University of Northern British Columbia PhD Thesis Proposal

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Broad-scaled Avian Biodiversity Assessment with Passive Acoustic Monitoring

Abstract

In recent decades, the use of Autonomous Recording Units (ARUs) has gained traction to census birds through passive acoustic monitoring. ARUs have been shown to provide equal or better results for species detection than non-recorded, real-time point counts conducted by observers. Furthermore, the development of hardware and analytical tools (e.g., automatic identification of species) have recently expanded the potential uses of passive acoustic monitoring. This project will focus on applying passive acoustic monitoring with machine learning techniques to assess avian biodiversity in an ecosystem in central BC that spans a large spatiotemporal scale. The acoustic data is being collected from ARUs placed in sites that vary in stand composition and forest age within a mixed-wood, sub-boreal spruce ecosystem (the John Prince Research Forest, Ft. St. James, BC). I will first use this large dataset, collected over a three-year period, to evaluate the accuracy of a machine learning technique, BirdNET, on species identification within ARU recordings (Chapter 1). I will then explore the capacity of passive acoustic monitoring for different aspects of animal monitoring: to individually identify birds within a species by their vocalization (Chapter 2); to determine species-level daily and seasonal song activity patterns (Chapter 3); and, to assess community-level biodiversity in relation to habitat composition (Chapter 4). Overall, this project aims to explore the potential applications and limitations of passive acoustic monitoring and the machine learning technique in avian acoustic studies.

Background

Study area and audio data

The data has been collected at the John Prince Research Forest (54° 27'N, 124° 10'W, 700 m a.s.l) during 2020 (May – July), 2021 (February – April, May – July), and 2022 (February – April, May – July). ARUs (AudioMoth; Open Acoustic Devices, 2020) were deployed at 66 sites distributed across the region, representing multiple age classes and compositions of forest/harvesting indicative of the region (Fig. 1). Adjacent sites were at least 3km apart, ensuring independent sampling given the ARUs audio detection radius (i.e., approximately 100m for smaller bird species, and approximately 500m for species with longer propagation distance, such as owls). All recorders were deployed under an identical recording schedule during a given day/season.

