Using Commercial Machine-Learning Software to Conduct Bird Species Inventories

by

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Bachelor of Science with Honours, University of New Brunswick – Saint John, 2018

A Thesis Submitted in Partial Fulfillment
of the Requirements for the Degree of

Master of Science in Acoustic Ecology

in the Graduate Academic Unit of Biology

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This thesis is accepted by the
Dean of Graduate Studies

THE UNIVERSITY OF NEW BRUNSWICK

May, 2020

ABSTRACT

Bird species inventories are an effective way to measure changes in an ecosystem. They can be conducted using automated sound recorders. Birds vocalizing in recordings can be found using manual detection (an observer finds and identifies the sounds), or automatic detection (machine-learning software finds and identifies the sounds, and an observer verifies). Here, I present a method of training software to identify regional birds and a method to efficiently verify its identifications. I then compared the number of species detected by manual and automatic detection using ~625 hours of field recordings/site over 29 sites. Automatic detection found ~45% more species/site (average: 28 vs. 19 species/site, $P<0.01$), but each method detected species that the other didn't. Automatic detection finds more species when effort constraints limit manual detection to a small portion of the audio, but for the most complete species list I recommend using a combination of manual and automatic detection.

ACKNOWLEDGEMENTS

Thank you to the Biology department of UNBSJ, anyone whose donation has provided bursaries for students, my internal and external reviewers, and Dr. Jeff Houlahan.

Table of Contents

List of Tables

List of Figures

Introduction

Preamble

Effective ecosystem management often requires species inventories to monitor whether a system is changing over time but gathering the data can be time-consuming, expensive, and difficult. The purpose of this thesis is to present a method of using commercially available machine learning software to automate the processing of audio recordings and more efficiently obtain bird species inventories.

Ecosystem Management and why we Conduct Species Inventories

Ecosystem management is designed to minimize negative changes to the environment by actively managing human activities, measuring how those activities change the ecosystem and responding if the system begins to shift into a less desirable state. Ecosystem resilience is the ability of an ecosystem to absorb disturbance without a change in state (Holling, 1973). Variables important to the functioning of the ecosystem (e.g. diversity) are identified, tracked over time, and used as a diagnostic for ecosystem health.

Biodiversity contributes to an ecosystem's resilience (Peterson et al., 1998); changes in species richness can cause changes in ecosystem function (Moore et al., 1989; Pielou, 1975). Thus, species richness is often measured as a component of ecosystem management (Munn, 1992; Woodley et al., 1993). For example, eutrophication is a proven threat to wetland integrity (Moore, 1990), and wetland plant diversity has been successfully used as an indicator for eutrophication (Moore & Keddy, 1989). However, diversity/species richness are not always adequate for evaluating ecosystem health because it has been shown that ecosystems can show large responses when sets of key species change (Estes & Duggins, 1995; Terborgh et al., 2001) or even a single species (Bellwood et al., 2003).

Diversity generally provides redundancy for important functional groups within the system (Norberg et al., 2001; Walker, 1992). Functional groups can be defined as species that perform similar roles in contribution to an ecosystem function (Naeem, 1998). For example, all photoautotrophs use light to convert airborne carbon into energy, and all decomposers make accessible otherwise inaccessible organic matter (Naeem, 1998). Thus, there may not be much discernible change in a system's ability to recycle nutrients should a single species be extirpated because another may be able to expand and fill the niche. However, variation in species richness within an ecosystem can lead to variation in the number of functional groups (Naeem, 1998) as well as the rate those groups perform the necessary function (Wohl et al., 2004). Thus, diversity and species richness are related to ecosystem health, are simple metrics to gather, and are easily communicated to and interpreted by stakeholders.

Birds are a good taxon for ecosystem monitoring because their populations show quick responses to ecosystem changes (Mikusiński et al., 2001; Rochlin et al., 2011) and rely on easily detected vocalizations often unique to each species. Birds are often sampled using surveys such as point counts, where an observer records all birds seen or heard at a specific location for a specified duration. Point counts require the physical presence of someone skilled at bird identification, which limits the number and duration of surveys. This can be mitigated by using several surveyors but differences in skill among surveyors at different sites may be a confounding factor (Joshi et al., 2017). Further, species identifications made during point or transect counts cannot be verified resulting in frequent observation errors (Zwart et al., 2014).

Technological Advances for Bird Sampling - Audio Recording Units

Audio Recording Units (ARUs) are weather-proof audio recorders that can be installed at sites for long time periods and programmed to record at precise times and for specified durations. They mitigate some of the issues with physical sampling by automating the data collection, potentially reducing the time and money required to collect sound samples at a site. However, because initial equipment cost and time to process large amounts of data are high, ARU usage is better suited to larger-scale monitoring programs (Rempel et al., 2005). Otherwise they may not always be cost effective (Hutto & Stutzman, 2009, Shonfield & Bayne, 2017).

Studies using ARU's benefit from reducing the need for a physical presence to conduct surveys so that many sites can be sampled simultaneously and intensively (e.g. Goyette et al., 2011; Tegeler et al., 2012). Recordings can be processed after sampling is completed, which allows for repeated listening of difficult-to-identify vocalizations and reduces the overestimation of species richness (Campbell & Francis, 2011). ARU's also allow for archiving recordings of vocalizations from a particular place and time and allows for comparisons over time (e.g. frequency changes of bird song with increasing noise (Luther & Derryberry, 2012). Further, as sound recognition technology improves, re-analysis and detections and/or additional analyses can occur. This is not the case for physical surveys, where data collected is only what the observer recorded.

ARUs have drawbacks including a lack of a visual component to surveying, meaning some less-vocal bird species may be missed, which has resulted in fewer species being detected with ARU's than physical surveys in some studies (Hutto & Stutzman, 2009; Klingbeil & Willig, 2015; Leach et al., 2016). Humans may also be able to detect species at a greater distance than ARUs (Sedláček et al., 2015; Sidie-Slettedahl et al., 2015; L. A. Venier et al., 2012) though this is dependent on the quality of recording equipment (Campbell & Francis, 2011). Unnoticed equipment failure is a risk (Shonfield & Bayne, 2017) and there is also a challenge with processing the large amounts of data generated through ARUs. The ease of increasing sampling effort can negate the cost/time-saving benefits of automated sampling if there is not an efficient way to process the data (Hutto & Stutzman, 2009).

Processing Audio Data through Manual Detection

One way, manual detection, of identifying the bird species present on a recording is for human observers to listen to all or a portion of the audio and record the species they can hear and identify. Shonfield & Bayne (2017), in a review of 21 published comparisons, found that manual detection detects about the same number of bird species as physical surveys. However, the authors note that many researchers controlled for effort in their comparisons so that the expert only subsampled audio over the same periods as the physical surveys were conducted. Species inventory surveys using ARUs would not typically use only a single 10-minute recording (Holmes et al., 2014) because the ease of increasing the sampling time is one of the most important advantages of ARUs (L. Venier et al., 2017). Of the four studies where the duration of sampled recordings was longer than the duration of point counts/transects, two studies found similar richness values between physical surveys and manual analysis of recordings (Holmes et al., 2014; McGuire et al., 2011) and two studies detected more species using manual detection (Acevedo & Villanueva-Rivera, 2006; Wimmer et al., 2013). ARUs have great potential, but there is only weak evidence that manual detection detects more species than traditional physical surveys.

Processing Audio Data through Automated Detection

An alternative method of processing audio data from ARUs, automatic detection, uses sound recognition software to identify recorded bird vocalizations that are then verified. Different approaches include band-limited energy detectors (Mills, 2000), binary point matching (Katz et al., 2016), random forests (Ross & Allen, 2014), spectrogram cross-correlation (Katz et al., 2016), hidden Markov models (Wildlife Acoustics, 2011), convolutional neural networks (Knight et al., 2017) and clustering algorithms (Wildlife Acoustics, 2019). Songscope, Kaleidoscope (both by Wildlife Acoustics, Maynard, Massachusetts, USA) and Raven Pro (Cornell Laboratory of Ornithology, Ithaca, New York, USA) are commercial software that have incorporated these techniques. Open-source R packages such as “monitoR” (Hafnet and Katz 2017) and “warbleR (Araya-Salas and Smith-Vidaurre 2017) are also available. Most commonly these software use machine learning techniques to build representative models of bird vocalizations. The models are used to search recordings for matches. Matches are pulled from the audio and identified by the software. It is important to note that these methods make too many errors to be entirely automated, so human verification of the identifications is required (Sidie-Slettedahl et al., 2015; Zwart et al., 2014).

Automatic detection may detect more species than manual detection because the software can scan entire recordings more quickly, but there are few comparisons in the literature and these comparisons are generally limited to select species rather than a total species inventory. Comparisons between automatic detection and point counts have shown mixed, species-specific results, and manual detection results are similar to point counts (Shonfield & Bayne, 2017). One study has shown automatic detection to better capture European Nightjar (*Caprimulgus europaeus*) presence (Zwart et al., 2014). Another found automatic detection and point-counts performed similarly for detecting the Acadian Flycatcher (*Empidonax virescens*) and Cerulean Warbler (*Setophaga cerulea*), but point counts performed better for the Prothonotary Warbler (*Protonotaria citrea*) (Holmes et al., 2014). And another study covering ten species saw species more often detected by automatic detection and missed by manual detection than the converse, when manual detection covered a 10-minute sample and automatic detection scanned 35-63 times as much audio. (L. Venier et al., 2017).

Larger scale processing of entire bird communities was difficult because until 2016, commercially available software could only search for one type of vocalization at a time and verifying hits is necessary and time-consuming. For example, in a related Honours project (Hines, 2018) automatic detection took approximately eight hours to scan 625 hours of recordings for a single species at a single site using Songscope by Wildlife Acoustics. For that project the program was trained to detect 40 species and it took ~5-minutes for each species at each site to prepare the data and verify the 25 most-likely detections(hits). The alternative, verifying all hits, would conservatively take 5.5 hours/species/site, estimating a 10-second average time to verify a detection and conservatively estimating 2,000 hits per species (i.e. approximately 65 times as long as to prepare and verify the top 25 hits). These time estimates are highly variable among species and sites. Another alternative is to record fewer hours and verify all hits within a pre-set level of similarity between the sound and the model (based on an index describing the distance between the sound and the model for a particular species). One time-estimate using this approach is 2.5-7 min./species/site for ~28 hours of recordings (Holmes et al., 2014) and another averaged 5.7 min/species/site for 23-42 hours of recordings (L. Venier et al., 2017).

Verification of all hits within a certain ‘score’ threshold is effective, but automatic detection works better for some species than others, so each species requires a unique threshold (L. Venier et al., 2017). For larger audio datasets containing species for which the ideal search parameters (e.g. score threshold) are unknown, verification of all detections would negate the time/cost-saving potential of automated detection. However, discarding unverified detections raises the likelihood of missing a species that was present and vocalizing in the recording but not included within the subset of detections which were verified. (Type II error).

