still considered a SAR, just not one with a status that requires identification of critical habitat at the national level; however, the Province is required to designate core habitat (SARA, 2002). One of the main pieces of legislation protecting the OSFL is the Migratory Birds Convention Act (MBCA), a treaty signed with the United States of America as a joint effort to protect migratory birds that appear seasonally in both countries (ECCC, 2017). The MBCA protects most species of birds in Canada and is currently the only federal policy in place to protect SAR birds (MBCA, 1994). Unfortunately, the MBCA is rarely enforced, and the lack of prosecution suggests that the act has not been effective at protecting Canada's birds (Cheskey, 2020). Therefore, more must be done.

Conservation Strategies

With the OSFL population decreasing in Canada, governments have stepped in with conservation measures to help stem the decline and promote recovery. In 2016, the Canadian government published a recovery plan that was adopted in 2021 by the Nova Scotia Department of Lands and Forestry for a five-year period (NSDLF, 2021). Due to the lack of knowledge as to where OSFL habitat is located around the province, the recovery plan was unable to provide meaningful strategies to help promote the recovery of the OSFL in Nova Scotia. The report is useful in aggregating the current state of knowledge of the species and identifying gaps in our knowledge that prevent more effective recovery strategies from being implemented. The "precautionary principle" was the only strategy recommended in the report, and future conservation and recovery of the species is expected to revolve around protecting current breeding and non-breeding habitats, once the locations are identified (NSDLF, 2021).

Protected Areas

Habitat is a limiting factor for the OSFL; however, it is unknown to what extent breeding habitat vs non-breeding habitat is limiting (NSDLF, 2021). Because the OSFL is a migratory bird that overwinters in South America, it has been hypothesized that populations are affected mostly by loss or alterations of habitat in wintering grounds, but no work has been conducted to examine this (Altman & Sallabanks, 2020). Regardless, adequate breeding habitat must be conserved to ensure species recovery, and given the rate of population decline in the eastern part of the OSFL range, conservation in the Maritimes may be important for sustaining the species' existing range (Westwood, 2016). Efforts to reduce species decline often include habitat conservation or establishment of protected areas in potential breeding habitat (Kerr & Cihlar, 2004). In Nova Scotia, provincial protected areas are established to preserve ecologically important habitat for biodiversity, but they are designated based on remoteness, rarity, species richness, restoration potential, and connectivity potential (Province of Nova Scotia, 2013). They are not established specifically for the conservation of SAR. National parks alone are insufficient to maintain viable regional populations since only 1.2% of the estimated eastern OSFL population is found in national parks (Westwood, 2016) and almost 70% of Nova Scotia is privately owned land (Government of Nova Scotia, n.d.-a).

Anthropogenic Impacts

Anthropogenic activity such as forest silviculture poses one of the biggest threats to OSFL breeding habitat in Canada (NSDLF, 2021). Canada is one of the few places retaining extensive tracts of forests, yet with ongoing habitat loss, the rates of species endangerment are similar to other countries in the Americas (Kerr & Deguise, 2004). Although new silviculture guidelines in Nova Scotia avoid harvesting in forested wetlands on Crown lands (McGrath et al., 2021), throughout the OSFL's range, forested wetlands have experienced historical pressure from the forestry sector and climate change that decreased the availability of these habitats (CCFM, 2023), with ~18% decline of OSFL habitat over 35 years in eastern Canada (Betts et al., 2021). It has been hypothesized that habitat destruction through wetland loss and forestry activities on breeding grounds are a cause of population decline (Riordan et al., 2006). In addition, it is suggested that songbird communities may be especially sensitive to the changes in landscape structure caused by forest harvesting practices (Taylor & Krawchuk, 2005). A report from the Nova Scotia Department of Natural Resources (2017) discusses how most of the silviculture on Crown land has been clear cutting and that the province required the regeneration of forests to be managed or planted to produce "optimal stocks" (i.e., typically soft-wood species as they produce the highest yield). This has resulted in an even-aged coniferous forest composition within stands across the province (NSDNR, 2017) that may negatively affect OSFLs (Kotliar, 2007). These changes to age-class and forest composition impact the forest structure and demonstrate how habitat degradation can be more impactful than loss of habitat as the main driver for avian population declines (Betts et al., 2021).

There have been numerous studies that report positive numerical responses from OSFLs to some type of harvested forest (Altman & Sallabanks, 2020). But in the west, OSFLs have been shown to be less abundant or absent in harvest units, particularly clear cuts, due to lack of cover (Kotliar, 2007). One study in Nova Scotia identified that habitat occupied by OSFLs did not differ between recently harvested or unharvested sites, suggesting that features can be retained in managed forest landscapes (Westwood, 2016). However, there are concerns about creating ecological traps, where habitats aesthetically mimic desirable features, but not the fundamental quality of natural habitats (Roberston & Hutto, 2007). Ecological traps can be unsuitable for the survival or reproduction of species, as evidenced by the observation that nests in close proximity to timber harvests are less productive and less successful due to higher nest predation rates and increased competition for resources (Hoover et al., 1995; Robertson & Hutto, 2007). Forest harvesting can also reduce the availability of arthropods (Duguay et al., 2000), therefore decreasing the OSFL's food source. Even though anthropogenic activities pose one of the greatest threats to the OSFL (NSDLF, 2021), a study suggests that with proper forest management, important habitat features could be maintained (Westwood, 2016). Therefore, in order to promote the conservation and the recovery of the species, their habitat needs to be located so that action can be taken to mitigate habitat degradation from anthropogenic activities.

Habitat Conservation in the Context of Forestry

Beneficial Management Practices (BMPs) can be applied to mitigate habitat degradation caused from anthropogenic activities. BMPs appear to be successful in agriculture, where several studies have shown that they are effective in mitigating environmental impacts of the industry (Asgedom & Kebreab, 2011). BMPs are not yet widely applied in forestry but are being developed to reflect the habitat requirements specific to individual species and should be continuously monitored and updated based on the best available science (NSDLF, 2021). The current draft for the OSFL BMP for Nova Scotia recommends leaving a buffer of at least 50m of coniferous forests around wetlands and leaving snags, coarse woody debris, and clumps of tall trees after forest harvest (McLean, 2021). Nova Scotia's current cutting regulations to reduce impact caused by silviculture mandate the retention of small patches and riparian buffers (Province of Nova Scotia, 2002). It is suggested that the OSFL BMP be updated to specify tree retention details (such as species, abundance, tree height and density; McBeath, 2023), and increasing riparian and wetland buffers to 100m – 250m around cuts (Westwood, 2016). The reason for the suggested changes is because under the current buffer regulations, trees and snags would be removed from the landscape and existing leave patches would not be large enough to retain habitat for the OSFL (Westwood, 2016). Updated BMPs would adjust forestry practices to integrate forest management planning (LSARFWP, n.d.), which is necessary to conserve habitat and identify key locations for regional management to prevent species extirpation (Westwood, 2016).

Previous Habitat Studies in Nova Scotia

Overview

To develop effective conservation strategies for the OSFL, studies first need to characterize their habitat and identify the features important for the species. The occurrence of a species in a given habitat is linked to forest vegetation structures, and understanding these structures can help inform timber harvesting practices and mitigate the negative impacts (Marzluff et al., 2000; Sallabanks et al., 2006). The main habitat studies for the Nova Scotia population of the OSFL include studies by Westwood (2016), Staicer (2017; 2018), Simai (2019), and McBeath (2023). Westwood (2016) aimed to characterize fine-scale habitat for SAR in Nova Scotia in order to suggest habitat-maintaining forest management practices. Using a multivariate method of analysis, Westwood (2016) identified the vegetation species and structure of sites occupied and unoccupied by OSFLs, as well as contrasting occupied sites in areas of recent harvest and those in areas not recently harvested. Simai (2019) classified sites where OSFLs were present and absent using vegetation features, focusing on data-poor regions of the province. McBeath (2023) assessed whether OSFL foraging space requirements explained their association with open forest and their perch preferences. The Staicer (2017; 2018) studies intended to identify high quality habitat for the OSFL by analyzing population information, such as densities, level of breeding evidence, and persistence of site occupancy to indicate the relative quality of the habitat at different sites.

Each study obtained vegetation data along 50-100m long and 6-10m wide transects to identify vegetation characteristics within the OSFL's habitat. The belt transects in McBeath (2023) were anchored around trees on which an OSFL was observed to be perched, allowing for the mapping of trees to quantify spacing within the habitat and how much foraging space there is for the species. McBeath (2023) focused on characterizing forest structure, recording every tree that an OSFL landed on and noting the tree species, height, crown class, health, height of surrounding treetops, distance to nearby clearing, and density and dispersion of trees in the area.

These studies revealed specific variables important for OSFL breeding habitat in Nova Scotia, most abundant in coniferous bog/fen and coniferous treed swamps (Simai, 2019). The vegetation and structural complexity in the upper strata were most important to characterize OSFL-occupied sites (Westwood, 2016), and the habitats typically have lower amounts of canopy cover than other SAR landbird habitats in Nova Scotia (Staicer, 2018). Additionally, while there were differences observed between occupied and non-occupied sites, no significant difference was observed between occupied sites in harvested and non-harvested forests (Westwood, 2016). McBeath (2023) analyzed the same transects used in my study and found that the foraging spaces available in OSFL habitat in Nova Scotia were consistent with studies conducted in western populations, when assessing factors related to availability of open spaces and perch trees that provided for foraging. However, OSFL territories tend to be very large (10-20ha in size; Altman & Sallabanks, 2020) and patchy, so a small plot or belt transect only captures some of the habitat features. Therefore, the results of these habitat studies characterized OSFL breeding habitat in Nova Scotia, but only in "small" sample areas.

Habitat Characteristics

When selecting breeding habitat, species choose based on environmental and structural cues that have become reliably correlated with habitat quality (Hutto, 1985). Habitat selection is not a conscious choice, but rather involves a weighing of intrinsic and extrinsic evolutionary constraints for various habitat types (Hutto, 1985). Due to the vast forested areas of Canada, the environmental influences vary from the eastern to western portions of the OSFL's range, resulting in slightly different habitats and therefore different preferences for the Maritime population (Kotliar and Melcher, 1998; Westwood, 2016).

Throughout their breeding range, OSFLs are associated with coniferous forest habitat, in forest openings and edges occurring in mature forests and following natural and anthropogenic disturbances that open up the canopy and allow them to forage more effectively (Kotliar, 2007; Altman & Sallabanks, 2020). In Nova Scotia, OSFLs typically inhabit forested wetlands dominated by black spruce trees, with perch trees being on average 1.6 times taller than the surrounding vegetation (Westood, 2016; Staicer, 2017; McBeath, 2023). Wetlands are an understudied environment in Nova Scotia that provide critical habitat for many wildlife species and are in decline due to anthropogenic activities (Government of Nova Scotia, 2011). OSFL sites were often characterized by extensive *Sphagnum* moss cover, abundant tall snags, and coarse woody debris (Staicer, 2017). Foliage cover exceeded more than 80% in the low shrub layer likely due to the openness of the tree canopy as a result of poor and wet conditions that limit tree growth (Staicer, 2017). The presence near water may reflect higher insect abundance in these areas (Altman & Sallabanks, 2020).