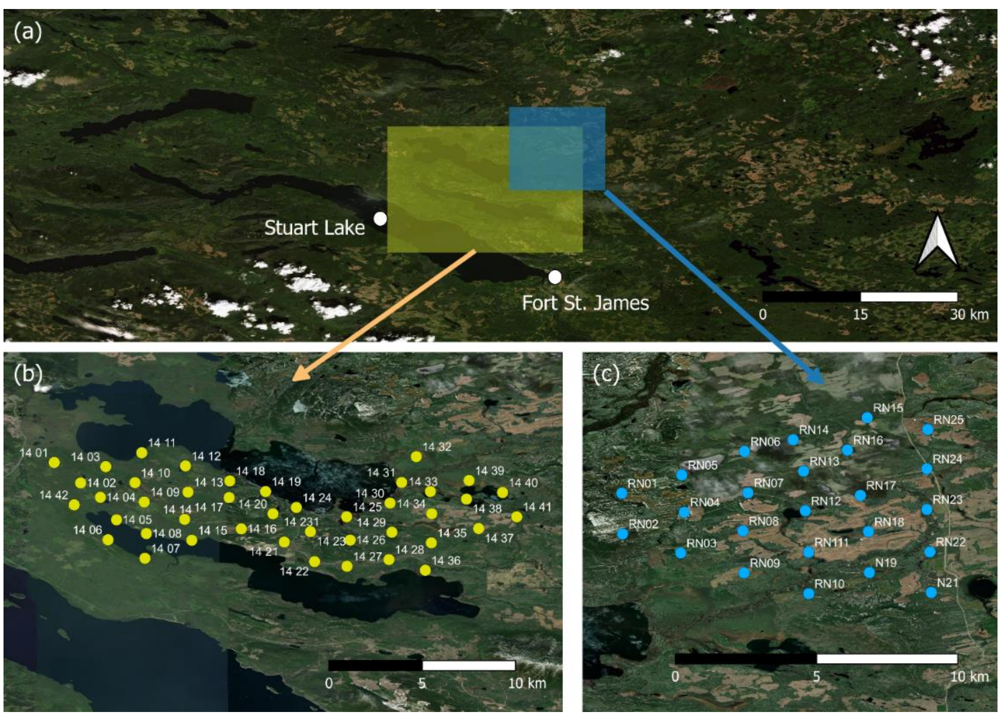


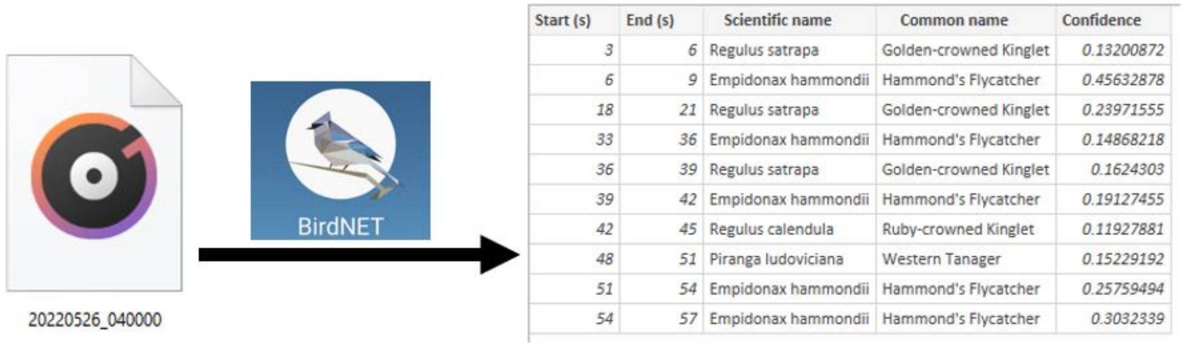
Fig. 1. Locations of recording sites. (a) all sites are located in or around the John Prince Research Forest, north of Ft. St. James, BC. (b) 42 sites are within the research forest. (c) 24 sites locate northeast of the research forest.

During 2020 to 2022, from May through July, which is the breeding season associated with most passerines (i.e., songbirds), we initiated recordings in early May to coincide with the early-breeding species and extended through July to catch later-breeding species. ARUs were set to record daily starting at 4 am and ending at 7 am; this recording window corresponds to the peak period of dawn singing characteristic of most passerines. Each recording day, ARUs actively recorded for one minute followed by four minutes of no recording and repeated this cycle throughout the three-hour recording window. This resulted in a total of 36 one-minute recordings per day, per site.

During 2021 and 2022, from February through April, corresponding with seasonal peaks in vocal activities of owls, we initiated recordings to monitor the owl songs. The recording window was from 6 pm to 10 pm daily. ARUs were set with 10 minutes of active recording followed by 20 minutes of no recording and repeated this cycle throughout the four-hour recording window. The greater amount of recording compared to the breeding period was due to the lower density and vocal activity of owls compared to passerines. Our setting results in a total of 8 ten-minutes recordings per day, per site.

Machine learning as species classifier – BirdNET

BirdNET, a deep neural network-based bird sound classifier, is capable of identifying 984 North American and European bird species by sound. The classifier analyses recordings in 3-sec segments, and within each segment detects any of the 984 recognized species with a 'detection confidence' between 0 – 1, with higher values associated with greater possibility of true detections (Fig. 2). BirdNET requires several input arguments during analysis (Table 1). Arguments in BirdNET allow the researcher to specify parameters to increase the performance of the algorithm. If not otherwise specified, the model uses default values for these settings. I will run BirdNET analysis on the High Performance Computing lab in the University of Northern British Columbia. Specifically, I will use the Intel Xeon Silver 4114 cluster containing 16 compute nodes, each with 36 Intel Xeon Gold 6140 core processors.



Start (s)	End (s)	Scientific name	Common name	Confidence
3	6	Regulus satrapa	Golden-crowned Kinglet	0.13200872
6	9	Empidonax hammondii	Hammond's Flycatcher	0.45632878
18	21	Regulus satrapa	Golden-crowned Kinglet	0.23971555
33	36	Empidonax hammondii	Hammond's Flycatcher	0.14868218
36	39	Regulus satrapa	Golden-crowned Kinglet	0.1624303
39	42	Empidonax hammondii	Hammond's Flycatcher	0.19127455
42	45	Regulus calendula	Ruby-crowned Kinglet	0.11927881
48	51	Piranga ludoviciana	Western Tanager	0.15229192
51	54	Empidonax hammondii	Hammond's Flycatcher	0.25759494
54	57	Empidonax hammondii	Hammond's Flycatcher	0.3032339

Fig. 2. The input and output products of BirdNET. BirdNET takes audio files (e.g., .wav or .mp3) then predicts a list of bird species included in the audio clip, with each of the detection having a corresponding confidence value.

Table 1. Input arguments in BirdNET and the argument values in this study. Information retrieved from BirdNET Github page (https://github.com/kahst/BirdNET).