Recent advances in commercial software have greatly sped up the scanning process and is no longer a ‘one-species-at-a-time’ approach. This, combined with an efficient verification process, allows for species inventory comparisons between manual and automatic detection using more species over longer temporal scales than what is currently in the literature.

Objectives:

Sound recognition software that allows multiple species to be identified in a single scan has the potential to greatly decrease processing time. This may allow for detecting more species than traditional sampling methods and thus provide more complete species lists. The primary objective of this thesis is to compare the numbers of bird species detected in recorded audio by manual detection compared to automatic detection. I will use the cluster-based, machine-learning program 'Kaleidoscope', by Wildlife Acoustics to:

1. a. Train software to simultaneously recognize, extract, and identify multiple bird species' vocalizations.
   b. Determine detection and identification capabilities for local bird species using test data.
   c. Optimize the process of verifying vocalizations using test data
2. Compare the number of species found through automatic detection against that found through manual detection

Methods

Site Description

The field data used for the comparison between manual and automatic detection were collected from 29 recording sites at CFB Gagetown, a military facility covering approximately 1100 km^2 in southwestern New Brunswick, Canada (45°50′16″N 066°26′12″W). New Brunswick is a part of the heavily eroded Appalachian mountain Range and CFB Gagetown contains portions of the St. Croix Highlands along its southern and western portions and the Acadian Forest ecotype (Government of New Brunswick, 2019). Before expropriation in 1958 and conversion to a military base, approximately 900 families who lived in the area were engaged in relatively small-scale agriculture and forestry operations (Town of Oromocto, 2019).

Since 1958 the landscape has been heavily modified to build and facilitate military ground/air training operations. In the 1990s large portions of forest were clear-cut and removed. Topsoil was then scraped and piled, leaving nutrient-poor habitats colonized by stunted trees, lichens, small shrubs, and wetland flora/fauna around ponds created during the scraping. The berms created from piled topsoil have since regrown tree cover of species similar those found before clearcutting and topsoil removal such as speckled alder (*Alnus incana*), trembling aspen (*Populus tremuloides*), birch (*Betula sp.*), spruce (*Picea sp.*), and white pine (*Pinus strobus*).

CFB Gagetown is on federal lands and has a legal obligation to manage the lands for environmental sustainability. The Houlahan lab at the University of New Brunswick was contracted by The Department of National Defense to deploy audio recorders to monitor bird and amphibian communities at several sites in CFB Gagetown experiencing different kinds of land use (e.g. prescribed burns, tracked vehicle maneuvers, and herbicide spray). The overall monitoring program took place over several years in the 2010s, but the data used here were recorded in 2014.

Objective 1a: Train Software to simultaneously recognize, extract and identify multiple bird species vocalizations.

I used the Maritime Breeding Bird Atlas (*Maritimes Breeding Bird Atlas—Atlas des oiseaux nicheurs des Maritimes*, 2017) to compile a list of 200 species that have been found in New Brunswick, Nova Scotia, and Prince Edward Island, and therefore might be present within the field study site located in New Brunswick during either migration or the breeding season.   I then obtained high-quality recordings of those species from the University of Cornell's Lab of Ornithology to use as training data (Cornell University, 2017b). The training data is a commercially available set of identified, high-quality audio recordings of North American bird species that have been submitted to the MacAulary Library Online Database and chosen by members of the University of Cornell's Lab of Ornithology as representative vocalizations for different species. The recordings are packaged together in a commercially available dataset named the 'Cornell Master Set', hereafter the 'Training Data'. The number of vocalizations per species is unknown and recording length per species is variable (Total:1877 recordings, Average: 29 sec., Range 1-128 sec., Standard Deviation: 17 sec, Table A3). Geographic range is also variable but many species known to have regional dialects are identified as such (e.g. the Dark-Eyed Junco, *Junco hyemalis*, recordings are grouped into five different morphs, and many species are distinguished between Western and Eastern subspecies).

I scanned the training data using Kaleidoscope's (v.5.1.9) default settings for bird monitoring. The default settings above are recommended by Wildlife Acoustics for general species inventories (Wildlife Acoustics, 2019).:

1.) A frequency between 250-10,000Hz

2.) A total length between 0.1-7.5 seconds

3.) A maximum gap of 0.35 seconds between syllables

Kaleidoscope detected sounds from the training data that fit the above characteristics and grouped the detected sounds by similarity. The similarity is determined by image recognition techniques that convert spectrograms into numerical data which outline the position of pixels, and then statistical techniques to group the converted spectrograms. The technical details of these techniques are beyond the scope of this thesis. A brief overview summarized from the user guide of Kaleidoscope is provided below (Wildlife Acoustics, 2019).

The spectrogram of each sound is converted into vectors using Discrete Cosine Transformations, and those vectors are arranged by similarity using Hidden Markov Models. Broadly, the numerical representation of each spectrogram gives the position of each brightly coloured pixel, a pixel representing a sound heard at a certain frequency, volume, and time. This vector can be plotted on a multi-dimensional grid. Similar sounds will have similar spectrograms, and therefore the vectors representing them will be similar numerically. Similarity can be measured as the Euclidean distance between two vectors (sounds). A cluster is formed when two or more sounds fall within a set distance of the central point between them. A maximum distance of 1.0 was used here, as recommended by the user guide. Thus, each cluster contains sounds with similar spectrograms, and the cut-off point for similarity is 1.0 from the center of the cluster formed by grouping them. Because each sound is labelled, each cluster can serve as a model for the bird species vocalization which is most commonly found in the cluster. A new sound is assigned the species identification of the cluster centroid that it is closest to.

To train Kaleidoscope to identify bird sounds, I scanned the training dataset by running Kaleidoscopes ‘Scan and Cluster Recordings’ function on the folder containing the Training Data and using the parameters outlined above. It clustered sounds together which had a maximum distance of 1.0 from each other. This maximum distance was recommended from the user guide for general-purpose bird surveying. Lowering this value increases the specificity of each cluster, where raising it broadens the cluster. The initial scan simply groups similar sounds from each scanned file together, organizing them together within clusters in a table of results, each cluster having a generic name at this stage (e.g. Cluster001).

The clusters are then labelled based on the most common sound found within it. For example, if a cluster contained 100 sounds – 79 identified as a Swainson’s Thrush’s (*Catharus ustulatus*) song and 21 identified as a Hermit Thrush’s (*Catharus guttatus*) song the cluster would be labelled “Swainson’s Thrush - Song”. Identifications were based on the identification given by the curators of the training dataset, Cornell University’s Lab of Ornithology). It should be noted that many species have different types of vocalizations (e.g. breeding song and alarm call) and thus, may have multiple clusters, one for each type of vocalization. If the same vocalization type had been separated into different clusters due to variability, those clusters can be combined by labelling them identically.

I then did a second round of training to break apart clusters in which similar-sounding vocalizations/noise belonging to different sources had been clustered together. I used the Kaleidoscope function 'Re-scan recordings to create pairwise classifiers' to manually label each sound within each cluster. This drew separating lines through mixed clusters and formed new, more homogenous clusters. Kaleidoscope saves the area of the plot where a cluster was named to serve as a model for each vocalization.

When the trained Kaleidoscope is applied to new data it again identifies characteristics of the spectrogram images of all sounds, assigns each sound to the most similar cluster from the training data and labels the new sound with the label of the training data cluster (Fig. 1). The similarity is determined by the distance to the nearest cluster centroid

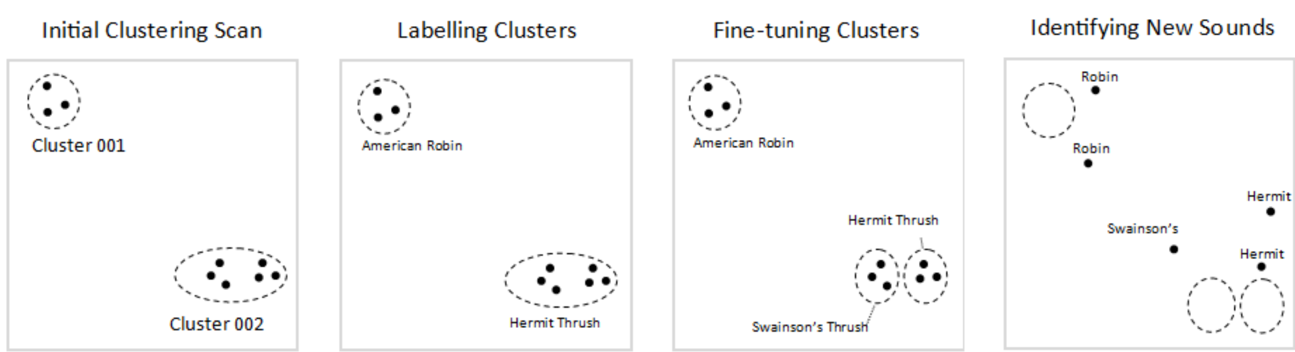


Figure 1: Conceptual diagram showing the process of training Kaleidoscope to identify bird species. Similar sounds within an audio dataset are clustered, I labelled each cluster based on the identity of the species most commonly found within it and then identified each individual sound within the clusters to separate similar but different clusters. When new audio is scanned, the name of the nearest cluster centroid is given as identification for each new sound.

Objective 1b: Determine detection and identification capabilities for local bird species using test data

It is possible to miss a species that was present and vocalizing within the recorded audio in two ways. 1.) If all vocalizations for that species were either assigned to the wrong cluster due to the correct model not being the most similar model to the detected vocalization or 2.) Not assigned to a cluster at all because there were no models similar enough to be included within the results based on the maximum distance allowed in Kaleidoscope results file. The first case would result in both false positives (Type I error) and false negatives (Type II error), while the second case would only result in false negatives. False positives (Type I errors) are removed by verifying each identification but Type II errors are difficult to estimate without knowing the true species list of the recording. To test the models, ideally, the field recordings from the CFB Gagetown site would have been used to estimate the error rates. However, finding the true number of species in our field recordings to estimate error rates was not possible within a reasonable timeframe due to the verification time that would have been required (300+ hours/site x 29 sites = ~10,000 hours), so I used the Xeno-Canto database as a test dataset.