Small-scale patchiness may also be particularly important in southwestern Nova Scotia, where the natural disturbance regime is dominated by small gap creation and the topography is variable, leading to a diversity of microsites (Neily et al., 2003). That said, clearings >200 m may not be used by OSFLs due to lack of nearby trees for cover (Kotliar, 2007). Habitat selection reflects how a species uses their habitat, and OSFL habitat is characterized by a wet, open-forest structure with variable tree height that provides protection, as well as allowing for adequate spacing for their foraging technique.

Habitat Modeling

After identifying the characteristics of OSFL habitat, habitat models have attempted to predict where else comparable characteristics exist in the province that could indicate potential habitat for the species. When characterizing habitat, it is necessary to ensure that input variables accurately represent the level at which a species operates in order to produce suitable results (Addicott et al., 1987). When studying the distribution of species, variables measured at local or fine scales are often better predictors than coarser scales (DeGraaf et al., 1998). Songbird occurrences, in particular, vary significantly between scales (Girard et al., 2004).

Previous Habitat Models for Nova Scotia

Two previous studies modeled the OSFLs in Nova Scotia (Westwood et al., 2019; Bale et al., 2020). Westwood et al. (2019) created a species distribution model to predict the distribution of OSFL based on topological and hydrological variables related to wetness in four maritime national parks. This model provided the first population density and size estimates for the four national parks by comparing BAM project occurrence points to three different methods for delineating wet areas to see which was best at predicting OSFL habitat (Westwood et al., 2019).

When comparing the three different methods for delineating wet areas, Westwood et al. (2019) found that the best performing model to predict OSFL habitat used a wetness interacted with forest cover layer (WETxFOR). The WETxFOR layer considered areas with <1m depth to water table to be areas which may support forested wetlands because the values correspond to field measurements in forested wetlands collected by the Forest Watershed Research Centre (2012). However, the spatial covariates used as inputs for this model had to be standardized to a 250m spatial resolution raster layer for model predictions due to computational limitations.

The other model by Bale et al. (2020) used Maximum Entropy modeling (MaxEnt 3.3 software) to predict OSFL habitat in Nova Scotia based on a combination of topographic and forest covariates. This model took occurrence data from the Maritime Breeding Bird Atlas database and observations by individuals and research groups. For environmental variables, Bale et al. (2020) used the provincial Forest Inventory Data (FID) that provides tree heights and a measure of canopy cover at the stand level. Bale et al. (2020) included abiotic features in the model as these features can promote "ecological memory" and are generally less affected by climate change than biotic features (Holling, 1992).

The interaction between forest cover and wetness from Westwood et al. (2019) was further supported by the Bale et al. (2020) model, where it was found that topographic features can have a predictive value, with OSFLs being found in valleys and low slopes. Overall, the forest covariates were more explanatory than topography (Bale et al., 2020). The Bale et al. (2020) model was based on raster layers with a spatial resolution of 150m and appeared to have less predictive ability than other models for different species in the same study. Staicer (2018) suggests that the lesser predictive power of this OSFL model was likely due to a generalizing of tree characteristics at the stand level to predict within-stand variation that characterize OSFL habitat. The model used FID, comprised of a polygon layer for each stand of trees, with a single value representing each attribute, such as height and canopy cover for each stand, as well as classifying it as either deciduous or coniferous. These inputs resulted in higher average canopy heights and lower canopy heterogeneity in areas determined to be suitable for the OSFL (Bale et al., 2020).

The use of coarser spatial resolution data and habitat characteristics at a stand level are limitations of studies modeling OSFL distribution (Betts et al., 2022; Hack et al., 2023). The inputs for the model should be made to reflect the scale at which the species operates (Addicott et al., 1987), as predictions can only be as fine as the coarsest layer of input data (Franklin, 2009). Inputs that result in a data value representing an average at the stand-level make it impossible to calculate or consider within-stand variation, despite within-stand features having been identified as important to the species (Altman & Sallabanks, 2020). The previous models' input data was restrained by the data available at the time and did not take into consideration data from field surveys that identified the within-stand features of the forest structure that the OSFL utilizes to select their habitat. Fortunately, as technology improves and more studies are done, new data becomes available for models to be altered and refined to become more accurate in their predictions.

Filling in Knowledge Gaps

Considering Foraging Ecology

Although studies have identified that foraging ecology associated with the OSFL requires the bird to operate at within-stand levels (Westwood, 2016), previous OSFL models have not taken into account habitat characteristics associated with foraging ecology. It is important to identify within-stand tree characteristics, irrespective of stand boundaries, that enable the OSFL foraging strategies because food is an important factor in habitat selection. Intrinsic factors such as the presence and abundance of food, perch characteristics, and branch configuration contribute to a bird's choice about the precise location within which to feed (Hutto, 1985). Optimal foraging theory involves patch choice, which suggests that as long as there is a limited supply of food, there will be selective pressures on individuals to use the space in the most profitable way possible (Pyke et al., 1997). Therefore, habitat selection can be considered a logical extension of patch choice as long as there is a limited supply of food, as it will result in there being better and worse places to settle, with selection favouring discrimination among sites on that basis alone (Pyke et al., 1997).

The OSFL depends solely on one method of foraging called "sallying", which is when a predator leaves an observation perch, captures an airborne insect on the wing, and then returns to a perch (Eckhardt, 1979). They show preference for a specific tree as a perch and will often return to the same perch after an attempt to capture their prey (Eckhardt, 1979). Specific foraging microhabitats are important to the OSFL due to their within-stand preferences that include foraging from a high prominent perch, which is often a snag or dead tips of the uppermost branches of tall trees that overlook surrounding vegetation (Wright, 1997; Altman & Sallabanks, 2020). Species distribution models show that the occupancy of OSFLs in a particular habitat is most closely tied to fine-scale forest structure that they use for foraging (Hack et al., 2023), and efforts to model their distribution have been less successful compared to other species distribution models due to the fine-scale forest structure associated with OSFL habitat being poorly captured by satellite imagery (Betts et al., 2022). In Nova Scotia, the OSFL's selection of habitat is consistent with their foraging requirements, with OSFLs selecting habitat based on tree types, heights, and spacing (McBeath, 2023). Because of their exclusive dependence on one foraging technique, the OSFL requires specific characteristics within stands that facilitate their hunt for food. We can measure these habitat features in the field (in a small area) and more broadly with drone data to identify these important within-stand determinants of OSFL habitat.

New Approaches to Modeling

As technology advances and becomes increasingly accessible, it helps overcome previous limitations with data collection and analysis. One of the most impactful contributions to studying and modeling habitats is the increased use of remote sensing technologies. Unmanned aerial vehicles (UAVs), such as drones, allow for capturing images at low altitudes with high-resolution onboard sensors to collect high-spatial resolution imagery (Mathews, 2021). The use of drone imagery is extremely effective when analyzing defined areas (such as the OSFL's territory which is usually 10ha – 20 ha in size; Altman & Sallabanks, 2020), to provide an understanding of the structure and ecology of the habitat (Mathews, 2021). The high-resolution imagery makes it easy to pick out features without having to conduct time consuming and intensive field surveys. However, with the high-spatial resolution comes a requirement for more digital storage and a higher computational capacity to work with this data at larger scales. Therefore, it is unreasonable to use drone imagery for a model of a large area like that of the Kespukwitk area used in my model, and other technology is needed.

The development of the remote sensing technology, Light Detection and Ranging (LiDAR), has revitalized and strengthened studies with applications to forest inventory and ecological research, especially for habitat studies of flying vertebrates (Jaime-González et al., 2017). LiDAR is an active sensor that relies on its own source of energy to emit a light in the direction of a target, and captures and measures the portion of light that was not absorbed but was reflected back to the sensor (Singh, 2021). LiDAR is now widely used to measure tree height, terrain features, and topography, and is extremely beneficial to modeling on a large scale (Jaime-González et al., 2017). LiDAR data with a spatial resolution of 1m was collected in 2019 for everywhere in the province, with some areas being updated in subsequent years (Government of Nova Scotia, 2023). The provincial LiDAR data was not available when the previous models identifying OSFL habitat in the province were created. Therefore, the Westwood et al. (2019) and Bale et al. (2020) studies were limited to coarser data and forest data at the stand scale. However, the effectiveness of using LiDAR for greater identification of ecologically relevant features for species was recommended by Westwood (2016) once it becomes more available.

Combining the strengths of the various approaches should result in a more effective model, with the potential to help address current knowledge gaps as to where the species is located and therefore help promote the application OSFL recovery strategies.

Methods

Overview

The current recovery strategy for the OSFL identifies a lack of knowledge relating to habitat locations for the species as the limiting factor for implementing more effective recovery strategies (NSDLF, 2021). This study aims to help address this gap in knowledge by using drone imagery to inform the selection of provincial LiDAR metrics to be used as inputs for a Maximum Entropy (MaxEnt) model to predict potential OSFL breeding habitat locations in southwestern Nova Scotia. By using LiDAR metrics informed by drone imagery, I aim to identify and incorporate the within-stand variability that is important for the OSFL, a crucial aspect that I believe was missing from previous models that attempted to predict OSFL breeding habitat in NS.

Study Area

This study's predictive habitat model will be applied to the Kespukwitk area, an area of conservation priority of Nova Scotia (NCC, 2024) which includes the five western-most counties and parts of two others that fall within the Annapolis and LaHave watersheds (NSECC, 2008). The model is informed by drone imagery collected from 12 managed forest blocks on crown land dispersed across the province (Figure 1). Each site had at least one transect conducted, with a total of 19 transects each placed in the territory of a different male OSFL: ten in southwestern Nova Scotia, two in the eastern shore, and seven in Cape Breton (Table 1). Because OSFLs are highly territorial, their territories do not overlap (Short, 2017). Two of the upland forest sites in southwestern Nova Scotia were post-burn sites (Figure 2).

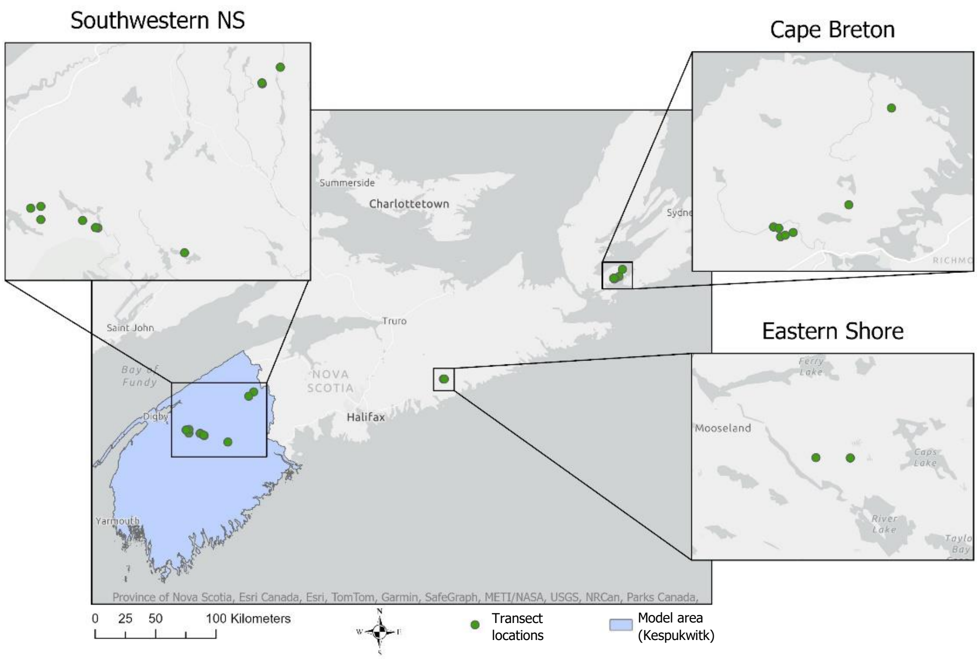


Figure 1: Map of study sites where transect surveys and drone imagery were collected in Olive-sided Flycatcher (*Contopus cooperi*) habitat across Nova Scotia. Delineated with blue is Kespukwitk, the areas that this study's habitat model will represent.