Arguments	Definition	Values set in this study
i	Path to input file or directory.	--
o	Path to output directory. If not specified, the input directory will be used.	--
filetype	Filetype of soundscape recordings. Defaults to ‘wav’.	‘wav’
results	Output format of analysis results. Values in [‘audacity’, ‘raven’]. Defaults to ‘raven’.	‘raven’
lat	Recording location latitude. Set -1 to ignore.	--
lon	Recording location longitude. Set -1 to ignore.	--
week	Week of the year when the recordings were made. Values in [1, 48]. Set -1 to ignore.	--
overlap	Overlap in seconds between extracted spectrograms. Values in [0,0, 2.9].	0
spp	Combines probabilities of multiple spectrograms to one prediction. Defaults to 1.	1
sensitivity	Sigmoid sensitivity; Higher values result in lower sensitivity. Values in [0.25, 2.0]. Defaults to 1.0.	1.0
min_conf	Minimum confidence threshold. Values in [0.01, 0.99]. Defaults to 0.1.	0.1

Chapter 1 – Testing the Accuracy of BirdNET

In each of its detection, BirdNET provides a confidence value, ranging from 0 to 1, to indicate the likelihood of the inclusion of specific species (Fig. 2). When using the audio data for any ecological inference, however, researchers need categorical result (i.e., a bird is presence or absence) instead of continuous values (i.e., confidence value from 0 – 1). Therefore, determining a “threshold” of what confidence values to accept as a positive detection is critical for turning continuous values into categorical result. That is, detection with confidence value higher than a predetermined threshold is categorized as positive detection, otherwise negative detection. The optimal threshold should achieve high precision and high recall, and this optimal threshold might differ among different species. In this study, I will compare the detections made by BirdNET against spectrographically confirmed species identification to determine the optimal thresholds for species occur in John Prince Research Forest. This study can serve as a protocol for future studies applying BirdNET.

Research questions

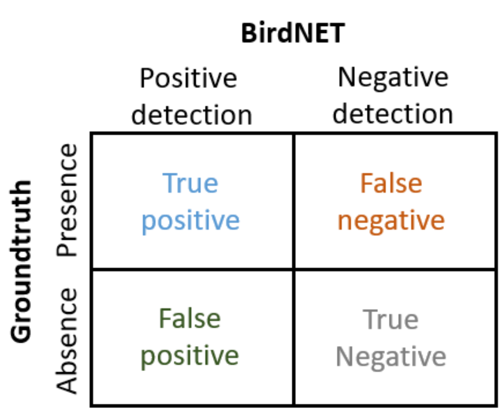
1. How many sound segments are needed to determine the optimal threshold for each bird species?
2. What are the optimal thresholds for species occurring in the John Prince Research Forest?
3. What is the recommended evaluation protocol for future studies applying BirdNET?

Methods

Audio data from 2020 and 2021 breeding season were used. In practice, sampling segments without sound of specific species is easy because most animals produce sounds in a limited time of a day. On the other hand, sampling segments with sounds of target species, especially for cryptic species, can be hard. In order to get a balanced evaluation dataset for each target species, I applied BirdNET on all audio data, then used stratified random sampling to select segments based on their BirdNET confidence value. Detections with a confidence value below 0.1 were assumed to be true negative and dismissed by BirdNET to reduce the computational burden (see Table 1, parameter “min_conf”). The evaluation dataset for each target species were formed by randomly selecting segments where the species was detected with a confidence value, in 0.05 range intervals: i.e. 0.1 – 0.15 (low confidence value), 0.15 – 0.2, 0.2 – 0.25, etc. all the way up to 0.95 – 1 (high confidence value).

Ground truth were obtained by audio and visual inspection of spectrograms in the evaluation dataset, and categorized each segment into presence or absence. Using the same evaluation dataset, I applied thresholds, ranging from 0.125 to 0.975 with an increment of 0.05, to categorize segment into positive detections or negative detections. The segments in the evaluation dataset were then classified as true positive, false negative, false positive, or true negative, based on the ground truth and BirdNET results (Fig. 3). I will then calculate the Precision (the fraction of BirdNET positive detections that are true positives), and compare this with Recall (the fraction of ground truth presence that retrieved by BirdNET positive detections) (Fig. 3). The optimal threshold was to set for individual species identification that results in a Precision higher than 95%, while retain a reasonable Recall of around 70%.

This process will be applied to species that occur in the John Prince Research Forest. The species list was retrieved from one previous study in the same area (Wheelhouse et al., 2022). A total of 20 species will be examined and their optimal threshold will be listed (species list link: https://academic.oup.com/view-large/368348659).



$$Precision = \frac{\#\ of\ true\ positives}{\#\ of\ false\ positives\ + \#\ of\ true\ positives}$$

$$Recall = \frac{\#\ of\ true\ positives}{\#\ of\ false\ negative + \#\ of\ true\ positives}$$

Fig. 3. Categorization rules for segments in the evaluation dataset, and the formula of precision and recall.