The Xeno-Canto database is archived at an online, publicly accessible website devoted to sharing user-submitted (and user-identified) vocalizations of birds from around the world. At the time of this project, it contained 322GB of audio data and over ~40,000 recordings of 200 birds which have been found in the maritime provinces of

Canada, the location of my study site. Each recording has an identification of the species and the quality of the recording, provided by the user who submitted it. Recordings were taken from locations across Canada and the United States. The number of vocalizations per species is variable and unknown. The 'quality' rating scales from A-E, with 'A' being a clear vocalization with little background noise and 'E' being a very unclear recording with excessive background noise. Quality levels A through C contained approximately 6,000 – 14,000 recordings each, where the remaining quality levels only contained ~3000 recordings. Testing was only performed on levels A through C. So, the testing dataset contained recordings of 200 bird species, grouped at three levels of recording quality: A quality being recordings which are 'Loud and Clear', B: 'Clear, but bird a bit distant, or some interference with other sound sources' and C: Moderately clear, or quite some interference. These ratings were subjective and provided by the user who submitted the recording. Though the number of species is known, the true number of vocalizations is unknown. The location of the recording and total recording length was variable among species. Table 1 shows an overview of the recordings included within the testing dataset.

Table 1: An overview of the recordings included within the testing dataset based on the quality level, A being highest and C being lowest.

Quality	# of Recordings	Average Length (m:ss)	Range (mm:ss)	Standard Deviation (m:ss)
A	10256	1:05	0:01-15:14	1:26
B	14442	0:53	0:01-25:24	1:12
C	6882	0:51	0:01-17:47	1:25

I used the trained Kaleidoscope algorithm to scan for the 180 species that had models created during training at each recording quality level. Recordings were grouped by their quality and scanned separately. The program searched for matches to the models of vocalizations for each species created during training. This was generally a representative song, though multiple different songs were represented within the training data for some species and so multiple models were created and searched for. Recordings generally contained examples of the vocalizations for a single species, but often many examples of that vocalization. I verified the identifications given to all detections ('hits') by matching the identification given by Kaleidoscope with that given by the user who submitted the recording and then viewing the spectrogram to confirm. For each sound detected from each group, I identified whether that sound was correctly or incorrectly (Type I Error) identified by matching the identification of each sound given by Kaleidoscope with that which was given by the user who submitted the recording, as well as by viewing the spectrograms. I also tracked how many species in the training data Kaleidoscope failed to detect even though they were present (Type II errors) as well as the percentage of incorrect identifications (Type I errors). This was a favorable test in the sense that the vocalizations were relatively clearly recorded compared to typical ARU recordings, but gave an initial estimate of Type I errors. If a species were missed in this favourable test, then it would also likely be missed in the field data. It also provided insight into where best to spend effort verifying detected sounds ('hits') given that the number of hits within the ~625 hours of field recordings/site makes it necessary to only verify a portion and discard the remainder. Further, these data are readily available and are an easily replicated source for comparing training methods.

Objective 1c: Optimize the process of verifying vocalizations using test data

Error rates with automatic identification are too high to be accepted without human verification (Buxton et al., 2016; Sidie-Slettedahl et al., 2015; Zwart et al., 2014). False positives (Type I errors) are common due to ambient noises that resemble bird vocalizations and similarity between different bird species vocalizations. Manual validation of automated detections is one way to mitigate the problem of false positives. Manual validation requires confirmation of at least one hit as a true positive before concluding that a particular species was present at a specific site. Because there are often 500,000 hits/site under our recording schedule (~139 hours of validation at ~1 sec./hit) we do not have the resources to validate all 'hits' so we must choose a subset of all hits for validation. Here, I describe a method to optimize the selection of the validation subset to maximize bird species detected per unit-effort.

Kaleidoscope computes an index for each detection of how similar the sound is to the sounds used to 'build' the cluster it is assigned to (i.e. the distance to the nearest cluster centroid). A sound with characteristics identical to those of a cluster centroid would have a distance value of zero. The maximum distance value which can be included in Kaleidoscopes results is 2. This can be adjusted to lower the number of hits, but lowering it increases the risk of missing "true" vocalizations. I ranked 'hits' in ascending order by distance and verified a subset of the hits most similar to training data examples for each species.

I also verified all hits by randomly sampling them and measured how many hits it took per species to capture at least one true positive identification. I compared the number of hits/species when random sampling was used (averaged over 1000 randomizations) to the number of hits/species when hits were ranked by distance.

A species accumulation curve was built using the ranked position of the first true positive across species to determine when verifying additional hits turns up no additional species. The ranked position of the first true positive is the position of the first correctly identified hit when all hits are ordered from smallest to largest by distance value. For example, if the first correctly identified Blue Jay (*Cyanocitta cristata*) sound was found at ranked position #13 the 'rank of first true positive' was 13, meaning 12 false-positive identifications were closer to the cluster centroid of the Blue Jay model (i.e. had a lower distance value and were more similar to the model than the true vocalization). If across all species, the 'first true positive' was never found beyond ranked position number 13 and there were hundreds of hits per species, then there would be support for discarding hits beyond rank 13. Hits from the testing data were verified by comparing Kaleidoscope's identification with that provided by the person who submitted the recording. I used this species accumulation curve to obtain initial estimates of how many 'hits' to verify when working with field data where there is an unknown total number of species.

Objective 2: Comparing Automated to Manual Detection Methods using Field Data

Data Description

Audio data were collected at each site using automated recording units (ARUs) from Wildlife Acoustics (SM2+ Model). Each ARU weighs slightly over a kilogram with four D-cell batteries installed and measures around 21.5 x 17.8 x 6.4 cm. Recorders have two inputs for secured digital memory cards (SD cards) to store the data. The recorders are weatherproof and can be used at temperatures from -20 C to + 70 C with built-in stereo omnidirectional microphones with a sensitivity of -35 +/- 4 dB and a frequency response of 20 Hz – 20,000 Hz with a signal-to-noise ratio of >62 dB.

ARUs were deployed at 29 wetland sites around CFB Gagetown by attaching them to nearby trees at a height of 1-2m. Recorders were programmed to record for 90 minutes at dawn, 60 minutes at dusk, and 5-minutes at the beginning of each hour throughout the day. All recorders were deployed in mid-late April 2014 and recorded until mid-August to early October depending on battery life. (Range: 08/12/2014 – 10/03/2014). This resulted in the collection of accumulated about 625 hours of audio data per site.

Automated Detection Method

I used the Kaleidoscope (v. 5.1.9), trained as outlined in the 'Objective 1a', to scan field recordings from the 29 wetland sites. The algorithms extracted all sounds within the default parameters, listed in the Methods of "Objective1a: Training...". Each sound from the field recordings matching the characteristics was identified based on the name of the nearest (most similar) cluster that was built during training.

For many site/species combinations there were >10,000 potential matches for each species vocalization(s). As some species have more than a single vocalization type, I sorted the hits within each group of sounds assigned to a species cluster by distance value and determined how many hits to verify within each group to maximize species capture per unit-effort, as described above. Results from scanning the test dataset showed that validating 400 hits ranked by distance values captured more than 95% of all species detected by automated detection across three independent audio sets of varying recording quality (See 'Testing' in Methods and Results). Thus, I sorted the field data hits by distance within each group and then verified the top 400 hits per group (i.e. cluster).

To validate the identifications, I compared each of 400 hits per species vocalization in descending order by their distance value against confirmed examples for that species. Example vocalizations were obtained from the identified training data vocalizations provided by Cornell University's Lab of Ornithology and the website Allaboutbirds.org, also by Cornell University (Cornell University, 2017a). Each of the top 400 'hits' was compared by ear, spectrogram, and by reviewing species biology to ensure the dates/times of the detections made sense for that species in the research area. All hits that were a match for sound, spectrogram, and biology were treated as true positives. A single, clear true positive at a particular site was considered evidence of species presence at that site.

Manual Detection Method

Manual detection was carried out by an expert from the New Brunswick Museum Zoology Department with more than five years of experience conducting bird surveys professionally. The expert observer listened to a total of 21-minutes of recordings per site (798 minutes total across sites), comparable to typical physical survey times and manual detection surveys.

The expert haphazardly chose three recording days from the beginning of May to the end of June. For each of the three days, they listened to 1-minute immediately before dawn, 2-minutes at dawn, and two 2-minute sessions haphazardly distributed throughout the day for a total of 7-minutes per day. Thus, all sites were sampled for 7 minutes on each of three different days. The expert listened and viewed the spectrograms for all the recordings that they reviewed. All bird species detected were identified and reported as present for the site.

Statistical Analysis

To compare the number of species detected by manual and automated detection, I ran a pairwise t-test in R on the number of species found by each method at each site.

Results

Summary

Scanning the Cornell Master set created at least one model (cluster) for 180/200 bird species. Often multiple clusters were created for a species to represent unique vocalizations by that species within the training data. Those clusters detected 99-121/200 species from a test dataset, depending on the quality of the audio recording. Often 10,000+ sounds were identified as a particular species within both the testing dataset and ~625 hours of field data but only 400 hits/vocalization model was needed to be verified to capture a true positive for most species if the hits were ranked as outlined in 'Methods'. Verification of a maximum 400 hits/species took roughly 6 hours/site. Verification can be largely completed with minimal expertise by comparison to confirmed recordings and spectograms. I chose to validate 400 hits but >90% of species would be detected if the validation threshold could was to 100-200 hits. When used on field data, automatic detection found an average of 47% more species/site than manual detection (28 vs. 19 species).

Objective 1a: Train software to simultaneously recognize, extract, and identify multiple bird species' vocalizations.

A total of 328 unique clusters were created (Table 4A) and of the 200 species recorded vocalizing within the training data, 180 were represented by at least one cluster (Table 2).

Table 2: Species that were in the training data but for which no cluster was built

Common Name	Binomial Name
Barn Swallow	*Hirundo rustica*
Blue-winged Teal	*Anas discors*
Bonaparte's Gull	*Chroicocephalus philadelphia*
Chimney Swift	*Chaetura pelagica*
Cliff Swallow	*Petrochelidon pyrrhonota*
Hooded Merganser	*Lophodytes cucullatus*
King Rail	*Rallus elegans*
Merlin	*Falco columbarius*
Nelson's Sparrow	*Ammodramus nelsoni*
Northern Goshawk	*Accipiter gentilis*
Razorbill	*Alca torda*
Rock Pigeon	*Columba livia*
Rough-legged Hawk	*Buteo lagopus*
Ruddy Duck	*Oxyura jamaicensis*
Ruffed Grouse	*Bonasa umbellus*
Semipalmated Plover	*Charadrius semipalmatus*
Turkey Vulture	*Cathartes aura*
Yellow Rail	*Coturnicops noveboracensis*
Yellow-bellied Sapsucker	*Sphyrapicus varius*

Objective 1b: Determine detection and identification capabilities for local bird species using test data

Of 200 original species (note: for 20 of the 200 species there was no identifier so, a maximum of 180 species could have been identified), each represented in multiple recordings at each quality level, Kaleidoscope correctly detected and identified 104 (A Quality), 99 (B Quality), and 126 species (C Quality). Thus, 58% (104/180), 55% (99/180) and 70% (126/180) of species that could have been detected, were detected.