Table 1: List of the 12 sites across the province where the 19 transect surveys and drone imagery were collected for this study. The table shows how many transects were conducted at each site (representing the number of individual OSFL territories at each site).

Region	**Site**	**Transects (number of territories)**
Southwestern NS	End Victory Rd	1
	Harvest Block 13	1
	MCFC Burn	1
	Palmer Lake	1
	Stillwater	2
	Tupper Barrens	1
	Twin Lakes Burn	2
	Victory Rd Swamp	1
Eastern Shore	Otter Ponds	2
Cape Breton	Long Lake	1
	Reagans Extension	1
	River Tillard	5
Total:	12	19

Reagans Extension (Cape Breton)

River Tillard (Cape Breton)

End Victory Rd (Southwestern NS)

Otter Ponds (Eastern Shore)

Tupper Barrens (Southwestern NS)

Twin Lakes Burn (Southwestern NS)

Figure 2: Photos of six sites where transect surveys were conducted, showing the range of forest types and the structural variability of Olive-sided Flycatcher habitat across the province. Photos taken from McBeath (2023), except for the Twin Lakes Burn image take by D. Burns.

Sampling

Field Observations

At each site, a belt transect was surveyed (50m x 10m), mapping the location of trees and snags to the nearest 0.1m and recording their height, a measure of canopy cover for the transect, and a measure of health for trees and decay for snags. Each transect was anchored around trees on which an OSFL was observed to be perched. The transect data helps provide an understanding of the vegetation structural diversity and the space available for foraging in the habitat. Of the 19 transects used for this study, 16 were measured in 2022 and summarized in McBeath (2023). That study concluded that tree heights and spacing were consistent with previous studies of foraging behaviour conducted in western populations when assessing factors related to availability of open spaces and perch trees that provided for foraging space requirement. The other three transects (Twin Lakes #2 and River Tillard #4 & #5,) were assessed in 2023 after McBeath's study. The transects provided ground-truthing for the drone and LiDAR data.

Drone Imagery

Drone imagery was collected at each site, using a Phantom 4 RTK drone that corrects satellite signals in real time to get more accurate location coordinates for each photo using cell signal (if available) or by a base station on site, to receive corrections from satellites (DJI Enterprise, n.d.). The drone was flown at 100m above the ground, with approximately 80% overlap between adjacent photos. The imagery was collected during the growing season when the trees were leafed out, between 4 June – 19 September 2022, except for Harvest Block 13 and River Tillard 4, where drone imagery was collected in August 2023. The imagery was then processed using AgiSoft Metashape (Agisoft), a software product that performs photogrammetric processing of digital images to generate 3D spatial data (Agisoft, 2023). Agisoft creates an orthomosaic (geotiff) with a resolution of 2.7cm/pixel, and a digital surface model (DSM) and digital terrain model (DTM) with a resolution of 6cm.

The drone imagery was collected to encompass the bulk of each bird's territory. A 5ha plot centered on each transect and encompassing all occurrence observations of the OSFLs was used to quantify the habitat. These 5ha areas were used to compare the drone and LIDAR data.

Analysis of CHMs

This study followed the steps outlined in Figure 3, starting with preparing the LiDAR and drone data. Variables from the two data collection methods were compared through a correlation test to identify LiDAR metrics that show the within-stand variability visible in the drone data and important for OSFL habitat. The identified LiDAR metrics were then turned into raster layers to be used as inputs alongside other environmental and occurrence data into a MaxEnt model to predict OSFL habitat in the Kespukwitk area.

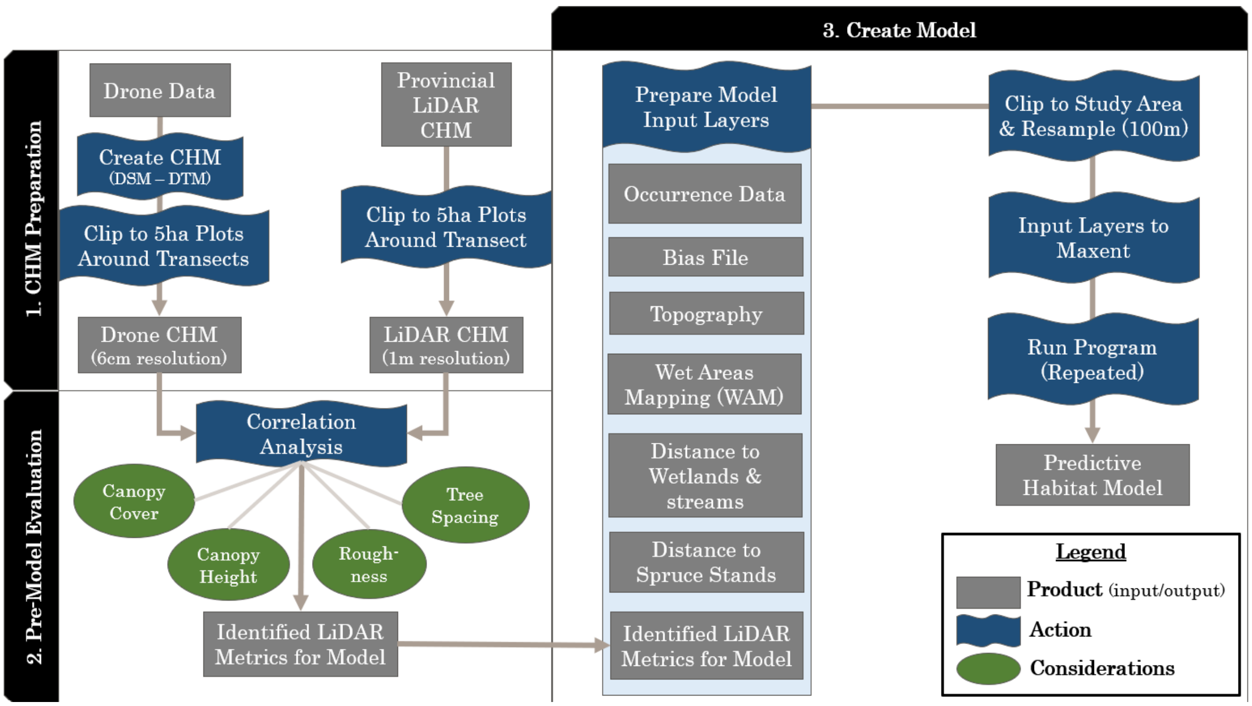


Figure 3: Flow chart outlining the input and output products, actions, and associated considerations for each step needed to complete the study.

A provincial canopy height model (CHM) based on LiDAR data is available as a raster layer with a spatial resolution of 1m (Government of Nova Scotia, 2023). However, to determine if the spatial resolution of the LiDAR is fine enough to identify within-stand variation of forest structures, I compared the metrics derived from the LiDAR CHM to a drone CHM from each site. To do so, I first created CHMs with the drone data, which can be done by subtracting the digital terrain model (DTM) from the digital surface model (DSM) (Nasiri et al., 2021), creating a drone CHM with a 6cm spatial resolution. Both the LiDAR and drone CHMs were clipped to the same 5ha areas around the transects at each site, for a sample size of 19. The drone CHM is assumed to be more accurate in identifying fine-scale forest structure due to the higher spatial resolution. Therefore, a correlation analysis was used to assess the strength of relationship between measurements obtained from the two different CHMs. The outputs of the correlation test show how well the variation in the 1m spatial resolution of the LiDAR data aligns with variation in the drone data. The correlation analysis involved assessing six variables from the CHMs: canopy cover, tree heights (mean and standard deviation), number of trees, tree spacing, and rugosity (i.e., surface roughness). Canopy cover and height were calculated by identifying individual trees within the 5ha plots using the ForestTools R package (Plowright, 2023). The ForestTool treetops script uses a local maximum variable window function to identify individual trees, providing coordinates and a height value for all identified trees. I followed the variable-window equation from Swayze & Tinkham (2022), recommended for high-resolution CHMs:

$$F(h) = 0.1*h$$

This equation determines the variable window radius (in meters), adjusting the size by a factor of 0.1 in relation to h, the height value of the cell (Swayze & Tinkham, 2022). After identifying individual trees, the canopy was extracted using the ForestTools crowns outline script, set with the same parameters of a 5m minimum height to outline each tree's crown as a vector polygon. However, in the years between the collection dates of the drone imagery and the LiDAR data, several of the sites experienced some sort of disturbance that decreased the number of trees in the area, either as a result of forest fires, harvesting, or blowdown from storms; changes are outlined in Appendix A. As a result, the CHMs had to be standardized. This was done in ArcGIS Pro by selecting only the LiDAR tree points within the drone's outlined crown polygon layer. The selected LiDAR tree points were exported as their own file and used to select only the LiDAR tree crown polygons that had the selected tree points within. This standardized the trees in the 5ha LiDAR CHM plots to only show the trees that are still present in the drone 5ha plots, allowing for calculated variables to be comparable to each other.

The mean and standard deviation of tree heights were calculated from all the identified tree points for each site and an average nearest neighbor test was used to assess tree spacing. Each site's canopy was calculated as a sum of each tree's crown outline area, divided by 5ha to represent the percent of canopy cover in each plot. The rugosity is a measure of surface roughness and is calculated through a rumple index: the ratio of canopy outer surface area to the ground surface area to give a measure of structural heterogeneity of CHMs (Kane et al., 2010). Rugosity can help identify gaps within stands, more mixed-aged forest stands with multiple canopy levels, and can be a predictor for areas that experience more disturbance (Kane et al., 2010). This can be an important variable for predicting OSFL habitat because they have been described as a post-disturbance species, arriving at sites after a recent disturbance that causes trees to fall and open up canopy within the habitat (Robertson & Hutto, 2007). Rugosity was calculated using the lidR R package rumple index that assess cells in the context of their neighbors to create an output value for the whole site (Roussel, 2024).

After collecting the measurements, a correlation test was used to test the strength of the relationship between the metrics observed in the drone and LiDAR CHMs. The metrics with a significant ($p < 0.001$) and high correlation ($r > 0.7$) relationship were considered the LiDAR metrics that can show the within-stand variability important for OSFL habitat that are then used as inputs for the habitat suitability model.