Preliminary results

I tested how the size of evaluation dataset would influence the result in determining the optimal threshold. Focusing on Olive-sided Flycatcher, I randomly selected 10 – 50 segments from each of the 18 confidence value ranges (0.10 – 0.15, 0.15 – 0.20, …, 0.95 – 1.00). Then, I calculate the Precision and Recall with thresholds ranging from 0.125 to 0.975 with an increment of 0.05. The value of Precision and Recall stay stable regardless of the size of evaluation dataset (Fig. 4), which provides rationale to only use small evaluation dataset for other species to save human efforts. Thus, I only selected 10 segments from each confidence value range, resulting a total of 180 segments, for other species. Among seven tested species to date, only Olive-sided Flycatcher has a higher optimal threshold as 0.475, all the other species have their optimal threshold as 0.125 (Fig. 5). Further, BirdNET can achieve Precision between 95 – 99% and Recall 69 – 98% for tested species.

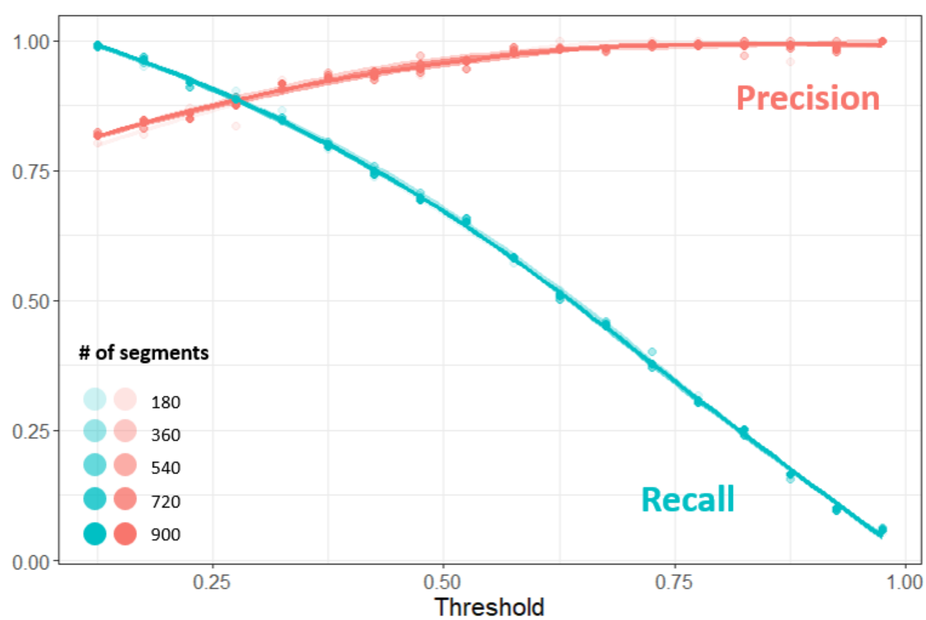


Fig. 4. The effect of evaluation dataset size on the determination of optimal threshold. The higher the threshold, the higher the Precision and lower the Recall. The curves from different numbers of segments almost completely overlap with each other, hence appearing as a single.