Error rates varied from 0% to 100% depending on the specific vocalization detected but were typically higher than 90% (Table 3). Detections/species were also highly variable. Across three replicate scans on each of the quality levels, the number of hits and distance value for each hit was identical so, there is no variation in hits among scans of the same recording.

Table 3: Results from scanning the Testing Dataset of recorded bird species vocalizations (Xeno-Canto Database) with trained automatic detection software. Quality represents the level of noise within the audio as rated by the recordist, A being high and C being low. Error rates were determined by matching the identification given to the sound by the software with that given by the recordist. Standard deviation is represented as S.D.

Quality	Hours of Audio	Hits	Average Error Rate	Error Rate Range	S.D of Error Rate
A	186	521,259	98%	22% - 100%	7%
B	213	52,880	93%	0% - 100%	16%
C	114	213,434	98%	56% - 100%	5%

The average ranked position of the first true positive (across all species was 13th, 15th, and 65th in ‘A’, ‘B’, and ‘C’ quality recordings, respectively. The latest a ‘first true positive’ for a species was encountered was at ranked positions 381, 361, and 819 (Fig. 3).

Objective 1c: Optimize the process of verifying vocalizations using test data

The total number of species detected increased with the number of hits verified per species but approached an asymptote between 100 and 300 validations, although high-quality recordings approached the asymptote with fewer validations than lower quality recordings (Fig. 3). The number of detections that were needed to be verified per species to reach the first true positive identification varied amongst species (Fig. 2, Table A1).

Verifying detections ordered by ‘distance’ as opposed to randomly sampling them reduced the number of false positives encountered before finding a true positive by 50-70% (Fig. 3). Further, verifying the first 400 detections when ordered by distance detected all 104 and 99 species for ‘A’ and ‘B level recordings, respectively and 121 of 126 species for ‘C’ level recordings compared to 97, 97, and 115 species when sampled randomly.

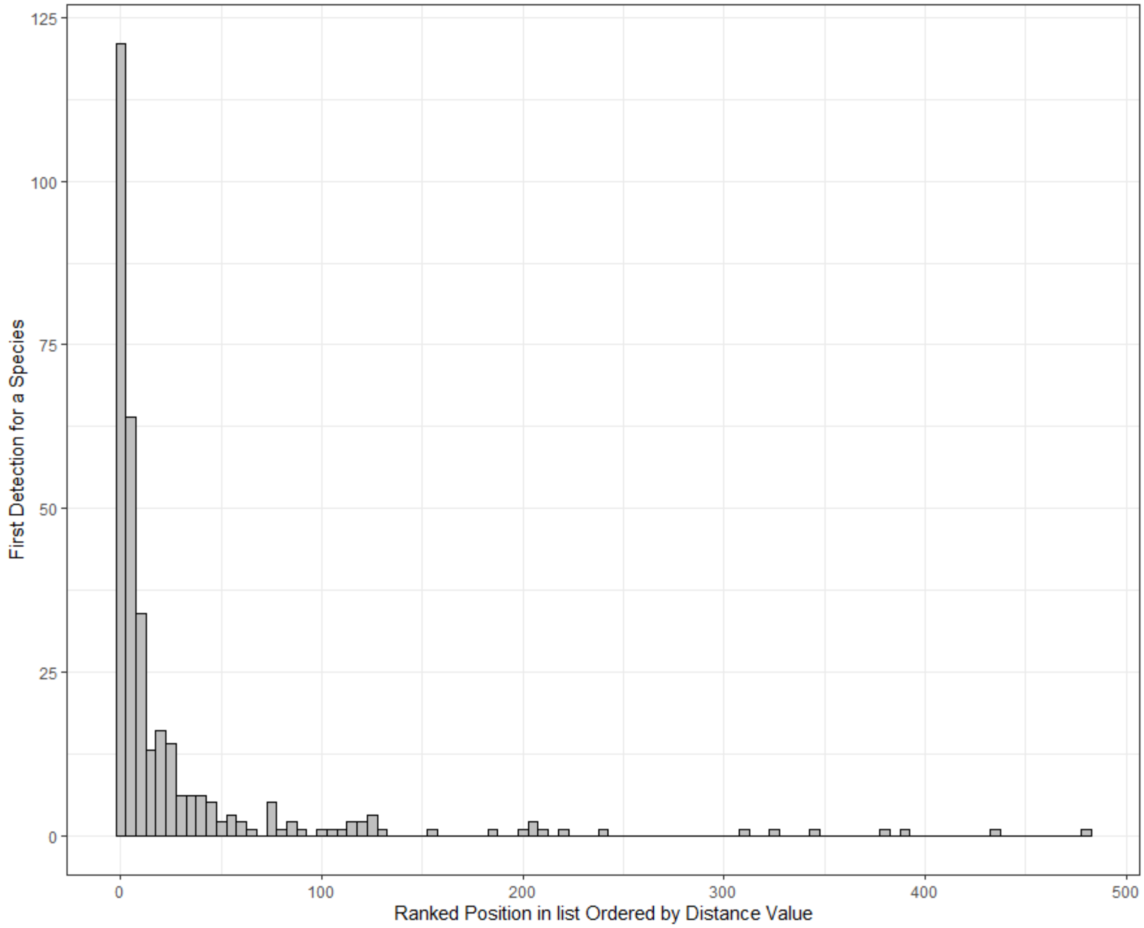


Figure 2: Distribution of the positions of the first true-positive hit per species, across all three (combined) levels of recording quality when ranked by distance. Distance is an index of the similarity between a hit and the species cluster to which it has been assigned. Bin width = 5.

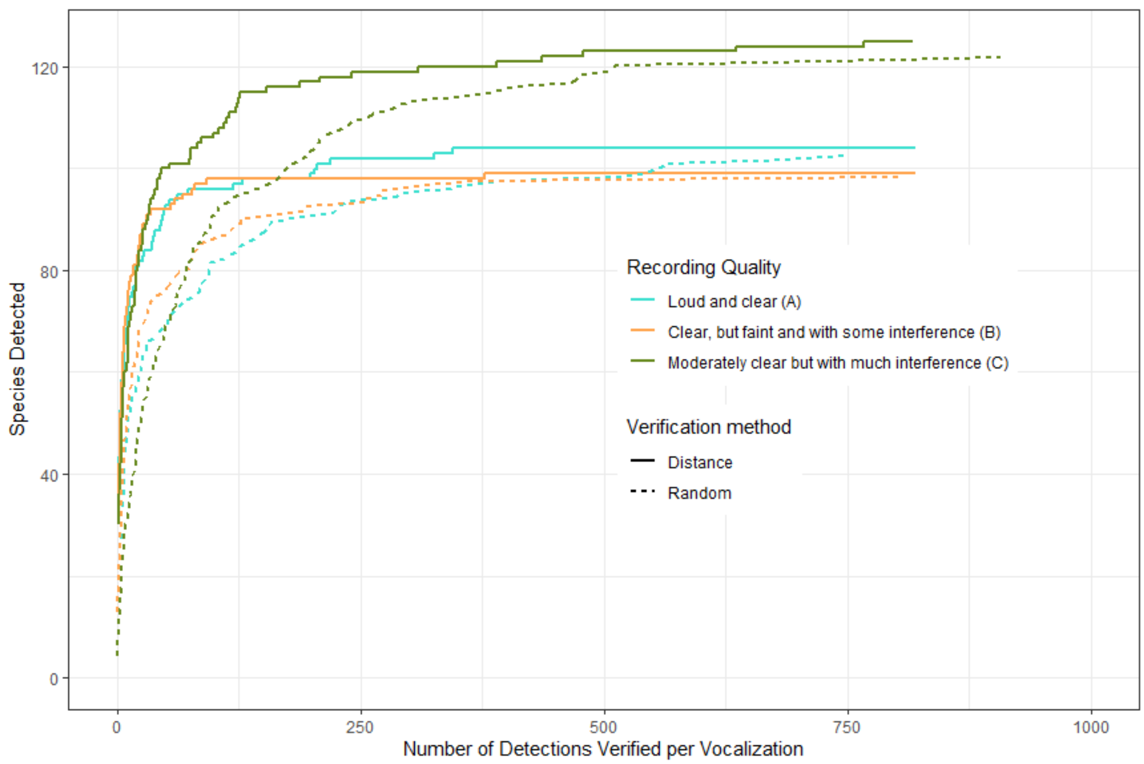


Figure 3**:** Number of species detected and correctly identified depending on how many hits verified per species vocalization when ranked by distance to the nearest cluster centroid, at three different levels of recording quality (solid line) compared to the number of species detected and correctly identified by randomly sampling all hits

Objective 2: Comparison between Automatic and Manual Detection on Field Data

Automatic detection captured a mean of 28 species/site (range: 14-38) from scanning ~625 hours of audio/site while manual analysis detected 19 species/site on average (range: 10-28) from a 21-minute sample of the same number of hours of recorded audio/site (Fig. 4, Fig. 5; p: < 0.001). Species richness approached an asymptote at around 250-300 detections verified for each species (Fig. 6).

On average across 29 sites, automated analysis detected 20.06 species that manual analysis missed (range: 14-28, SD: 4.3) and manual analysis detected 9.82 species that automated analysis missed (range: 7-16, SD: 2.9). On average 9.59 species/site were detected by both methods (range: 5-15, SD: 2.6) (Table A2).

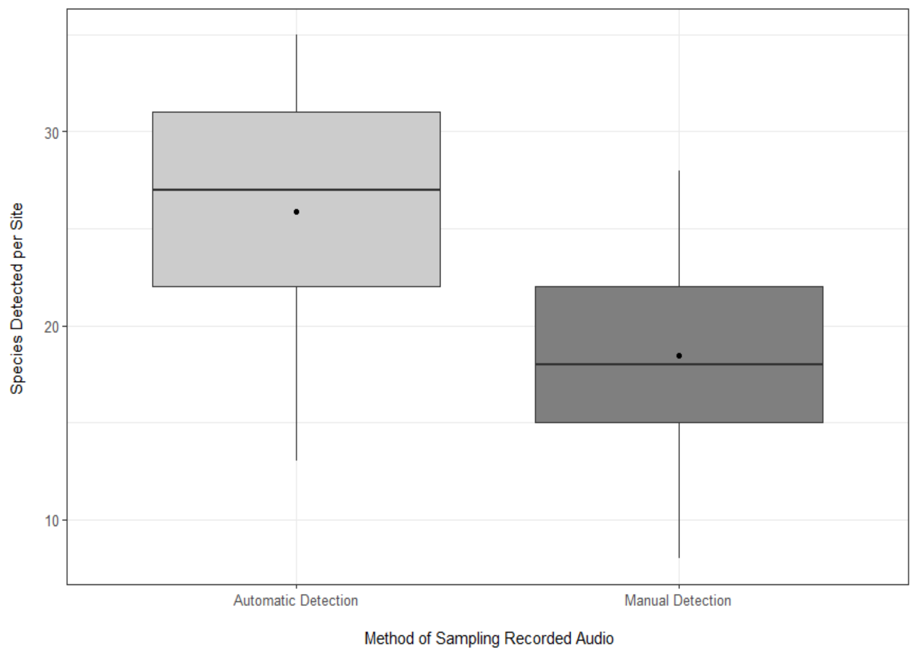


Figure 4**:** Boxplot of the number of bird species detected by automated versus manual analysis (See Methods for descriptions of automated and manual analyses). The horizontal bar is the median, the box contains the 25th to 75th interquartile range and the whiskers contain all of the data. The filled circle is the mean.