Modeling Methods

Maximum Entropy Modeling

I used Maximum Entropy (MaxEnt) modeling to create my habitat model. MaxEnt is a species distribution model tool used for predicting the distribution of species from a set of occurrence records and environmental predictors (Fourcade et al., 2014). It is robust to small sample sizes and is ranked among the top presence-only modeling approaches (Elith et al., 2006). It uses species occurrence data to create a predicted distribution that is then referenced to environmental data to create a habitat suitability map that predicts potential suitable habitat for the species. I ran the model with settings set to 5,000 maximum iterations, 30 cross-validated replicates, and a maximum of 10,000 background points. The environmental input data I used for the model do not currently exist in a form that can just be imported into MaxEnt software, and therefore required some type of manipulation (Table 2). Environmental data layers were selected based on the literature and previous models (Westwood et al., 2016; Staicer 2017; 2018; Westwood et al., 2019; Bale et al., 2020; Staicer et al., 2023). The occurrence data was compiled by Dr. Staicer, from the Atlantic Canada Conservation Data Centre (AC CDC) records, updated May 2023, and Staicer lab research data from summer 2023.

Table 2: List of input variables for the MaxEnt habitat suitability model, their source, and the rationale for including them in this study.

Data Type	Input Variables	Source	Applicability
Occurrence Data	Occurrence Data • With accurate GPS locations • Observations > 1 km from each other • Within the breeding season	Atlantic Canada Conservation Data Centre (AC CDC) SAR occurrence data and Staicer lab occurrence data updated May 2023.	Extracting observations within the breeding season and with accurate GPS locations to make the MaxEnt habitat suitability predictions most accurately reflecting OSFL breeding habitat. Removing observations too close to each other removes some spatial autocorrelation of observations.
Bias File	Available survey locations and SAR occurrence data	Created from known locations where people have found or looked for birds (e.g., breeding bird atlas and breeding bird survey points).	Helps reduce surveying bias associated with occurrence data which is often spatially biased towards areas that are more easily accessible or more often surveyed.
Environmental Data	Depth to water table	Extracted from the new LiDAR-based Wet Areas Mapping (WAM) model from John Gallop, NS department of Environment and Climate Change – wetlands program.	This source is a more up-to-date version than what is available online from the NS department of natural resources. Westwood et al. (2019) found WAM to be a strong predictor of OSFL distribution. WAM is more effective at identifying wet areas under forest cover which is a limitation to the wetlands layer. When cross-referenced with forest cover, helps identify areas that could support forested wetland habitats.
Environmental Data	Wetland habitats	Wetland polygons were extracted from the Forest Inventory Data (FID) from the Province of Nova Scotia GeoNova online database, to create a "distance to" layer.	Wetland habitats are important for OSFLs. These layers were used to calculate a distance to wetlands layer to identify wet areas without some of the limitations from the WAM.
Environmental Data	Topography (topographic position index)	Derived from the provincial LiDAR DEM from the Nova Scotia GeoNova online database.	Regional topography creates microclimates and regulates accumulation of water on the landscape and has been shown to be an important predictor of OSFL habitat from the previous OSFL habitat models.
Environmental Data	Tree species data	Tree stands were extracted from the Forest Inventory Data (FID) from the Province of Nova Scotia GeoNova online database.	Stands dominated by the OSFL's preferred spruce species (black, red, and black and red mixed stands) were extracted to create a distance to spruce stand layer.
Environmental Data	Identified LiDAR Metrics	From the provincial LiDAR data. Specific metrics to be determined by comparison to drone data.	These variables will help identify the within-stand variation independent of stand boundaries important for OSFL habitat. Variables include: tree heights (mean and standard deviation), canopy cover, canopy clumping, canopy surface roughness.

Environmental Data

The environmental covariates used as inputs for the model all represent features associated with OSFL habitat. The datasets used to create the covariate layers are largely maintained and distributed by Nova Scotia Department of Natural Resources available through GeoNova, or from contacts at NS Department of Environment and Climate Change. All the environmental covariate layers were prepared with the same spatial resolution (100m), projection (NAD 1983 UTM Zone 20) and spatial extent in Esri's (n.d.) ArcGIS Pro 3.1.0 to attain consistent spatial resolutions and extent among layers and to reduce the computational intensity of the model. The creation of each layer is explained in greater detail in Appendix B.

Regional topography creates microclimates and regulates the accumulation of water on the landscape (Lawler et al., 2015), and will be used for this study to determine potential areas with forested wetlands around the province suitable for OSFL breeding habitat. Topographic covariates include: i) a topographic position index (TPI) of local topographic position (i.e., elevation) relative to the surrounding "neighborhood" calculated from the LiDAR DEM (Weiss, 2001); ii) a depth to water table extracted from an updated provincial Wet Areas Mapping (WAM) model that can more accurately identify forest wetlands; and iii) a distance to delineated wetlands assuming that habitat suitability varies in relation to wetland proximity. Each of these topographic covariate layers were created according to regional indices specific to Nova Scotia.

Forest characteristics are important to the OSFL, who have shown preferences for tree species, heights, canopy cover, and spacing of perch trees within their habitat (Altman & Sallabanks, 2020). Forest data was obtained from the provincial Forest Inventory Database (FID) with measurements at the tree-stand level, and from the provincial LiDAR data. Forest covariates include a distance to spruce-dominated stands that show habitat suitability in relation to proximity to the quality type of spruce trees, and five LiDAR CHM derived metrics consisting of: i) the proportion of canopy cover per 100m^2; ii) a measure of canopy clumping to show where canopy was adjacent to other canopy, calculated as the sum of the focal cell and its eight nearest neighbor pixels; iii) a terrain ruggedness index (TRI) of canopy relative to the surrounding "neighborhood" to identify trees emerging from surrounding canopy; iv) a focal statistics layer calculating the mean height values of the CHM; and v) a focal statistics layer calculating the standard deviation of canopy height values of a pixel and its surrounding "neighborhood". Canopy clumping was calculated on a finer-scale (3x3 pixel window) than the other LiDAR CHM metrics calculated using focal statistics (10x10 pixel window) to stay consistent with McBeath (2023) who identified a scale of tree clumping at 0.5m – 1.5m.

All final versions of the LiDAR-derived environmental layers used as inputs for the MaxEnt model were resampled to a 100m spatial resolution using a bilinear method, except for the mean canopy cover layer that had binary values aggregated by mean to a 100m grid tessellation over the study area that was then converted to raster with a cell size of 100m.

Occurrence Data

Methods that use presence-absence data are generally considered to be more accurate than presence-only methods (Brotons et al., 2004). However, absence data was not available for the OSFL, therefore limiting our approach. MaxEnt only uses presence data without the need for absence data. The occurrence data was sourced from the AC CDC, with additional records from Staicer's lab that were not already in the database. The occurrence data was processed following the methods used in Staicer et al. (2023), retaining records for birds with dates during the breeding season (17 May to 14 August) and removing records with a location uncertainty greater than 250m. To reduce spatial autocorrelation in the occurrence data, records that were within 1km of other records were removed, retaining the most recent record with the highest precision and farthest from roads.

Bias Layer

A bias layer was created to further reduce sampling bias of occurrence points, which is often spatially biased towards areas that are more accessible or more often surveyed (Petersen et al., 2021). Applying occurrence data in conjunction with a bias grid was determined to be among the most effective methods of reducing the effects of sample bias in MaxEnt (Syfert et al., 2013).

The bias layer is a grid that is based on areas of known locations where people have looked for the birds, created as a kernel density of expected counts and a search radius of 10km. This grid does not change the number of background (occurrence) points, but when the grid is applied, the background points are sampled at a greater density around clusters of presence points, rather than evenly sampled throughout the entire study area—as it would be when no bias grid is used (Bale et al., 2020). The bias layer will help improve MaxEnt's ability to distinguish between true absences and absences due to areas not being surveyed (Staicer et al., 2023).

Reverse Stepwise Elimination

After all the environmental data layers were prepared, they were clipped to the Kespukwitk area in southwestern Nova Scotia and input into MaxEnt to create a predictive model for suitable habitat in the area. The program was run repeatedly to apply a reverse stepwise elimination process that identifies the most crucial subsets of covariates to include in the model (Bale et al. 2020). Each time the model ran, it generated a percent contribution, a permutation importance (calculated according to the drop in AUC that occurred if the variable is excluded from the model; Phillips, 2005), and a response curve to show how impactful each variable is at predicting OSFL habitat alone and in combination with the other variables in the model. The variable contributing the least was removed at the end of each run, and the model ran again without it. This was repeated until the best fit model was identified, where at least half the initial input variables were removed (to prevent over-fitting) and if the Area Under the Curve (AUC) mean value for cross-validated run decreased by >1% (Haughian et al., 2019).

Although many studies use Akaike's Information Criterion (AIC) to identify the best fit candidate, recent evidence shows that this method for selecting the best fit model in ecological niche models such as MaxEnt may lead to erratic model performance and oversimplified response curves that do not reflect complex species-environment relationships (Low et al., 2021). AIC values are best used for explanation-oriented models that estimate the fundament niche (Velasco & González-Salazar, 2019). Studies interested in prediction-oriented models would benefit more from "traditional" measures of model performance such as AUC results from cross-validated models, which allows for straightforward evaluations (Low et al., 2021).

Model Evaluation

The AUC provides a measure of likelihood that randomly selected presence points have a higher suitability score than randomly selected background points (the MaxEnt equivalent of absence; Fourcade et al., 2014). The AUC ranges from 0 (no discriminatory power) to 1 (perfect discriminatory power), with 0.5 being a reference that model predictions are no better than random (Elith et al., 2006). The best fit model was then evaluated by comparing the expected and observed omission rates, where I adopted 2 thresholds, the lowest presence threshold (LPT) and the 10% presence threshold (10PT) to determine how many points were excluded when these thresholds were applied on test data (i.e., observed omission rates). LPT is the lowest predicted suitability value associated with training occurrence data, where no presence locations are incorrectly classified as background points, and the 10PT refers to the suitability score where the lowest 10% of the training presence data is omitted, assuming that the occurrence data's lowest 10% of suitability measurements are errors. A LPT omission rate closer to 0% and a 10PT value closer to 10% indicate a better calibrated model.

Limitations

Limitations for my model largely come from the input data layers. The wetlands layer is mostly only accurate for open wetlands, not forested wetlands (Gallop, 2023) which are important for OSFL habitat. Therefore, the Wet Areas Mapping (WAM) model was used to mitigate some of the limitations with the wetlands layer, as the WAM more accurately reflects wet ground. However, if WAM is determined by drilled well measurements, it could potentially record false water table depths if a well that measures the water depth is drilled into a confined aquifer (Greene, C., pers. com., 2023).

Another limitation of the input data is the difficulty to distinguish between black spruce (*Picea mariana*) and red spruce (*Picea rubens*). Because the FID uses remote sensing photo interpretation to identify tree species (NSDNR, 2021), it can be hard to identify one species from the other, especially because they often hybridize (Perron & Bousquet, 1997). Therefore, we can not be confident that the FID accurately identifies black spruce. To reduce the limitations, the black spruce, red spruce, and the black and red spruce mixed stands in my layer were included in the distance to spruce-dominated stand layer.

The spatial resolution of the predictions from this study's habitat suitability model may also be limiting, despite the high spatial resolution of several of the input layers. The predictive power of the model may not be much finer than 250m, as this is the maximum threshold for location accuracies in the occurrence data used. The breeding bird survey (BBS) data is collected from roadside stops, and rarely is a bird in a tree right next to the road. A bird could be singing from within a radius of 400m, the maximum distance from a point that you can note a bird according to the BBS guidelines (ECCC, 2023). It is common for people to detect an OSFL singing 100m – 200m away in forests, or 300m across bogs, clearcuts, or water bodies (C. Staicer, pers. com., 2023). However, the AC CDC data includes a measure of locational accuracy that was used to determine whether to retain an observation.