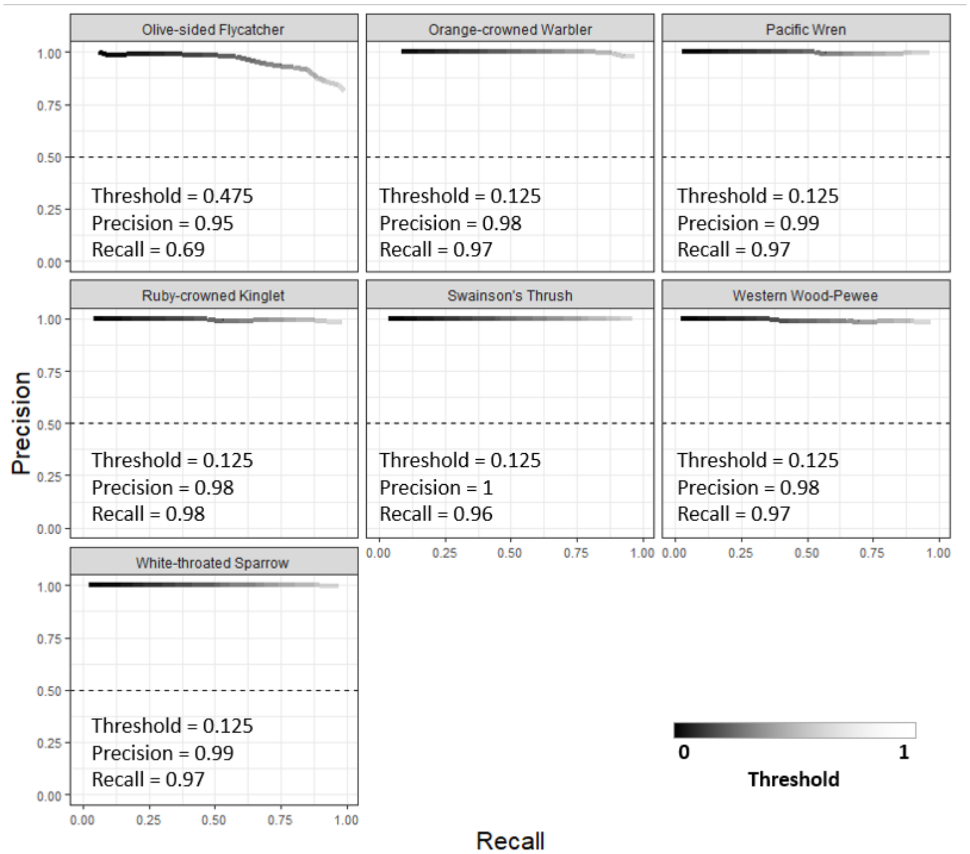


Fig. 5. The precision-recall curve for seven common species in the John Prince Research Forest. A perfect classifier has high precision regardless of any threshold.

Significance of the study and future directions

Next steps are to increase the total number of species evaluated. I have already selected three additional species common for the area that have slightly different vocal characteristics. I will then add at least five species that are the most commonly detected in sound files from the station and those that are the least likely detected. This will cover the species with diverse habitat preference, mixed vocal characteristics, and various vocal activities. The optimal thresholds defined in this study will be used in the following chapters of the thesis. The protocol provided in this study can provide objective evaluation for BirdNET, and can be used for consultants and future studies seeking to evaluate and utilize BirdNET on their audio files.

Chapter 2 – Individual Acoustic Monitoring of the Boreal Owl with Passive Recordings

The use of individuality to 'vocally tag' species allows for greater precision in accurate population censusing and decreases ethical issues in wildlife monitoring associated with the capture and tagging of individuals (McGregor & Peake, 1998). Vocal individuality has been studied and well discussed for the past decades (Terry et al., 2005). Many studies have suggested that vocal individuality can be used to monitor populations using automatic approach; however, few have explicitly tested passive acoustic monitoring in this role. Barred Owl (*Strix varia*) vocalizations have been proven to have vocal individuality (Freeman, 1991), and in this study, I will further investigate Barred Owl's vocal individuality using audio data collected by ARUs. This study would inform the potential of passive acoustic monitoring to be a long-term monitoring tool for owl population censusing or for owl site fidelity studies.

Research questions

1. What temporal or frequency feature of Barred Owl songs collected by ARUs can best distinguish one individual from another?
2. What is the accuracy of individually identifying Barred Owl based on their vocalization?
3. Can passive acoustic monitoring use as a method for Barred Owl individual territorial mapping?

Methods

In this study, I used the recordings collected in Feb – April of 2021 and 2022. I used BirdNET to detect Barred Owl vocalizations within recordings, isolating at least 30 songs per site, ideally, from at least 10 sites. All the frequency and temporal features were measured using Raven Lite, a free software to notate spectrograms, and the R package warbleR, a free modular tool for sound analysis and synthesis (Jerome Sueur et al., 2008). A total of 30 temporal and frequency features were measured for each Barred Owl songs (Fig. 6). These features are typical measurements in other vocal individuality studies of non-passerines (Holschuh & Otter, 2005; Tripp & Otter, 2006). Temporal features, measured in seconds, include: total length of song (sl), duration of individual syllables within the song (d1 – d8), the interval between 2nd and 3rd syllable (i1), interval between 4th and 5th syllable (i2), and interval between 6th and 7th syllable (i3). Frequency features, measured in kHz, include: range of dominant frequency in individual syllables (dfr1 – dfr8), minimum dominant frequency of the song (min_d), maximum dominant frequency of the song (max_d), and mean dominant frequency in syllables (md1 – md8).

I will use discriminant function analysis, a statistical method to categorize observations when there are more than two levels (different males in this study). The dataset will be randomly divided into training (80%) and test (20%) datasets. With the discriminate function analysis, variables will be assessed for their ability to correctly classify individuals to the ARU location (used as a proxy of an individual bird). Songs in the test dataset will be used to evaluate the model goodness of fit, and the proportion of songs that are correctly classified will be calculated.