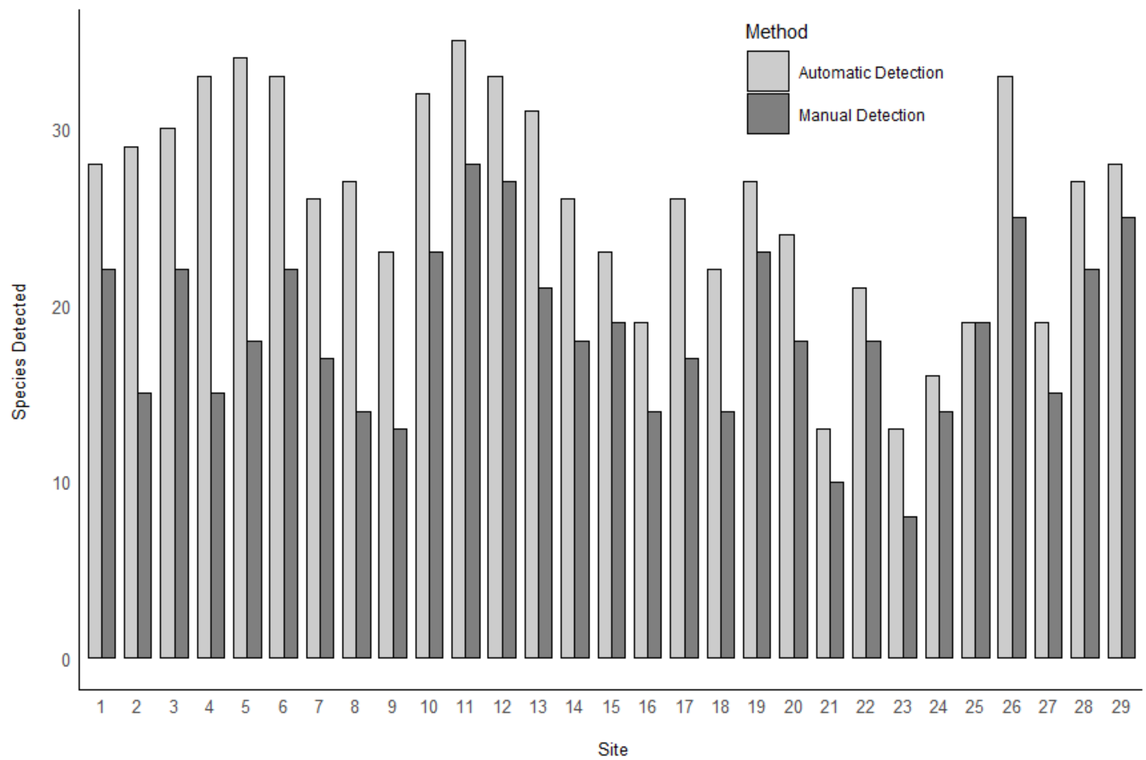
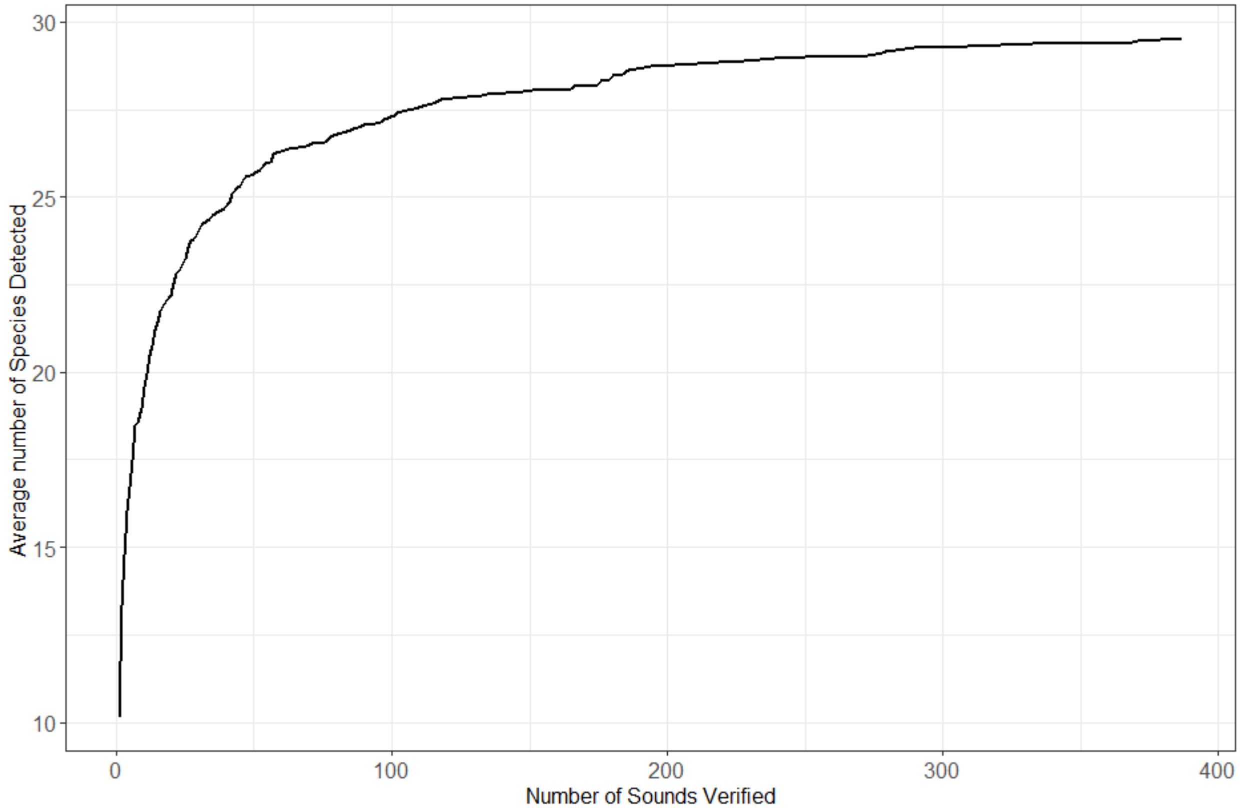


Figure 5: The number of bird species detected at each of 29 wetland sites in CFB Gagetown depending on the method of sampling for vocalizations within recorded audio (manual vs. automated detection).



<u>Figure 6:</u> Relationship between the average number of bird species detected at 29 wetland sites in CFB Gagetown and the number of hits verified per species vocalization when ranked by distance.

Discussion

Summary

The objectives of this thesis were to train the automatic detection software Kaleidoscope to detect and identify recorded bird sounds, to design an efficient process of verifying its identifications when used on field data, and then to compare the number of species detected by automatic detection of entire recordings to manual detection of a 21-minute subset of recordings. Training the program by scanning the commercially available Cornell Master Set created models for 90% of species found within the Maritime provinces, and these models detected 55-70% of the species within a test dataset. There were many thousands of hits for each species, most of which were false positives. However, to detect >95% of detected species it was only necessary to verify 400 identifications if the list of hits for each species were ranked by distance from the trained cluster. Automatic detection found more species than manual detection within field data, but there was little overlap between the species detected by each method.

These results indicate that automatic detection can be efficiently used to conduct bird species inventories and will build a more complete list than manual detection. However, I recommend a combination of the two methods given the tendency for many species to be detected exclusively by one method or the other. Conducting bird species inventories in this way will increase the number of bird species we can monitor at a site. Increasing the number of bird species we can monitor may increase our ability to detect human impacts on bird community diversity and composition.

Training

The training method presented here created clusters for 180 out of 200 species. Twenty species had no model created and could not be detected in a new dataset. A relatively small amount of training data for those species could be responsible, i.e. few/short recordings within the training data set. Many of the species also have vocalizations that do not fall within the parameters chosen for general purpose scanning. The Bank Swallow (*Riparia riparia*), for example, has a series of short but rapid sounds that form its typical vocalization and the gap between each syllable is too short for the general parameters to separate. This is confounded by the tendency for multiple individuals to overlap and form one long, continuous sound. The training may be improved by supplementing the training data where necessary and creating a separate training program with parameters designed for specific types of vocalizations.

Testing

This training method detected 52-63% of species whose vocalizations were present in the testing dataset. Of the 80-100 species (depending on recording quality) for which we had a recognizer cluster but were not detected in the test set, they may have had their vocalizations assigned to the wrong species cluster or not assigned to a cluster at all. If a species has a very simple vocalization, and there are many species with similar simple vocalizations, it is difficult to distinguish the two using spectrograms (Stevens et al., 2019) and possible for one species to be consistently identified as the other. Highly variable vocalizations are also problematic to capture in a model because the training data vocalizations may not accurately represent those in the test data.

Variability in vocalizations is especially problematic in this case because of the large geographic spread of the recordings contained within both the training and testing data. Regional dialects were accounted for in some species by building separate clusters when a subspecies was identified in the training data but this was relatively uncommon.

Automatic and Manual Detection – Species Richness Comparison on Field Data

This study is the first, to my knowledge, to compare this version of automated analysis (Kaleidoscope) against a typical manual detection. However, Stevens et al. (2017) compared point counts and Kaleidoscopes clustering abilities with all identifications provided by the surveyor. Kaleidoscope was used exclusively to detect sounds that may be a bird vocalization and group similar sounds together before a human observer provided the species identity. They found significantly more species using Kaleidoscope than they did from conducting point counts at the same sites but their method required more knowledge in bird identification than the method I used. It also required all sounds to be verified, which limited the amount of audio that could be sampled. Automatic detection using Songscope has shown improved detection rates for target bird species over manual detection if the software was allowed to scan longer than what the human sampled (L. Venier et al., 2017). This comparison was made for ten species, and performance varied among species.