The spatial resolution of the input data brings up another limitation which is storage capacity. Originally, this study aimed to apply a model to the provincial scale; however, the storage drives quickly ran out of space before finishing the first LiDAR metric layer. Therefore, instead of modeling the whole province, the scope was reduced to just the southwestern part of the province. Although the original methods and aim for this study involved modeling the entire province, this was not the realized case. The methods could be scaled up to the whole province, but the storage capacity would be far too much for the equipment used during this study.

Results

<u>Analysis of CHMs</u>

A visual analysis of the 5ha plots showed that 10 of the 19 sites experienced some sort of disturbance that resulted in a decreased canopy cover observed in the drone CHMs when compared to the LiDAR CHMs. The collection dates for the drone imagery and LiDAR CHMs, along with the type of disturbance experienced between the collection dates at each site is shown in Appendix A. As a result of the discrepancy in canopy cover between the two CHMs at several of the sites, the variables in the LiDAR CHMs were standardized to the drone CHM's canopy cover area to ensure I was only comparing metrics from trees and their canopy that were present in both CHMs (Table 3). Rugosity was the one metric not calculated from the standardized LiDAR CHM because the standardization of the CHMs involved vector points and polygons that are not conducive to conducting analysis of surface roughness.

Table 3: Change in canopy cover area in the LiDAR CHMs after being standardized to the drone CHM canopy area at each of the 19 sites.

	Canopy Cover Area (ha)			Change in LiDAR Canopy Cover
Site	**Drone**	**LiDAR**	**Standardized LiDAR**	**After Standardized (ha)**
End Victory Rd	1.63	2.30	2.28	-0.02
Harvest Block 13	2.57	2.47	2.47	0.00
Long Lake	1.63	2.36	2.33	-0.02
MCFC Burn	0.41	2.13	1.19	-0.94
Otter Pond East	2.69	4.51	3.71	-0.80
Otter Pond West	1.86	2.70	2.52	-0.18
Palmer Lake	2.74	3.01	3.00	0.00
Reagans Extension	1.81	2.41	2.40	-0.01
River Tillard 1	3.02	3.24	3.20	-0.04
River Tillard 2	1.68	2.44	2.20	-0.25
River Tillard 3	1.79	3.68	2.64	-1.04
River Tillard 4	0.71	3.21	1.33	-1.88
River Tillard 5	1.57	2.94	2.24	-0.70
Stillwater 1	1.20	2.45	2.08	-0.37
Stillwater 2	2.73	3.65	3.58	-0.07
Tupper Barrens	1.15	1.97	1.95	-0.02
Twin Lake Burn 1	1.43	4.52	1.50	-3.02
Twin Lake Burn 2	2.04	3.26	2.36	-0.90
Victory Rd Swamp	1.45	1.49	1.49	0.00

Measuring variables in the drone and LiDAR data involved comparing the CHMs, as well as the attributes of individual trees that were identified within each CHM using the variable-window function from Swayze & Tinkham (2022). This equation, set with additional parameters to select only trees >5m in height, had an accuracy of 90.5% and 90.0% for identifying trees in the drone and LiDAR CHMs, respectively. The measurements for each variable obtained from the drone and LiDAR CHMs are shown in Appendix C. A correlation analysis was then performed using these measurements to assess the strength of the relationship between variables in the two CHMs (Table 4). The drone CHMs consistently had a greater Rumple index (i.e., surface roughness) compared to the LiDAR CMHs. The drone CHMs also had more individual trees identified, on average, using the ForestTools local-maximum script to identify tree tops at each site. The spacing of trees was assessed through an Average Nearest Neighbor test, and because of the greater number of trees in the drone CHMs, the average nearest neighbor distance was less than half the size of the average nearest neighbor distance from the LiDAR CHMs. The LiDAR CHMs had higher mean tree heights than the drone CHMs across the 19 sites, but the standard deviation of the heights was more consistent between the two CHMs. There was less canopy cover in the drone CHMs at the 19 sites when compared to the LiDAR CHMs.

Table 4: Mean measurements of variables across the 19 sites and the correlation analysis results for the six metrics assessed between the drone and LiDAR CHMs.

Variable	Drone	LiDAR	Correlation (r value)	Significance (p value)
Rumple Index	3.42	1.83	0.183	0.452
Number of Trees	3656	1735	0.520	0.022**
Nearest Neighbor Distance (m)	1.54	4.15	0.404	0.087
Mean Tree Height	8.90	10.68	0.859*	2.49e-06***
Tree Height Standard Deviation	3.20	3.30	0.899*	1.71e-07***
Canopy Cover (%)	37.24	45.21	0.895*	2.38e-07***

*High correlation relationship (r >0.7)
**Significant at p <0.05
***Significant at p <0.001

Assessing the Relationships of Variables

The relationship between drone and LiDAR measurements for each variable was assessed through a correlation test which determined a high ($r > 0.7$) relationship between the drone and LiDAR measurements for three metrics: canopy cover ($r = 0.895$) and the mean and standard deviation of tree heights ($r = 0.859$ and $r = 0.899$, respectively; Table 4). These metrics were also the only identified metrics as having a highly significant ($p < 0.001$) relationship. Based on these assumptions, the other variables assessed (rumple index, number of trees, and average nearest neighbor distance) were not considered to show a positive relationship between the LiDAR CHM. The rumple index was calculated from the unstandardized LiDAR CHM, and thus calculated the roughness of trees present in the LiDAR CHM and compared it to the roughness calculated by a lack of those trees in drone CHM. This is likely not representative of the relationship between the LiDAR and drone CHMs. Therefore, because it is a strong measure for assessing important characteristics of OSFL breeding habitat (e.g., identifying gaps within stands and mixed aged forests with multiple canopy levels; Kane et al., 2010), I decided to include it as the fifth LiDAR metric input for the predictive habitat model.

Final Inputs for the Model

The environmental layers used as inputs for the MaxEnt model consisted of nine layers: i) proportion of canopy cover; ii) canopy clumping; iii) mean canopy height; iv) standard deviation of canopy height; v) canopy roughness (i.e., TRI); vi) topographic position (i.e., TPI); vii) depth to water table; viii) distance to wetlands; and iv) distance to spruce-dominated tree stands. The first five listed input layers were derived from the provincial LiDAR CHM.

From the 1,011 observations of OSFLs in the Kespukwitk area during the breeding season with location accuracies ≤250m, only 318 observations were used as the occurrence data after removing points in water or within 1km of each other. A bias layer created as a kernel density of expected counts with a search radius of 10km was created to further reduce the bias of the occurrence data to account for locations where people have conducted surveys in search of the bird or for standard Breeding Bird Surveys (Figure 4).

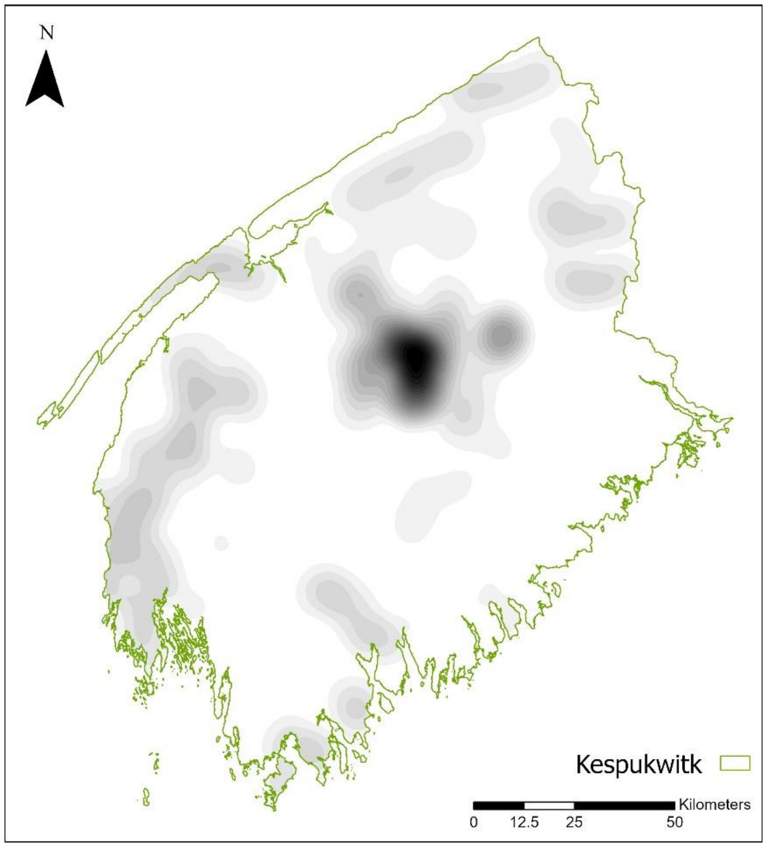


Figure 4: Kernel density maps showing the relative density of survey locations where people conducted surveys for the OSFL, with darker areas representing higher point densities. The kernel density was used as a bias layer to account for spatial bias with the occurrence data in training the MaxEnt model.

<u>Model Results</u>

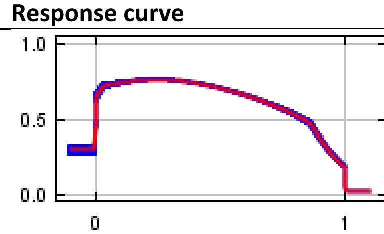
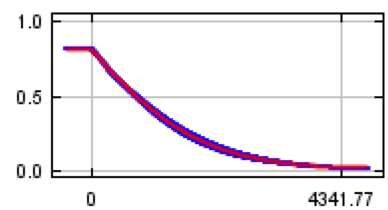
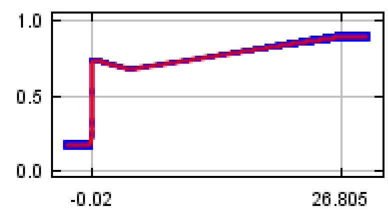
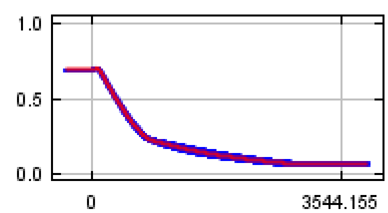
Run 6 was chosen as the "best" model because at least half the variables were removed, and both the regularized training gain and AUC decreased by >1% if the least important variable was removed (when compared to the subsequent run: Run 7; Table 5). The mean AUC_{train} (0.7066) and AUC_{test} (0.6908) values for Run 6 were fairly low but the AUC_{diff} value was also low (0.0158) across 30 cross-validated runs. The observed omission rates for the final best fit model was 0.91% higher than the expected omission rates for LPT and 11.33% higher than expected for 10PT. Therefore, both these metrics indicate that over-fitting did not significantly impact our species distribution model results. The final model included four covariates that represented a range of environmental features including distance to preferred habitat (wetlands and spruce trees) and the amount of canopy cover and the height of the canopy (Table 6).

Table 5: Results of the reverse stepwise elimination trials for determining the best fit model.