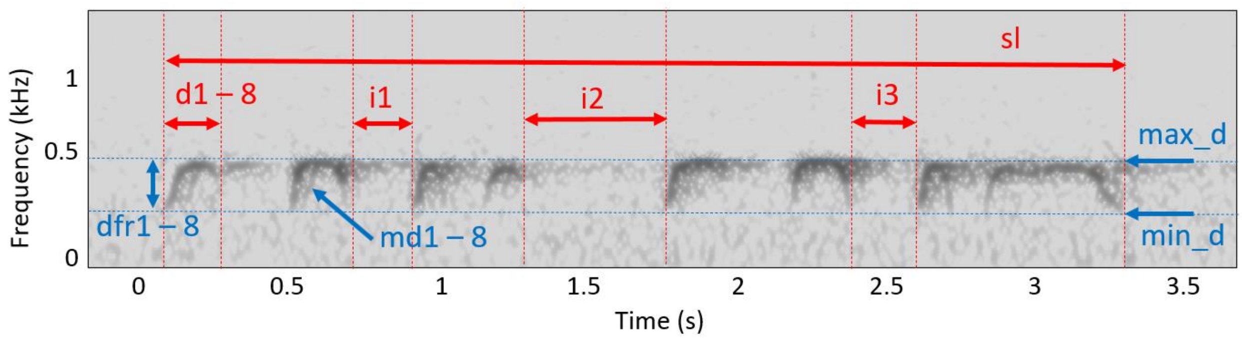


Fig. 6. Spectrogram of a typical Barred Owl song, consisting of eight syllables, with 30 features to be measured for vocal individuality. sl is song length, d is duration of syllable, i is interval between syllables, dfr is the range of dominant frequency, md is mean dominant frequency. max_d and min_d are max and min dominant frequency of the song, respectively.

Preliminary results

A total of 468 Barred Owl songs from 14 sites were identified, with features extracted. I selected the two sites (14_01 and 14_07) with the greatest number of vocalizations recorded for demonstrating the principal component analysis (PCA). I conducted PCA on songs from two sites, and results showed there was sufficient variation to suggest separation of vocal signatures of the owls (Fig. 7).

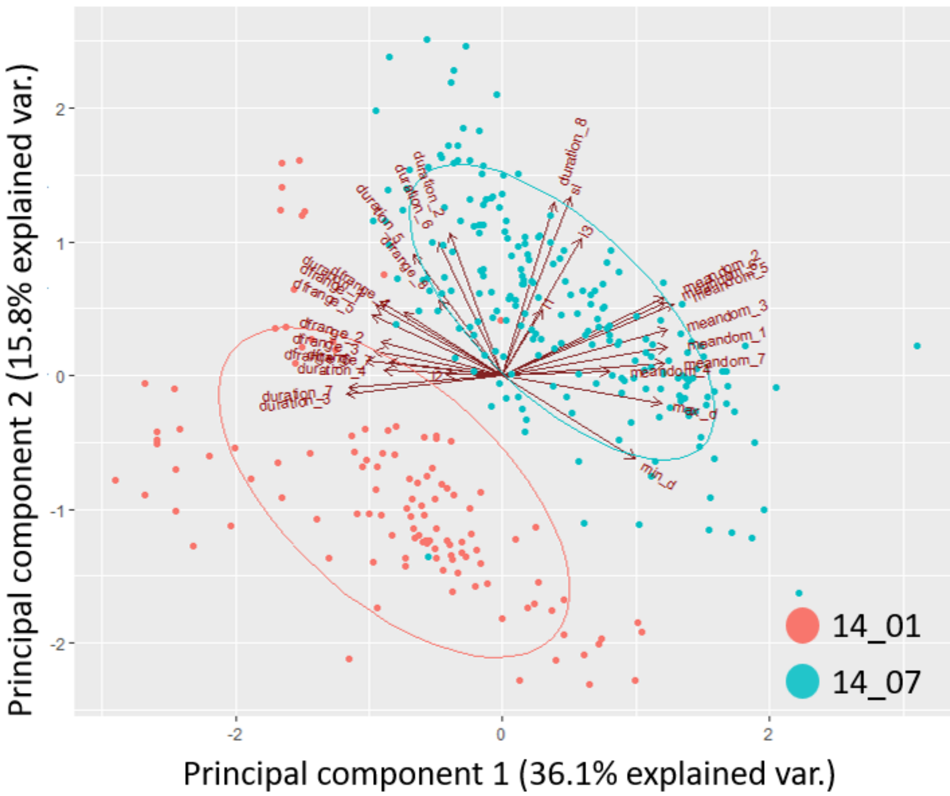


Fig. 7. Results of principal component analysis for songs collected within two sites in year 2021.

Significance of the study and future directions

Next steps in this analysis will be to continue notating the remaining songs from recordings collected in 2022 field season. I will not only compare ability to correctly classify songs recorded from a site within a single season, but will also compare songs from the same sites recorded across the two seasons. Previous studies (Tripp & Otter 2006) suggest high cross-classification between years within a site can be used as a metric of continuous occupancy by the same bird, whereas poor cross-classification between years is an indication of potential territorial turn over. Validating these measures with my dataset will give insight into the utility of passive acoustic monitoring to monitor occupancy and site fidelity in target species.