My results that automated detection detects more species because of the greater volume of recordings that can be processed are similar to previous research conducted with fewer species, fewer sites, and different versions of automatic detection which found automatic detection better able to detect certain species (Holmes et al., 2014; Joshi et al., 2017; Venier et al., 2017). Technological improvements in automatic detection software now allow for larger-scale comparisons than in the past. We are now able to scan more sites for more species in less time, as well as more quickly verify identifications. Increasing the scale of the comparison has confirmed that automatic detection can detect higher species richness values than manual detection.

Additional Comparisons between Automatic and Manual Detection Methods

Beyond the total number of species detected by each method, there were also differences in which species were detected at a site. An average of approximately 25% of species detected at a site were detected by both methods, meaning the remaining 75% of species were detected exclusively by one method or the other. Visual inspection suggests that automated analysis was better at detecting species with relatively simple, unique vocalizations but struggled with detecting species whose vocalizations were very similar to other species. However, identifying the specific vocalization characteristics that facilitate automatic detection will require additional song analysis. Automatic detection was also better able to detect species that vocalize outside of the dawn chorus because the entire recording was analyzed, whereas the manual detection sampling protocol used here prioritizes sampling at dawn. Manual detection also prioritized sampling during the breeding season and early migration, where automatic detection scanned for 2.5 months. Some warblers and sparrows have complex vocalizations that are difficult to model and require an experienced observer to identify. Visual inspection suggested manual detection more often captured such species with complex or variable vocalizations. However, this should be confirmed with additional song analysis in the future. Manual detection also seemed better able to separate similar-sounding species. Other studies have similarly found automatic detection to have difficulty distinguishing among species with similar vocalizations (Stevens et al., 2019; L. Venier et al., 2017), such as those who more typically call than sing. While I found that automated detection found more species than manual detection, a community analysis of the species detected by each method may lead to different conclusions. For example, automated detection might find more species but fewer functional groups than manual detection, and that may be more important for some ecosystem management objectives. Species richness was chosen here as a simple metric for stakeholders and is a standard metric for survey method comparisons (Shonfield & Bayne, 2017), but may only be the first step towards more advanced analysis.

The main advantage of automated analysis is an increase in the volume of recordings that can be processed, whereas manual analysis benefits from expert humans making fewer mistakes in identification than the software. Further research may allow us to determine what it is that a human expert can detect that software misses and build a separate training protocol for Kaleidoscope to target those specific attributes. Additional research may also improve manual analysis by identifying the sampling effort at which increased effort ceases to provide higher species richness estimates.

Automatic detection is generally well suited for the detection of rare species (Campos-Cerqueira & Aide, 2016; Rognan et al., 2012; Swiston & Mennill, 2009). The ability to increase sampling time in remote locations improves the likelihood of detection (Holmes et al., 2014; Swiston & Mennill, 2009). For example, the Eastern Whip-Poor-Will (*Caprimulgus vociferous*) is a federally listed Species-at-Risk with a

Threatened status (Government of Canada, 2019). This species vocalizes outside of the usual sampling period of manual detection, often an hour before dawn (Wilson & Watts, 2006). Within my field data, the Eastern Whip-Poor-Will was detected by both manual and automatic detection at 3 sites but detected exclusively by automatic detection at 4 additional sites.

However, the training protocol presented here was not designed to capture rare species. Typically automatic detection of rare species involves spending much more time training the program on specific sounds (e.g, (Holmes et al., 2014)) than the broader approach to training that Kaleidoscope enables. In this thesis, I used coarse-filter parameter settings to efficiently capture many species initially. It may be possible to train Kaleidoscope in a more focused way separately from this general training method and run a subsequent scan with fine-tuned parameters to capture specific, or rare, species if that is the objective.

Balancing Effort and Type II Errors

The identifications provided by automatic detection must be verified, but the time-saving benefits can be negated if too many hits must be verified. The high error rates of automatic identification found here confirm the need to verify the identifications. Balancing the number of hits verified (reducing Type I error) with the number discarded (which increases the risk of Type II errors) is a cost-benefit decision that has been addressed in two main ways in the literature. First, to limit the recording time so that all individual sounds can be verified (Knight et al., 2017). This ensures that all species present on recordings are detected but increases processing time and reduces the time-saving benefit of using recorders. Second, verifying only a subset of detections as was done here. Knight et al. (2017) set thresholds on the level of similarity to training data a sound must have for it to be considered a potential true positive, similar to the 'Distance' measurement used here (i.e. the 'Score' index in Songscope). The authors validated the subset of detections above the score threshold and found that lowering the threshold (verifying more sounds) increased the number of detections for the Common Nighthawk (*Chordeiles minor*) but the rate of accumulation slowed down as verification moved to sounds less similar to the training data (Knight et al., 2017). A score threshold may further reduce the number of hits which should be verified but the ideal threshold varies among species (Venier et al., 2017) and that threshold has yet to be determined for most species.

To balance effort and Type II errors in field data, I set a threshold on the number of hits to be verified per species vocalization so I could be reasonably certain that continuing to verify hits would yield few, if any, new species. I focused verification effort on those hits most likely to be a first true positive for a species at a site. All hits were first grouped within each site by species and vocalization type (e.g. song or call), sorted by distance within each group and up to the top 400 hits were verified, stopping when I verified the first true positive for that species at that site or reached 400 verified hits without a true positive. A single true positive was counted as presence. The remainder of the hits were discarded. I found that verifying only a small portion of total hits (i.e. 400 of many thousands) was sufficient to capture a true positive for >95% of the detected species in the testing dataset. A visual inspection of the species-accumulation curves suggested that the asymptote was at ~300-400 hits verified/vocalization in both field and test data

This protocol was based on the assumption that sounds ranked nearer to the top of a list are more likely to be true positives than those below. My results showed that a true positive identification was normally encountered within the first five positions, and that >95% of first true positives were encountered in the first 400 positions. Knight et al. (2017) similarly found that the portion of Common Nighthawk vocalizations detected increased as more hits were verified but eventually reached a point at which most of the true positives had been detected, leaving mostly false positives (Knight et al., 2017).

Setting a threshold on the total number of hits verified saves time because fewer false positives need to be checked overall. I have shown that this approach is effective for the majority of species across field sites and testing datasets. Within the testing data, if a true positive identification was present in the list of hits, then one was usually found in the first 100 hits. For ~10% of species, 100-400 hits needed to be verified to capture a true positive and for 1-5% of species >400 hits were needed to be verified, maxing out at 1000-3000 hits, all depending on the quality of the recording. Similarly, for the field data: if there was a true positive identification in the list of up to 400 hits/vocalization/site, then one was found in the first 100 hits verified for ~90% of species. Because, unlike the test set, I was unable to evaluate all hits in the field data, it is possible that occasionally, a site may have produced 400 false positives before the first true positive and in those cases, my method would result in a Type II error. However, the species accumulation curve for the field data suggest that is an uncommon occurrence. This problem might be addressed on a species-by-species and site-by-site basis by refining the algorithm to distinguish between true vocalizations and the confounding environmental noise or increasing the verification threshold for known problematic species.

Suggested Improvements and Further Research

One central problem is that trained models failed to detect 30-45% of species in the test set despite the trained model containing an identifier for those species. Some species were poorly represented within the testing dataset (i.e. with few/short recordings) and those should be supplemented with recordings from additional sources. For the species that were adequately represented, developing a separate training protocol to run subsequent to the one presented here is a priority. Additional clusters could be built to target specific segments of complicated songs, and the parameters could be altered to target specific frequency bands and separate syllables of faster songs.

Increasing the quality of the training data to create more discriminating classifiers may also reduce false negatives and positives. I used a 'coarse filter' approach to training, where less-than-perfect vocalizations for each species were manually identified during training as belonging to the species and therefore used to train the program. Training data were obtained from many locations other than the study site so I included lower-quality examples of species vocalizations to reduce the risk of training the algorithm to recognize only one geographic variation of a bird's vocalization. This increases the range of characteristics that determine whether a target sound is a match, which may increase the likelihood of detecting lower-quality vocalizations at a site but also potentially increase the number of misidentifications.

Increasing the number of misidentifications increases the time spent verifying and may push the first true positive detection for a species beyond the 400th ranked position. In addition, multiple algorithms could be trained separately, and more discriminately, for groups of species that the original algorithm had difficulty detecting. The algorithms could be run sequentially and this “multi-filter” approach may reduce the number of species missed.

It may be possible to further reduce error rates and improve the trained models by continuously adding to the training set as an inventory is being conducted. Sounds from field recordings can be corrected or confirmed to be true during the verification process and incorporated into training. This would be especially useful for multi-year studies to train how to distinguish problematic, site-specific noise.

The ability of recording equipment to separate signals from noise may influence the number of species detected because the recording quality was found to affect the performance of automatic detection. A signal-to-noise ratio (SNR) is generally provided for audio recorders. This ratio is a measure of the detectable difference in volume between the background noise generated by the recording equipment and a sound played at a fixed distance and volume, a higher number being better. Field recordings used here were obtained using Wildlife Acoustics SM2+, with an SNR of around 62dB. The same sound recorded with the company’s newer model of recorders, the SM4, had an SNR of 80dB. The difference may improve the detection ability of automated analysis by detecting quieter vocalizations at a greater distance. Future studies using automatic detection for species inventories should be aware of limitations introduced by recording equipment with a low SNR.

The results presented here are applicable for large datasets that cover sampling windows beyond the bird breeding season to capture any bird that may be using the site. The methods of manual detection used here focused sampling effort on the breeding season and early migration to maximize the number of species per unit of effort (May-June). However, the automatic detection method was able to sample for an additional 2.5 months after the breeding season (May – Early September) to reflect the increased sampling effort that is possible with automated recorders, which may result in more non-breeding species being detected. The extent to which this leads to overestimates of the number of breeding species needs to be explored.

However, demographic factors affecting bird populations do not occur exclusively during the breeding season (Calvert et al., 2009; Cox et al., 2018). Specifically, changes to non-breeding habitat can have consequences for abundance and population trends (Baker et al., 2004; Robbins et al., 1989; Sherry & Holmes, 1996). Ecosystem management generally has the goal to minimize these negative impacts. However, experienced researchers have often focused survey effort exclusively on the breeding season to maximize the value of limited effort (Stillman & Brown, 1995). Given that an important benefit of using automatic detection is little cost for increased effort (L. Venier et al., 2017), we felt it best to extend the comparison between manual and automatic detection beyond the breeding season.

Conclusion

Automatic detection software can be trained for general species inventories using an audio dataset of bird recordings non-specific to the study site. The Xeno-Canto database is an effective way to test the effectiveness of the training in terms of the number of species detected and the effort required to verify the identifications of those detections. Only a small subset of detections must be verified to capture a high percentage of species when the detections are organized by their similarity to the model built during training. My results suggest that the number of required verifications (400 detections/vocalization) was similar between the testing dataset containing birds from many regions (the Xeno-Canto database) and region-specific field recordings. It represents a good starting point that may be improved by tailoring the training data to specific sites. However, the best threshold may be site-specific. Given the choice between the automatic and manual the evidence presented here suggests automatic detection for the most complete species list but because each method finds species the other misses, a combination of the two would be preferred.