Model run	Regularized training gain	Change in training gain*	AUC_{test}	Change in AUC_{test}*	AUC standard deviation	Covariate removed
Run 1	0.3820	-	0.7100	-	0.0783	-
Run 2	0.3402	-0.0418	0.7022	-0.0078	0.0716	TRI
Run 3	0.3391	-0.0011	0.7075	0.0053	0.0674	WAM
Run 4	0.3207	-0.0184	0.7035	-0.0040	0.0690	Canopy Clumping
Run 5	0.3034	-0.0173	0.6899	-0.0136	0.0673	TPI
Run 6	0.3035	0.0001	0.6908	0.0001	0.0681	SD Heights
Run 7	0.2896	-0.0139	0.6827	-0.0081	0.0699	Distance to Spruce

*Calculated as the difference of values between the current run and the previous run.

Table 6: The covariates used in the final best fit model and their percent contribution (i.e. to training gain), permutation importance, and response curves. The y axis of all response curves represents relative habitat suitability, where suitability increased from 0 to 1.

Covariate	Percent Contribution (%)	Permutation Importance (%)	Response curve
Proportion of Canopy Cover	56.74	60.38	
Distance to Wetland	29.05	20.07	
Mean Tree Heights	7.34	9.68	
Distance to Spruce	6.87	9.87	

The final map of relative suitability shows that suitable habitat for the OSFL is abundant and distributed in the Kespukwitk area (Figure 5). The maximum training sensitivity plus specificity (MaxSS) threshold was applied to create a binary layer identifying suitable vs. unsuitable habitat, where the model predicted that 48.90% of the Kespukwitk area (including lakes and rivers) is suitable for the OSFL (Figure 6). MaxSS optimizes sensitivity and specificity values and was identified as the most robust threshold by Liu et al. (2013). After extracting clusters of "suitable" habitat with a total area large enough for an OSFL's territory (10-20ha in size; Altman & Sallabanks, 2020), the amount of suitable habitat had minimal change (Table 7).

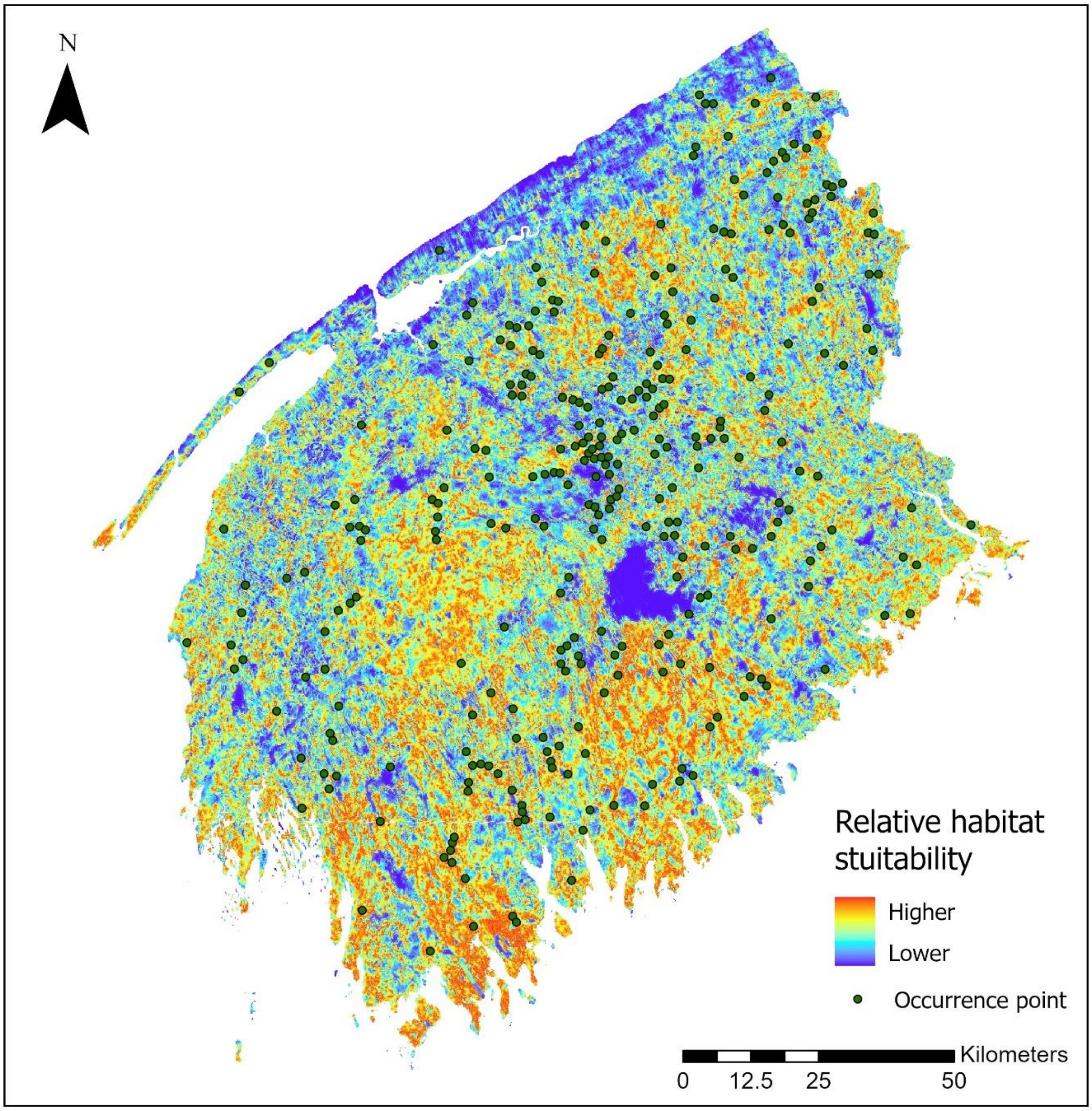


Figure 5: Species occurrence data overlayed on top of the MaxEnt output heat maps of relative habitat suitability for the Olive-sided Flycatcher.

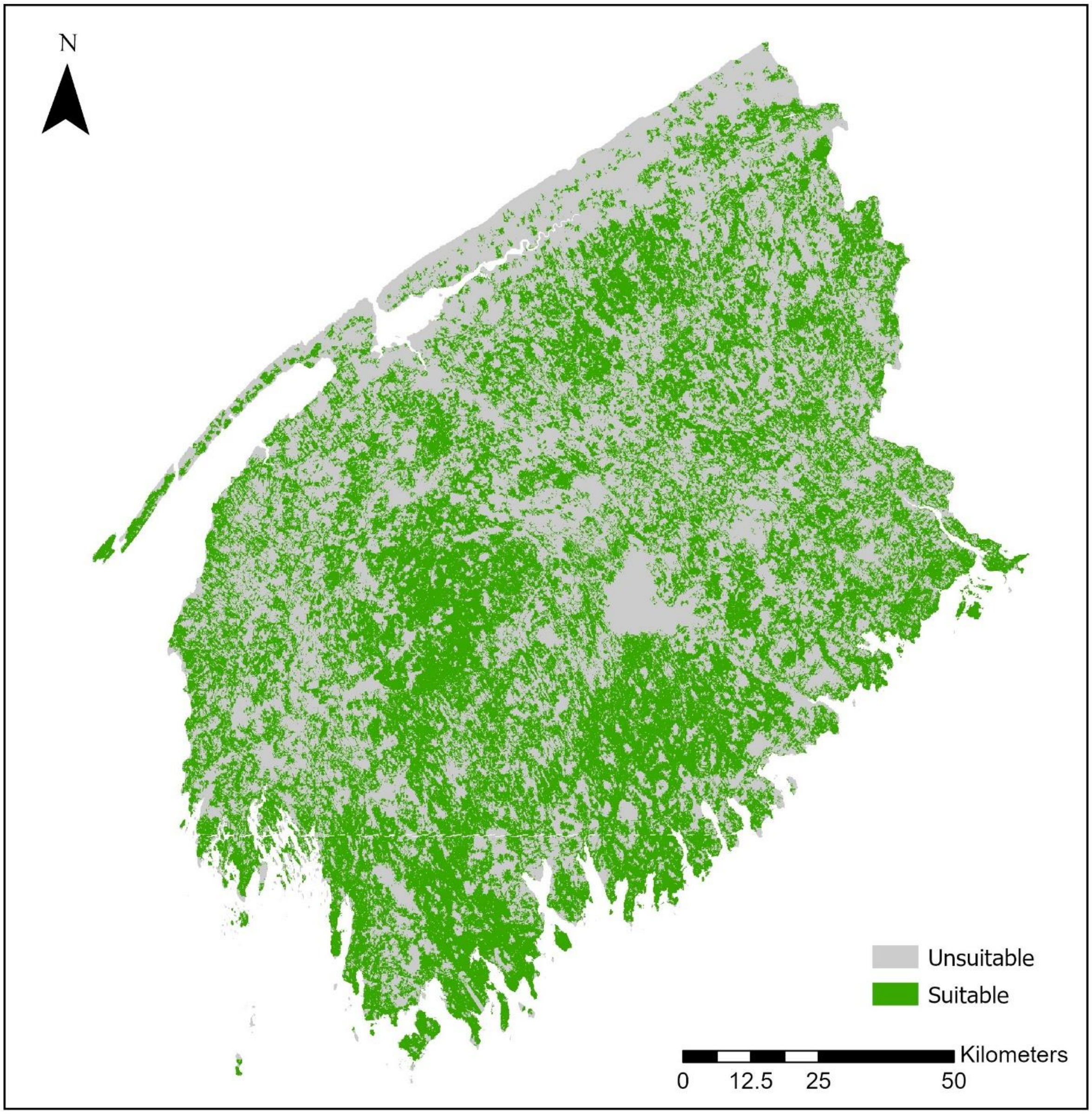


Figure 6: Binary habitat suitability maps created by applying the MaxSS threshold (0.4638) for the Olive-sided Flycatcher, showing suitable habitat in green and non-suitable habitat in grey.

Table 7: Amount of suitable habitat in the Kespukwitk area after applying the MaxSS threshold with additional minimum area sizes for groupings of "suitable" pixels.

Minimum territory size	Total suitable area (ha)	Percent of the Kespukwitk area
No minimum size	791299	48.90
10ha	753086	46.54
20ha	741419	45.81

Discussion

The final predictive habitat model consisted of four input variables to characterize OSFL habitat in the Kespukwitk area of southwestern Nova Scotia: distance to wetlands, distance to spruce-dominated stands, proportion of tree cover, and the mean height of tree cover, which aligns with the features characteristic of OSFL habitat observed in previous habitat studies.

While the 1m spatial resolution of the LiDAR CHM was conducive to identifying some within-stand variation, it was too coarse to identify other metrics observed in the finer resolution drone CHMs. The differences in the spatial resolution of drone and LiDAR CHMs directly influenced the measurements obtained by some of my methods for comparing the CHMs at the 19 study sites. These discrepancies between LiDAR and drone CHMs are logical and for the most part follow results I anticipated to see when comparing the two types of CHMs. The higher rugosity can be attributed to the higher spatial resolution of the drone CHMs being able to measure and show slighter changes in the canopy surface. In contrast, the LiDAR has a smoother surface due to having to represent a larger area of canopy surface by one 1m pixel, thus losing the complexity that is seen in the drone CHM.