Chapter 3 - Seasonal and Daily Vocalization Patterns of Olive-Sided Flycatcher using Passive Acoustic Monitoring

Olive-sided Flycatcher (*Contopus cooperi*) is considered under special concern in Canada (COSEWIC, 2018), however, part of its status concern is related to ability to detect the species in acoustic/visual surveys, so determining what affects singing activity might inform methodology to employ during surveying. In this study, I will investigate the seasonal and daily song activity patterns of Olive-sided Flycatchers. I will investigate biotic and abiotic factors that influence Olive-sided Flycatcher song activity, such ambient temperature, precipitation, cloud cover, and the co-exist of other flycatcher species. This research will provide baseline information for when best to set ARUs for monitoring presence/absence of this species, but also demonstrating the use of passive acoustic monitoring on investigating population singing activity across a season and between years.

Research questions

1. What is the seasonal and daily song activity patterns of Olive-sided Flycatcher?
2. What are the factors that affect the singing activity of Olive-sided Flycatcher?

Methods

In this study, I will use the data collected in May – July during 2020 – 2022. The presence of Olive-sided Flycatcher songs and calls will be extracted using detections in BirdNET, applying the detection threshold I established in Chapter 1. I will then summarize several attributes that can be determined from the BirdNET detections (Table 2). Seasonal patterns are defined as the change of song activity (defined in Table 2) in daily intervals; while daily singing patterns are defined as the change in proportion of positive occurrence (defined in Table 2) throughout the daily monitoring time (i.e., 4am to 7am), that is, the probability of detecting an Olive-sided Flycatcher within a specific minute of recordings collected each day.

Abiotic factors (i.e., ambient temperature, precipitation, and cloud cover) will be derived from John Prince Research Forest weather station. To also look at how the biotic factors might affect singing patterns, I will compare the species richness of competing flycatchers on song activity of Olive-sided Flycatchers. I will calculate this flycatcher species richness as the appearance of other flycatcher species per site per day. Other flycatcher species include Least Flycatcher (*Empidonax minimus*), Alder Flycatcher (*Empidonax alnorum*), Western Wood-PeeWee (*Contopus sordidulus*), Dusky Flycatcher (*Empidonax oberholseri*), Willow Flycatcher (*Empidonax traillii*), and Hammond's Flycatcher (*Empidonax hammondii*).

I will use linear mixed effects models to investigate the relationships between song activity (defined in Table 2) and abiotic/biotic factors, where site will be included as a random effect:

$$Song\ activity \sim f(abiotic\ factors +\ biotic\ factors)$$

Table 2. Data attributes that will be summarized, along with their definition and values. OSFL: Olive-sided Flycatcher.

Attributes	Definition	Values
Recording information		
Julian date	The Julian date when the recording was collected	~100 days
Minute	The minute that the recording represented for that day	[1, 36]
Site	The site where the recording was collected	~66 sites
Occurrence	Are there any OSFL detected in that recording	[Y, N]
Singing rate	# of 3-sec segments/min with OSFL detections	[0, 20]
Day and site level		
Song activity	The probability of detecting OSFL on specific day and at specific sites (# of 1-min recordings with positive OSFL detections, out of 36 recorded each day)	[0, 1]
Averaged singing rate	# of 3-sec segments/min with OSFL detections (averaged across all recordings per day where OSFL were detected)	[0, 20]

Significance of the study and future directions

Olive-sided flycatchers are an example of a species where sampling bias may have resulted in some of the concern over local status of the species. Past surveys for these birds in central BC have failed in the past to detect occupation of suitable habitat, and resulted in reports of local declines (E. Bonderud, pers comm). However, surveys were conducted based on when flycatchers were anticipated to return to the region from migration, using sighting data from resources like e-Bird, rather than measure of vocal activity. Preliminary analysis of detection from ARU recorders (Wheelhouse et al. 2022) in the same year as these surveys suggested that vocal activity of the birds peaked several weeks after surveys were collected, and had surveys been timed around vocal activity the results would have been much different. The results of this study will focus on how ARU can be deployed to determine and analyze this vocal activity over extended time periods to provide better methodology on optimal times for censusing, which in turn would provide better data for assessing the relative status of species of concern.

Chapter 4 – Assessing Avian Community Habitat Suitability with Passive Acoustic Monitoring

Predicting species distributions and identifying biodiversity hotspots are essential components of designing conservation strategies. Observation data covering large spatial scale are needed when creating species distribution models across a landscape. Given its ease of deployment and ability to sample over extensive areas simultaneously, passive acoustic monitoring would be an effective method to obtain avian biodiversity data across a large region. In this study, I will investigate the relationships between avian biodiversity and vegetation features, representing the habitat surrounding the ARU sites. Avian biodiversity will be determined from ARU recordings using several metrics, including sound indices such as Acoustic Complexity Index (Pieretti et al., 2011), Acoustic Diversity, and Evenness indices. Vegetation features will be collected using vegetation plot surveys, satellite spectral information, and airborne laser scanning datasets. The models will then be used to predict the species distribution and identify avian biodiversity hotspots in the John Prince Research Forest region. Overall, this research will determine how avian biodiversity (as assessed by audio monitoring) is influenced by habitat features, and also demonstrate the use of passive acoustic monitoring on landscape scale community monitoring.