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Appendix A – Supplementary Tables

Table A 1**:** Listing of species detected and correctly identified within the Xeno-Canto dataset by the trained machine-learning program Kaleidoscope. 'A' quality represents clear recordings with no interference, 'B' is clear but some interference and 'C' represent moderately clear recordings with much interference. Each cell represents how many false positives were discarded before reaching the first true positive when each sound detected as ordered by its similarity to the training data examples. Green shading represents a species was detected, yellow shading and 'N/A' means a species vocalization was present but not detected.

Species	A Quality	B Quality	C Quality
Alder Flycatcher	2	27	2
American Bittern	N/A	N/A	N/A
American Black Duck	N/A	N/A	N/A
American Coot	2	N/A	12
American Crow	17	22	14
American Goldfinch	N/A	N/A	34
American Kestrel	N/A	N/A	208
American Redstart	206	1	38
American Robin	1	2	1
American Wigeon	8	N/A	636
American Woodcock	1	1	1
Bald Eagle	N/A	N/A	N/A
Baltimore Oriole	12	3	4
Bank Swallow	N/A	N/A	N/A
Barn Swallow	N/A	N/A	N/A
Barred Owl	13	8	6
Bay-breasted Warbler	326	378	30
Belted Kingfisher	N/A	N/A	N/A
Bicknell's Thrush	N/A	N/A	N/A
Black Guillemot	N/A	N/A	N/A
Black-and-white Warbler	1	1	2
Black-backed Woodpecker	N/A	N/A	N/A
Black-billed Cuckoo	N/A	N/A	N/A

Species	A Quality	B Quality	C Quality
Blackburnian Warbler	3	3	6
Black-capped Chickadee	1	5	2
Blackpoll Warbler	1	1	18
Black-throated Blue Warbler	1	6	20
Black-throated Green Warbler	2	6	7
Blue Jay	11	6	13
Blue-gray Gnatcatcher	3	3	76
Blue-headed Vireo	N/A	N/A	N/A
Blue-winged Teal	N/A	N/A	N/A
Blue-winged Warbler	20	2	1
Bobolink	N/A	N/A	N/A
Bonaparte's Gull	N/A	N/A	N/A
Boreal Chickadee	5	N/A	N/A
Boreal Owl	1	1	1
Broad-winged Hawk	5	24	3
Brown Creeper	1	N/A	1
Brown Thrasher	N/A	N/A	125
Brown-headed Cowbird	1	6	126
Canada Goose	4	6	3
Canada Warbler	N/A	N/A	1
Cape May Warbler	46	N/A	11
Carolina Wren	3	1	1
Cedar Waxwing	7	5	1
Chestnut-sided Warbler	N/A	N/A	76
Chimney Swift	N/A	N/A	N/A
Chipping Sparrow	1	1	18
Chuck-will's-widow	1	1	5
Clay-colored Sparrow	27	13	1
Cliff Swallow	N/A	N/A	N/A
Common Eider	9	24	25
Common Gallinule	6	7	767
Common Goldeneye	N/A	N/A	N/A
Common Grackle	N/A	31	N/A
Common Loon	1	1	1
Common Merganser	N/A	N/A	N/A
Common Murre	47	N/A	4
Common Nighthawk	1	1	1
Common Raven	1	4	1
Common Yellowthroat	N/A	2	27

Species	A Quality	B Quality	C Quality
Cooper's Hawk	N/A	N/A	N/A
Dark-eyed Junco	120	9	12
Double-crested Cormorant	N/A	N/A	479
Downy Woodpecker	N/A	N/A	N/A
Eastern Bluebird	3	13	1
Eastern Kingbird	1	1	3
Eastern Meadowlark	3	1	10
Eastern Phoebe	N/A	14	42
Eastern Screech-Owl	1774	59	3
Eastern Whip-poor-will	1	2	1
Eastern Wood-Pewee	N/A	N/A	2
European Starling	48	N/A	N/A
Evening Grosbeak	N/A	34	99
Field Sparrow	8	1	1
Fox Sparrow	36	11	122
Gadwall	N/A	N/A	N/A
Golden-crowned Kinglet	3	4	6
Gray Catbird	2	2	4
Gray Jay	50	6	87
Gray-cheeked Thrush	20	N/A	N/A
Great Black-backed Gull	N/A	1	7
Great Blue Heron	38	3	N/A
Great Crested Flycatcher	1	10	104
Great Horned Owl	1	1	1
Greater Scaup	345	17	N/A
Greater Yellowlegs	3	3	42
Green-winged Teal	15	26	18
Hairy Woodpecker	199	1	16
Hermit Thrush	73	23	1
Herring Gull	N/A	N/A	N/A
Hooded Merganser	N/A	N/A	N/A
Horned Lark	N/A	N/A	39
House Finch	N/A	1	12
House Sparrow	N/A	N/A	N/A
House Wren	N/A	N/A	N/A
Indigo Bunting	N/A	N/A	2
Killdeer	1	N/A	N/A
King Rail	N/A	N/A	N/A
Least Bittern	N/A	N/A	3
Least Flycatcher	4	2	5

Species	A Quality	B Quality	C Quality
Least Sandpiper	N/A	N/A	20
Lesser Scaup	N/A	N/A	N/A
Lincoln's Sparrow	N/A	N/A	N/A
Magnolia Warbler	N/A	N/A	33
Mallard	36	8	20
Marsh Wren	7	N/A	N/A
Merlin	N/A	N/A	N/A
Mourning Dove	1	21	32
Mourning Warbler	N/A	N/A	10
Nashville Warbler	N/A	1	1
Nelson's Sparrow	N/A	N/A	N/A
Northern Bobwhite	N/A	N/A	N/A
Northern Cardinal	20	2	1
Northern Flicker	8	77	N/A
Northern Gannet	N/A	N/A	N/A
Northern Goshawk	N/A	N/A	N/A
Northern Harrier	N/A	N/A	N/A
Northern Mockingbird	5	1	1
Northern Parula	N/A	N/A	12
Northern Saw-whet Owl	5	1	1
Northern Shoveler	N/A	55	309
Northern Waterthrush	N/A	N/A	23
Olive-sided Flycatcher	1	1	241
Osprey	1	9	8
Ovenbird	N/A	N/A	1
Palm Warbler	203	80	818
Peregrine Falcon	N/A	N/A	N/A
Philadelphia Vireo	1	N/A	14
Pied-billed Grebe	N/A	N/A	22
Pileated Woodpecker	54	17	45
Pine Grosbeak	N/A	3	154
Pine Siskin	2	8	N/A
Pine Warbler	1	3	4
Piping Plover	N/A	N/A	N/A
Purple Finch	10	3	1
Purple Martin	8	11	123
Razorbill	N/A	N/A	N/A
Red Crossbill	1	1	N/A
Red-bellied Woodpecker	N/A	N/A	N/A
Red-breasted Merganser	N/A	N/A	N/A

Species	A Quality	B Quality	C Quality
Red-breasted Nuthatch	11	1	110
Red-eyed Vireo	1	1	1
Red-headed Woodpecker	N/A	N/A	N/A
Red-shouldered Hawk	62	N/A	N/A
Red-tailed Hawk	129	N/A	N/A
Red-winged Blackbird	28	5	12
Ring-billed Gull	N/A	N/A	N/A
Ring-necked Duck	N/A	N/A	N/A
Ring-necked Pheasant	3	N/A	N/A
Rock Pigeon	N/A	N/A	N/A
Rose-breasted Grosbeak	1	2	1
Rough-legged Hawk	N/A	N/A	N/A
Ruby-crowned Kinglet	1	5	1
Ruby-throated Hummingbird	N/A	N/A	2
Ruddy Duck	N/A	N/A	N/A
Ruffed Grouse	N/A	N/A	N/A
Rusty Blackbird	N/A	1	26
Sandhill Crane	1	2	21
Savannah Sparrow	N/A	N/A	3
Scarlet Tanager	1	1	5
Sedge Wren	N/A	N/A	23
Semipalmated Plover	N/A	N/A	N/A
Sharp-shinned Hawk	N/A	N/A	N/A
Sharp-tailed Grouse	1	10	390
Solitary Sandpiper	N/A	N/A	N/A
Song Sparrow	N/A	N/A	N/A
Sora	2	21	N/A
Spotted Sandpiper	39	92	N/A
Spruce Grouse	N/A	N/A	N/A
Swainson's Thrush	N/A	N/A	436
Swamp Sparrow	N/A	N/A	6
Tennessee Warbler	1	1	29
Tree Swallow	N/A	N/A	54
Tufted Titmouse	1	1	74
Turkey Vulture	N/A	N/A	N/A
Upland Sandpiper	N/A	N/A	N/A
Veery	19	8	44
Vesper Sparrow	N/A	N/A	33
Virginia Rail	N/A	3	6
Warbling Vireo	1	1	1

Species	A Quality	B Quality	C Quality
White-breasted Nuthatch	3	30	1
White-throated Sparrow	1	1	1
White-winged Crossbill	N/A	3	20
Wild Turkey	11	12	12
Willet	N/A	N/A	N/A
Willow Flycatcher	N/A	N/A	187
Wilson's Phalarope	N/A	N/A	N/A
Wilson's Snipe	44	N/A	113
Winter Wren	1	1	6
Wood Duck	23	N/A	115
Wood Thrush	219	67	83
Yellow Rail	N/A	N/A	N/A
Yellow Warbler	N/A	N/A	N/A
Yellow-bellied Flycatcher	N/A	N/A	5
Yellow-bellied Sapsucker	N/A	N/A	N/A
Yellow-billed Cuckoo	1	1	1
Yellow-headed Blackbird	13	N/A	N/A
Yellow-rumped Warbler	N/A	N/A	26
Yellow-throated Vireo	10	1	5

Table A 2: The number of sites, of 29 surveyed, where automatic detection found a species that manual missed (A+M-), vice-versa (A-M+), or where both methods detected that species at a site (A+M+).