Even after standardizing the measurements from the LiDAR CHMs to the drone canopy area, the drone CHM had less canopy cover on average than the LiDAR CHMs. This is likely a result of the disturbance experienced between the drone and LiDAR collection dates creating more space for canopy to grow horizontally where there was otherwise another tree in the way at the time when the LiDAR data was collected. If the canopy of each tree increased in the drone imagery, then selecting the LiDAR trees by this area would expand the selection area and potentially cause the selection of additional trees in the LiDAR where the drone's canopy cover grew to overlap. By selecting these additional trees, their associated canopy would also be retained and could explain the greater amount of canopy cover identified in the LiDAR CHMs. Additionally, due to the discrepancy in the collection dates between the drone and LiDAR data, the tree heights were not expected to be similar as a result of more growing time for the vegetation observed in the drone imagery; however, it was surprising to see that the tree heights were taller on average in the LiDAR CHMs at the 19 sites. Yet, even with the difference in the tree heights, the standard deviation of the tree heights was more consistent between the two CHMs, and both variables were still considered to show strong relationships.

It was expected that the rugosity layer would reflect similar canopy variation as the standard deviation of canopy heights layer. Therefore, both were included in the model to see which was a more useful predictor of OSFL habitat. Yet, with rugosity being a good at identifying gaps within stands and mixed aged forests with multiple canopy levels (Kane et al., 2010), all of which are important characteristics of OSFL breeding habitat, I was surprised to see it be the lowest performing input variable in the initial run of the model. Perhaps the TRI did not calculate rugosity in a useful way. As such, further research is needed to identify the best way to incorporate measures of rugosity into future models.

The final covariates used for my model (distance to wetlands, distance to spruce stands, proportion of canopy cover, and mean tree heights) were similar to the final inputs for previous OSFL models. My results supported the conclusion of Westwood et al. (2019), with both of our studies demonstrating measures of wetness and forest cover as the best contributors for identifying for OSFL habitat. However, the Westwood et al. (2019) model used depth to water table to measure wetness, and this variable was one of the first covariates removed during my stepwise elimination, likely because a proximity to wetlands measures a similar variable that is related to a depth to water table. Distance to wetlands is also likely correlated to TPI because wetlands are in low lying areas (Province of Nova Scotia, 2014), which could explain why TPI was the fourth eliminated covariate in my stepwise elimination. In contrast, TPI was one of the top four best performing covariates in the Bale et al. (2020) model, where it likely performed better as a result of the greater topographical variation across the province. The Bale et al. (2020) model represented all of Nova Scotia, including northern Cape Breton where there is very high relief and more vertical variation in contrast to my model of southwestern Nova Scotia, which lies generally low. However, both of our models found that habitat in proximity to the OSFL's preferred tree to be important variables for predicting OSFL habitat. My final best fit model (AUC_{train} = 0.7066, AUC_{test} = 0.6908, LPT omission rate = 0.91%, 10PT omission rate = 11.33%) was very similar to the Bale et al. (2020) model (AUC_{train} 0.6850 and AUC_{test} 0.6674, LPT omission rate = 0.39%, 10PT omission rate = 11.98%), suggesting that although I used environmental covariates aimed to identify variability within OSFL habitat, these metrics may not be much more conducive to predicting habitat locations at this scale than previous models.

Despite two of the four environmental covariates in my final best fit model having been derived from LiDAR data, they did not measure much of the within-stand variability that I believed to be important identifiers for OSFL breeding habitat. The two final LiDAR metrics (proportion of canopy cover and mean tree heights) represented mean values for measures of within-stand variability. I believe this to be attributed to the coarse scale at which my input layers were standardized for analysis in MaxEnt. However, my model did use input layers at a finer spatial resolution (100m) than the two previous models by Westwood et al. (2019) and Bale et al. (2020) who standardized inputs to a 250m and 150m spatial resolution, respectively. Resampling data to any of these scales makes it difficult to accurately represent measures of within-stand variability. Just resampling measures of variability derived from the LiDAR CHM to coarser spatial resolutions loses the complexity of the area represented by each pixel. Therefore, future models that intend to use metrics that identify variability in LiDAR-derived metrics should create inputs based on a scale of the amount of variability observed within the area. For example, rather than calculating the standard deviation of tree heights and resampling the outputs to a 100m spatial resolution, a measure that shows the abundance or range of standard deviation values within the 100m^2 area could potentially be a stronger predictor of habitat suitability. This is seen in my results that show the proportion of canopy cover input layer as the best performing covariate. This layer was created with the aggregation of the 1m spatial resolution to a coarser scale being taken into account as the final pixel values, as opposed to the rest of the LiDAR input layers being created and then resampled to 100m.

The proportion of canopy cover had the highest performance of any other inputs, even greater than any inputs used in Bale's model. I was not expecting this to be the case, given that there isn't much in the literature stating that the amount of canopy cover is extremely important for characterizing OSFL habitat. This is further confusing given that OSFL habitat could be forest wetlands (with moderate amounts of canopy cover) or barrens and even post-burn sites where there is little canopy cover on the trees (McBeath, 2023). However, with how high of a contributing factor the proportion of canopy cover played in my model, even when alongside other inputs that were high-performing covariates in previous models by Westwood et al. (2019) and Bale et al. (2020), there is likely some sort of variation that is also being identified within this layer. An explanation for this could be that the proportion of canopy cover is also a proxy for other important characteristics of OSFL habitat, such as greater spacing between trees that would result in gaps in canopy cover, or identifying snags and dead tips of trees that are preferred perches for OSFLs (Altman & Sallabanks, 2020) and would have lower canopy cover.

The suitable habitat identified in my model was abundant across the study area, but most prevalent in areas with fewer OSFL occurrences. The OSFL occurrence points used as inputs for the MaxEnt model were largely clustered to the north-east quadrant of my study area; however, most of the suitable habitat was identified to the south-west portion. This shows the importance of the spatial thinning of the occurrence data and the use of a bias layer when running MaxEnt because the occurrence data was spatially biased towards areas that are more accessible, like Kejimkujik National Park, and frequently surveyed areas, evident by large clustering of points around areas with a high density of bird survey locations. There were fewer occurrences in the larger areas of predicted suitable habitat identified from my model, likely because the final environmental covariates indicate suitability relating to tall spruce stands with moderate canopy cover in proximity to wetlands. In its simplest form, this model was predicting forested coniferous wetland habitats, so the larger areas identified by my model also had fewer occurrence points likely because these locations are understudied in Nova Scotia and difficult to access (Government of Nova Scotia, 2011). However, it is precisely this reason that shows the importance of habitat modeling to identify these areas. We need to identify these larger suitable habitats in order to maintain them and prevent further habitat degradation or loss to effectively promote the recovery of the species (NSDLF, 2021).

Larger areas of suitable habitat are also important to identify because, with the spatial resolution of my predictive habitat model, bits of “suitable” habitat that are only a few pixels are un-inhabitable unless they are large enough to support a territory, which ranges from 10ha to 20ha in size (Altman & Sallabanks, 2020). Therefore, continuous clusters of pixels that cover at least 10ha are the smallest areas that can be considered “suitable” habitat. My model did not show much change in the amount of suitable habitat with this 10ha minimum cut off, but the total area of suitable habitat is unrealistically high for the area which likely suggests that using the MaxSS threshold to determine suitability is too low for this model. However, to be sure, the results of my model would need to be tested, which would require new field data to be collected in these “suitable” habitats.

Conclusion

The OSFL has experienced significant population decline since the 1970s (COSEWIC, 2019), and a lack of knowledge as to where their breeding habitat occurs around the province is preventing effective recovery strategies from being implemented (NSDLF, 2021). Therefore, the identification of OSFL breeding habitat is crucial to promote the recovery of the species. However, the previous models designed to identify OSFL habitat in Nova Scotia were not able to account for the fine-scale forest structure and variability within the habitat that is consistent with the requirements for the bird's foraging technique (McBeath, 2023).

My study aimed to identify how LiDAR data, which has revitalized habitat studies of flying vertebrates (Jaime-González et al. 2017) and was recommended for use of OSFL habitat modeling in previous studies (Westwood, 2016), could be used to improve predictive habitat models for the OSFL by accounting for the bird's foraging ecology. My analysis of the LiDAR data, when compared to high-resolution drone imagery, identified that the provincial LiDAR CHM could measure some types of within-stand variability of OSFL habitat, such as canopy cover and the mean and standard deviation of tree heights. These metrics were then used in my MaxEnt species distribution model to predict potential habitat locations in the Kespukwitk area of southwestern Nova Scotia, which showed that almost half of the area consists of suitable habitat for the OSFL.

Although I was able to identify LiDAR metrics that could show the variability within habitats, these metrics contributed to a predictive habitat model that performed similarly to what previous studies had done without the LiDAR metrics. My best fit model incorporated environmental covariates that measured comparable characteristics of OSFL habitat to previous habitat models, further supporting the importance of spruce forest cover, wetlands, and tall trees to characterize OSFL habitat. However, my model did identify a covariate that performed drastically stronger for predicting suitable OSFL habitat than any other variable used in previous models. This shows that measures of variability within habitats are important for identifying OSFL habitat, supporting recent research that indicates these fine-scale forest structure are among the most important habitat characteristics for determining OSFL occupancy rates (Hack et al., 2023). That this one measure of habitat variability derived from the LiDAR metrics outperformed other covariates shows that the way in which fine-scale forest structure and its variability is measured and represented has an impact on the layer's contribution to predictive habitat models. As such, future models that aim to identify the fine-scale variation within habitats using input layers at coarser spatial resolutions should develop their inputs to reflect the area represented by each pixel as opposed to resampling measurement to greater areas.

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APPENDIX A:
THE DISTURBANCE EXPERIENCED BETWEEN COLLECTION DATES OF THE DRONE AND LIDAR DATA AT EACH SITE

		Collection Date		
Region	**Site**	**Drone**	**LiDAR**	**Disturbance:**
Southwestern NS	End Victory Rd	2022-09-12	2019	None
	Harvest Block 13	2023-08-03	2019	None
	MCFC Burn	2022-07-14	2019	Burn
	Palmer Lake	2022-06-23	2019	None
	Stillwater 1	2022-07-10	2019	Blow down
	Stillwater 2	2022-07-10	2019	Blow down
	Tupper Barrens	2022-09-19	2019	None
	Twin Lake Burn 1	2022-09-13	2019	Burn
	Twin Lake Burn 2	2022-09-13	2019	Burn
	Victory Rd Swamp	2022-09-12	2019	None
Eastern Shore	Otter Pond East	2022-07-16	2019	Blow down
	Otter Pond West	2022-07-26	2019	Blow down
Cape Breton	Long Lake	2022-07-21	2018	None
	Reagans Extension	2022-07-21	2018	None
	River Tillard 1	2022-07-21	2016	None
	River Tillard 2	2022-07-21	2016	None
	River Tillard 3	2022-07-21	2018	Harvest
	River Tillard 4	2023-08-25	2016	Harvest
	River Tillard 5	2022-07-21	2018	Harvest

APPENDIX B:
CREATION OF MAXENT GIS INPUT LAYERS

Topographic Position Index. The topographic position index (TPI) is a measure of local elevation relative to the surrounding "neighborhood" (Weiss, 2001) calculated from the Provincial LiDAR digital elevation model (DEM) with a 1m spatial resolution. I ran the 'Focal Statistics' tool in ArcGIS on the DEM clipped to my study area to generate three new DEM-derived layers: the minimum elevation (DEM_{min}), maximum elevation (DEM_{max}), and mean elevation (DEM_{mean}) using a 10m x 10m square search window. Following the method in Bale (2017), a continuous TPI layer was then calculated for the study area using the 'Raster Calculator' tool with the equation: $TPI = (DEM_{mean} – DEM_{min}) / (DEM_{max} - DEM_{min})$

The spatial resolution of the continuous TPI layer was increased to 100m using the 'Resample' tool with a bilinear resampling method so that the resolution was consistent with all other environmental data layers. Lastly, using the 'Reclassify' tool, the continuous layer was converted to a categorical layer with five classes defined by standard deviation (SD): valleys (< -1 SD), low-slopes (-1 Sd to -0.5 SD), mid-slopes (-0.5 SD to 0.5 SD), upper-slope (0.5 SD to 1 SD), and ridges (>1 SD).