Research questions

1. What are the vegetation features that best predict the avian biodiversity in the John Prince Research Forest area?
2. Can we identify biodiversity hotspots using data collected by ARUs?

Methods

In this study, acoustic data collected during 2020 – 2022 June will be used. In each study site, three sound indices will be extracted using an R package soundecology (Villanueva-Rivera & Pijanowski, 2018): Acoustic Complexity Index (Pieretti et al., 2011), Acoustic Diversity, and Evenness indices. These sound indices have been tested to relate to bird species richness and infer the singing activity of an avian community (Fuller et al., 2015; Mammides et al., 2017; Sueur et al., 2014).

I will use vegetation survey data, satellite spectral information, and airborne laser scanning to classify habitat variation (Table 3). Vegetation survey were done during the 2022 field season, where canopy closure, tree counts, shrub, and coarse woody debris were measured. This data will be used along with spectral information from Landsat or Sentinel remote sensing imagery on Earth Explorer (USGS, 2022) for categorizing the vegetation features. Finally, airborne laser scanning (LiDAR) data were provided by the John Prince Research Forest. These three levels will provide subsite, site and landscape level information on the vegetative characteristics of the survey areas.

Table 3. Vegetation features for predicting avian biodiversity.

Group	Variables	Definitions
Vegetation plot survey	Large live tree density	# of large live trees/area of survey
	Large dead tree density	# of large dead trees/area of survey
	Small live tree density	# of small live trees/area of survey
	Small dead tree density	# of small dead trees/area of survey
	Percent canopy cover	Percentage of crown areas
	Vertical cover complexity	Cover pole measurements
Spectral	Tasseled cap transformation for wetness	A measured value of soil and canopy moisture
	Tasseled cap transformation for greenness	A measured value for vegetation
	Normalized difference vegetation index (NDVI)	(NIR - red)/(NIR + red)
	Normalized burn ration (NBR)	(NIR - SWIR)/(NIR + SWIR)
Airborne Laser Scanning	BA_sum	Sum of basal area of all trees
	cc1_3m	Average crown closure between 1 – 3m
	cc3_10m	Average crown closure between 3 – 10m
	cc10m	Average crown closure above 10m
	chm	Average canopy height
	CWD	Volume CWD
	d_VRI_rip_wet_st_le	Distance to VRI stream, wetland, lake edge
	d_VRIpolyedge	Distance to LiDAR stream, wetland, lake
	Dist_wet_lake_stream_lidar	Distance to lake edge
	Maximum height	Maximum return height

Significance of the study and future directions

For this study, one potential future direction is to compare the sound indices and the site richness to see how well the indices are actually reflecting the biodiversity value. Biodiversity hotspot mapping requires data collected across a large spatial scale to connect the biodiversity with habitat features. This study will demonstrate the ability of passive acoustic monitoring in large scale biodiversity monitoring and provide new insights on community ecology.

Concluding statement

This thesis will inform the potential for passive acoustic censusing and automated species recognition to inform various aspects of both population and community ecology of birds. Specifically, this project will focus on applying passive acoustic monitoring in 66 sites with machine learning techniques to assess avian biodiversity in an ecosystem in central BC that spans a large spatiotemporal scale. The capacity of passive acoustic monitoring for different aspects of animal monitoring was tested by evaluation of an automatic bird sound classifier (Chapter 1), investigation of possibility of individual censusing using passive acoustic monitoring (Chapter 2), observation of species daily and seasonal singing activity using passive acoustic monitoring (Chapter 3), and assessment of community level acoustical biodiversity (Chapter 4). Overall, this thesis will provide a general view of using passive acoustic monitoring in biodiversity assessment.

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Timeline and funding support

	2022			2023			2024			2025		
	1--4	5--8	9--12	1--4	5--8	9--12	1--4	5--8	9--12	1--4	5--8	9--12
Fieldworks												
ARU survey for passerines												
ARU survey for owls												
Vegetation plot measurements												
Supplimentary data collection												
Subproject 1: BirdNET evaluation												
Audio files upload to server												
Run BirdNET on cluster												
Sample recordings validation												
Manuscript writing												
Subproject 2: Boreal Owl individuality												
Run BirdNET on cluster												
Features extraction and modelling												
Manuscript writing												
Subproject 3: Olive-sided Flycatcher song activity												
Climate and biological data summarize												
Patterns summarize and model fitting												
Manuscript writing												
Subproject 4: Habitat suitabilty modelling												
Vegetation data summarize												
Data analyze and manuscript writing												
Research synthesis												
Complete and defend thesis												
Attend conferences												
Funding support												
UNBC Entrance Scholarship												
Mitacs PhD Fellowship												
NSERC PhD scholarship (applied)												
Teaching Assistant												