Depth to Water Table. A continuous index of the depth to water table (DTW) was used to delineate distance between the water-table and the soil surface. This layer was derived from the new LiDAR-derived Wet Areas Mapping (WAM) model obtained from John Gallop, Nova Scotia department of Environment and Climate Change – wetlands program, which is more effective at identifying forested wetlands in the province (Gallop, 2023). Using the 'Extract by Mask' tool, with my study area as the mask, the raw DTW values from the WAM within my study area were extracted and then resampled to a 100m spatial resolution using the 'Resample' tool and a bilinear resampling method.

Distance-based Layers. Two distance-based layers were created to delineate distance from wetlands and spruce-dominated stands, to show habitat suitability as a function of proximity to these two features, both of which are preferred habitat characteristics for the OSFL (Westwood, 2016). Both distance layers used delineated polygon features extracted from the provincial Forest Inventory Data (FID) using the 'Select by Attribute' tool to identify polygons with desired characteristics. Wetland delineated boundaries were identified through the "FORNON" field, where polygons were selected if the field was equal to 70 (general wetlands), 71 (beaver flowage – any area that is or has been occupied by beavers), 72 (open bogs), or 73 (treed bogs). Once the desired polygons were selected, they were exported to their own layer so that I could use the 'Euclidean Distance' tool to generate a continuous raster file (with cell size of 100m) identifying each pixel's distance to the nearest wetland. The same process with done to calculate the distance to spruce-dominated stands, where the FID polygons were identified by the "species" fields as having either of the top two dominant species in the stand be black spruce, red spruce, or mixed stands (i.e., SP1 or SP2 fields were equal to BS or RS or XS).

Proportion of Canopy Cover. A measure of canopy cover was included as an input layer to distinguish between forest and non-forest and to show the variability among tree stands. Canopy cover was derived from the provincial LiDAR CHM, where I used the 'Reclassify' tool to create a binary layer, reclassifying values between 5m and 35m (inclusive) to 1, and setting all other values outside of this range, including "NODATA" values to 0. Values <5m were believed to be too small to classify as trees, while values >35m were assumed to be too tall to be trees and more likely to be building. This binary layer of only 1 and 0 values was then aggregated by mean to a square tessellation with $100m^2$ grid cells using the 'Zonal Statistics as Table' tool. The output table with the mean values was then joined to the tessellation layer and then converted to a raster with a 100m cell size, where each pixel represented the average amount of canopy cover within the $100m^2$ area.

Canopy Clumping. A second canopy binary layer was calculated, this time considering 8m as the lowest threshold height for canopy. I chose to use a a minimum height of 8m to remove some autocorrelation with the proportion of canopy cover layer and because this was the lowest perch height at which an OSFL was observed to occupy at my study sites (McBeath, 2023). From this binary layer, a canopy clumping layer was calculated using the 'Focal Statistics' tool as the sum of the focal cell and the 8 cells surrounding it (1m radius square window size) to be consistent with the findings in McBeath (2023) who observed a scale of clumping for trees in OSFL territory between 0.5m – 1.5m. The output sum layer was then standardized using the 'Raster Calculator' tool, dividing the sum layer by 9 to show the amount of canopy clumping at each cell on a scale of 0 (no canopy cover around the focal cell) to 1 (focal cell is completely centered in canopy), with anything between showing a mix of canopy and no canopy. The spatial resolution of the final canopy clumping layer was then increased to 100m using the ‘Resample’ tool and a bilinear resampling method.

Terrain Ruggedness Index. A terrain ruggedness index (TRI) was used as a measure of elevation difference between adjacent cells to compare the complexity of neighbouring values (Riley, 1999). This index was used to show a measure of vertical heterogeneity of the canopy surface as a proxy measure for rugosity. The TRI was derived from the LiDAR CHM, manipulated using the ‘Set Null’ tool to only have values between 5m and 35m (inclusive), so that only canopy roughness was measured. The ‘Focal Statistics’ tool with a 10m x 10m window size was used to calculate the minimum, maximum, and mean from the manipulated CHM. A continuous TRI layer was then calculated using the ‘Raster Calculator’ with the same equation used to create the TPI, but this time with focal statistic output layers derived from the LiDAR CHM: TRI = $(CHM_{mean} – CHM_{min}) / (CHM_{max} – CHM_{min})$. The spatial resolution of the final TRI layer was then increased to 100m using the ‘Resample’ tool and a bilinear resampling method.

Focal Statistics Layers. Two focal statistics layers were created to show a measure of CHM heights, with one layer representing the mean heights and the other showing the standard deviation (SD) of the heights. The mean and SD layers were derived from the manipulated LiDAR CHM with only values between 5m and 35m (inclusive), and were calculated as the mean and SD, respectively, using the ‘Focal Statistics’ tool with a 10m x 10m window size. The spatial resolution of the final mean and SD layers was then increased to 100m using the ‘Resample’ tool and a bilinear resampling method.

APPENDIX C:

EXTENDED DATA TABLES FOR DRONE AND LIDAR CHM ANALYSIS

Extended Table 4a. Results from analysis of the 19 study sites for the rumple index calculated from the drone and LiDAR CHMs, and the mean and standard deviation (SD) of tree heights (m) calculated from the individual trees identified in the drone CHM and the trees in the LiDAR CHM standardized to the drone canopy cover area.

	Rumple index		Drone tree heights (m)		LiDAR tree heights (m)	
Site	**Drone**	**LiDAR**	**Mean**	**SD**	**Mean**	**SD**
End Victory Rd	3.5510	1.6680	8.2511	3.0905	9.4112	3.3393
Harvest Block 13	2.7247	1.4950	9.2993	3.2808	11.0968	3.2342
Long Lake	3.0876	2.0818	7.5942	2.1965	8.9307	2.2971
MCFC Burn	2.5588	1.9723	9.6597	3.9449	11.5499	4.0431
Otter Pond East	5.0211	2.1367	10.2126	4.3261	13.3518	4.4410
Otter Pond West	4.0161	1.9419	8.7918	4.0507	11.5321	4.6456
Palmer Lake	3.0665	1.8121	9.9179	3.7909	10.1706	3.1755
Reagans Extension	3.3633	2.0828	7.6917	2.1889	9.2258	2.5503
River Tillard 1	3.3503	2.0231	9.0491	3.0076	9.0817	2.6892
River Tillard 2	3.0132	1.8022	8.0795	2.4426	8.1467	2.3448
River Tillard 3	3.0898	1.7599	7.6836	1.9112	8.4934	1.9292
River Tillard 4	1.5497	1.6283	7.2908	2.0293	7.7503	2.1063
River Tillard 5	2.7477	1.7612	8.3342	2.4564	9.6771	2.3805
Stillwater 2	4.4506	1.7551	10.3436	4.8196	14.1013	5.0711
Stillwater 1	5.9646	1.6687	8.9383	4.8712	13.6989	6.6198
Tupper Barrens	3.3152	1.7689	8.1560	2.7660	9.6727	3.1340
Twin Lake Burn 1	2.7188	1.9986	11.0631	3.4180	13.6221	2.4203
Twin Lake Burn 2	4.5562	1.8472	10.6610	3.5251	14.5460	3.1938
Victory Rd Swamp	2.7470	1.5146	8.0358	2.7479	8.8863	3.1000
Mean	3.4154	1.8273	8.8975	3.2034	10.6813	3.3008

Extended Table 4b. Average Nearest Neighbor (NN) analysis of individual tree identified in drone CHM and the identified trees in the LiDAR CHMs standardized to the drone canopy area. Average NN analysis involves the observed average distance to the nearest neighbor (in metres), the expected vs observed NN ratio, the z-score, and its significance.

	Drone					LiDAR				
Site	# of Trees	NN distance	NN ratio	z-score	p-value	# of Trees	NN distance	NN ratio	z-score	p-value
End Victory Rd	3505	1.5125	0.7611	-27.0603*	0.0000	744	4.5605	1.0575	3.0004**	0.0027
Harvest Block 13	4450	1.4884	0.8883	-14.2609*	0.0000	765	4.2936	1.0706	3.7365**	0.0002
Long Lake	4667	1.2515	0.7764	-29.2291*	0.0000	1427	3.2890	1.1274	9.2065**	0.0000
MCFC Burn	1066	2.0839	0.5608	-27.4446*	0.0000	314	6.0320	0.8858	-3.8789*	0.0001
Otter Pond East	4078	1.4856	0.8468	-18.7151*	0.0000	873	4.7669	1.2598	14.6912**	0.0000
Otter Pond West	3276	1.4603	0.7480	-27.5985*	0.0000	657	4.9857	1.1496	7.3401**	0.0000
Palmer Lake	3545	1.6455	0.8622	-15.6972*	0.0000	1038	4.2285	1.2009	12.3900**	0.0000
Reagans Extension	5285	1.1861	0.7714	-31.7923*	0.0000	1294	3.4577	1.1210	8.3283**	0.0000
River Tillard 1	5950	1.3236	0.9136	-12.7570*	0.0000	10315	1.5359	0.9751	-4.8312*	1E-06
River Tillard 2	4624	1.3540	0.8139	-24.2090*	0.0000	7189	1.4952	0.7797	-35.7340*	0.0000
River Tillard 3	4802	1.5564	0.9622	-5.0149*	1E-06	925	4.1720	1.1376	8.0126**	0.0000
River Tillard 4	2722	1.8025	0.8127	-18.6967*	0.0000	4054	1.6272	0.6278	-45.3445*	0.0000
River Tillard 5	3239	1.7095	0.8676	-14.4199*	0.0000	747	4.2408	1.0367	1.9193**	0.0550
Stillwater 2	1758	1.8700	0.6449	-28.4900*	0.0000	475	5.4764	0.9837	-0.6820***	0.4952
Stillwater 1	4043	1.4905	0.7736	-27.5443*	0.0000	736	4.9399	1.1136	5.9012**	0.0000
Tupper Barrens	2865	1.4361	0.6813	-32.6448*	0.0000	571	5.4720	1.1647	7.5341**	0.0000
Twin Lake Burn 1	1788	1.8840	0.6525	-28.1207*	0.0000	396	5.2137	0.8551	-5.5225*	0.0000
Twin Lake Burn 2	3357	1.5067	0.7176	-31.3104*	0.0000	516	5.2011	0.9797	-0.8818***	0.3778
Victory Rd Swamp	3151	1.4161	0.6809	-34.2700*	0.00	524	5.0442	0.9962	-0.1669***	0.8675
Mean	3656	1.5444	0.7795			1736	4.1494	1.0193		

*Significant Clustering

**Significant Dispersion

***Random Distribution