Species	A-M+	A+M-	A+M+	A-M-
Alder Flycatcher	3	6	14	6
American Black Duck	0	3	0	26
American Bittern	6	0	1	22
American Crow	0	11	17	1
American Goldfinch	1	14	10	4
American Redstart	10	3	10	6
American Robin	0	0	29	0
American Tree Sparrow	0	0	0	29
American Wigeon	0	4	0	25
American Woodcock	1	8	4	16
Baltimore Oriole	0	1	0	28
Barred Owl	0	7	0	22
Bay-breasted Warbler	1	1	0	27
Belted Kingfisher	0	0	0	29
Black-and-white Warbler	6	5	1	17
Black-billed Cuckoo	2	3	1	23
Blackburnian Warbler	1	10	1	17
Black-capped Chickadee	0	12	16	1
Black-throated Blue Warbler	4	5	0	20
Black-throated Green	2	7	11	9
Blue Jay	0	19	2	8
Blue-headed Vireo	8	0	2	19
Boreal Chickadee	0	5	0	24
Broad-winged Hawk	0	0	0	29
Brown Creeper	0	8	0	21
Brown Thrasher	2	0	1	26
Canada Goose	0	12	5	12
Canada Warbler	1	1	0	27
Cedar Waxwing	0	27	2	0
Chestnut-sided Warbler	2	5	16	6
Chimney Swift	0	0	0	29
Chipping Sparrow	0	2	0	27
Common Grackle	2	0	3	24
Common Loon	0	8	0	21

Species	A-M+	A+M-	A+M+	A-M-
Common Nighthawk	0	11	3	15
Common Raven	0	17	8	4
Common Redpoll	0	0	0	29
Common Yellowthroat	0	3	25	1
Dark-eyed Junco	5	6	12	6
Downy Woodpecker	3	6	0	20
Eastern Meadowlark	1	1	0	27
Eastern Phoebe	0	2	0	27
Eastern Wood-Pewee	0	10	0	19
Evening Grosbeak	0	0	0	29
Fox Sparrow	2	0	0	27
Eastern Screech Owl	0	1	0	28
Eastern Whip-poor-whil	0	4	3	22
Golden-crowned Kinglet	1	19	0	9
Gray Catbird	1	1	1	26
Gray Cheeked Thrush	0	1	0	28
Gray Jay	0	4	0	25
Great Blue Heron	1	0	0	28
Great Horned Owl	1	4	0	24
Greater Yellowlegs	1	2	0	26
Hairy Woodpecker	9	1	5	14
Hermit Thrush	1	17	3	8
Herring Gull	0	0	0	29
Indigo Bunting	0	2	0	27
Killdeer	6	0	0	23
Least Flycatcher	1	3	3	22
Lincoln's Sparrow	11	0	1	17
Magnolia Warbler	1	10	1	17
Merlin	3	0	0	26
Mallard	0	6	0	23
Mourning Dove	1	4	1	23
Mourning Warbler	14	0	0	15
Nashville Warbler	3	11	6	9
Northern Flicker	8	5	6	10
Northern Parula	0	15	0	14
Northern Saw-whet Owl	0	3	0	26
Northern Waterthrush	0	0	0	29
Olive-sided Flycatcher	13	0	2	14
Ovenbird	1	17	3	8
Palm Warbler	0	15	1	13

Species	A-M+	A+M-	A+M+	A-M-
Philadelphia Vireo	0	0	0	29
Pied-billed Grebe	2	0	0	27
Pileated Woodpecker - Wuk	0	6	0	23
Pine Siskin	4	0	0	25
Purple Finch	5	0	2	22
Red-breasted Nuthatch	6	2	7	14
Red-eyed Vireo	4	15	3	7
Red-winged Blackbird	3	0	1	25
Rose-breasted Grosbeak	6	2	1	20
Ruby-crowned Kinglet - Long	0	2	0	27
Savannah Sparrow	2	0	0	27
Scarlet Tanager	3	0	0	26
Song Sparrow	6	0	3	20
Sora	2	0	0	27
Spotted Sandpiper	7	0	2	20
Swainson's Thrush	2	13	3	11
Swamp Sparrow	5	2	0	22
Tennessee Warbler	1	0	0	28
Tree Swallow	3	0	0	26
Upland Sandpiper	4	0	0	25
Veery	2	6	2	19
Vesper Sparrow	3	0	0	26
White-throated Sparrow	0	2	27	0
White-winged Crossbill	0	2	1	26
Wilson's Snipe	7	0	3	19
Wilson's Warbler	0	0	0	29
Winter Wren	3	5	2	19
Yellow Warbler	1	3	3	22
Yellow-bellied Flycatcher	0	0	0	29
Yellow-bellied Sapsucker	5	0	0	24
Yellow-rumped Warbler	3	9	2	15

Table A3: Summary of recordings obtained through the Cornell Master set of recorded bird vocalizations that were used as training data for Kaleidoscope.

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Alder Flycatcher	9	00:29	00:09	01:17
American Bittern	2	01:01	00:08	01:54
American Black Duck	2	00:21	00:18	00:23
American Coot	16	00:10	00:02	00:17
American Crow	19	00:29	00:03	00:53
American Goldfinch	11	00:30	00:07	00:47
American Kestrel	4	00:22	00:07	00:31
American Oystercatcher	3	00:19	00:09	00:24
American Redstart	9	00:21	00:07	00:30
American Robin	20	00:33	00:09	00:53
American Three-toed Woodpecker	7	00:17	00:09	00:29
American Wigeon	5	00:21	00:12	00:33
American Woodcock	12	00:22	00:13	00:46
Arctic Tern	21	00:25	00:05	02:07
Bald Eagle	5	00:21	00:14	00:28
Baltimore Oriole	12	00:47	00:14	02:05
Bank Swallow	3	00:25	00:17	00:35
Barn Swallow	7	00:27	00:12	00:49
Barred Owl	13	00:56	00:16	02:08
Bay-breasted Warbler	16	00:26	00:08	00:46
Belted Kingfisher	9	00:26	00:11	00:48
Bicknell's Thrush	8	00:29	00:15	00:57
Black Guillemot	2	00:40	00:22	00:57
Black-and-white Warbler	7	00:22	00:11	00:36
Black-backed Woodpecker	6	00:14	00:03	00:27
Black-billed Cuckoo	6	00:11	00:04	00:19
Blackburnian Warbler	14	00:28	00:18	00:45
Black-capped Chickadee	15	00:38	00:16	00:52
Black-legged Kittiwake	3	00:25	00:04	00:45
Blackpoll Warbler	5	00:23	00:16	00:28
Black-throated-blue Warbler	19	00:25	00:05	00:55
Blue Jay	32	00:27	00:11	00:54

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Blue-gray Gnatcatcher	10	00:31	00:17	00:53
Blue-headed Vireo	7	00:36	00:20	00:47
Blue-winged Teal	5	00:11	00:03	00:16
Blue-winged Warbler	16	00:33	00:04	01:05
Bobolink	21	00:27	00:04	01:38
Bonaparte's Gull	8	00:30	00:16	01:02
Boreal Chickadee	6	00:07	00:04	00:08
Boreal Owl	7	00:34	00:05	01:28
Broad-winged Hawk	5	00:19	00:03	00:42
Brown Creeper	9	00:42	00:12	00:55
Brown Thrasher	13	00:30	00:13	00:50
Brown-headed Cowbird	11	00:39	00:14	00:48
Canada Goose	12	00:31	00:18	00:54
Canada Warbler	6	00:34	00:14	00:51
Cape May Warbler	13	00:26	00:13	00:45
Carolina Wren	37	00:34	00:10	01:01
Cedar Waxwing	7	00:20	00:13	00:42
Chestnut-sided Warbler	7	00:24	00:14	00:37
Chimney Swift	4	00:19	00:05	00:40
Chipping Sparrow	9	00:32	00:07	00:42
Chuck-will's-widow	9	00:11	00:01	00:20
Clay-colored Sparrow	6	00:24	00:10	00:31
Common Eider	5	00:21	00:09	00:34
Common Gallinule	11	00:10	00:05	00:19
Common Goldeneye	4	00:12	00:07	00:24
Common Grackle	17	00:26	00:07	00:51
Common Loon	6	00:44	00:24	01:25
Common Merganser	2	00:13	00:11	00:15
Common Murre	7	00:59	00:09	02:00
Common Nighthawk	9	00:26	00:12	01:01
Common Raven	20	00:33	00:04	01:40
Common Yellowthroat	9	00:25	00:08	00:36
Cooper's Hawk	10	00:34	00:14	01:13
Dark-eyed Junco	11	00:21	00:06	00:32
Double-crested Cormorant	3	00:26	00:09	00:50
Downy Woodpecker	10	00:20	00:02	00:50
Eastern Bluebird	10	00:28	00:01	00:47

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Eastern Kingbird	8	00:29	00:07	00:47
Eastern Meadowlark	18	00:37	00:15	00:50
Eastern Phoebe	10	00:20	00:06	00:41
Eastern Screech-Owl	13	00:24	00:04	01:06
Eastern Towhee	7	00:28	00:14	00:41
Eastern Whip-poor-will	4	00:27	00:04	01:10
Eastern Wood-Pewee	6	00:25	00:09	00:51
Eurasian Wigeon	2	00:14	00:09	00:19
European Starling	7	00:41	00:20	00:57
Evening Grosbeak	14	00:29	00:11	01:13
Field Sparrow	6	00:30	00:10	00:38
Fox Sparrow	20	00:20	00:01	00:44
Gadwall	4	00:07	00:03	00:12
Golden-crowned Kinglet	8	00:35	00:17	00:49
Gray Catbird	15	00:31	00:14	00:53
Gray Jay	17	00:23	00:09	00:44
Gray-cheeked Thrush	11	00:36	00:01	00:53
Great Black-backed Gull	5	00:19	00:15	00:21
Great Blue Heron	7	00:20	00:08	00:45
Great Crested Flycatcher	8	00:23	00:08	00:48
Great Horned Owl	9	00:47	00:15	01:56
Greater Scaup	8	00:19	00:14	00:24
Greater Yellowlegs	9	00:28	00:08	01:44
Green-winged Teal	4	00:17	00:03	00:39
Hairy Woodpecker	9	00:25	00:19	00:41
Hermit Thrush	8	00:27	00:02	00:49
Herring Gull	4	00:18	00:16	00:20
Hooded Merganser	3	00:04	00:02	00:06
Horned Lark	9	00:34	00:02	00:55
House Finch	7	00:34	00:15	00:50
House Sparrow	9	00:15	00:14	00:16
House Wren	19	00:40	00:17	00:52
Indigo Bunting	11	00:35	00:15	00:54
Killdeer	10	00:31	00:12	00:54
King Rail	4	00:21	00:05	01:00
Least Bittern	3	00:07	00:03	00:14
Least Flycatcher	7	00:22	00:05	00:47

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Least Sandpiper	5	00:21	00:14	00:30
Lesser Scaup	4	00:14	00:09	00:17
Lincoln's Sparrow	15	00:43	00:14	01:31
Magnolia Warbler	18	00:34	00:11	01:04
Mallard	13	00:26	00:10	00:55
Marsh Wren	5	00:30	00:17	00:37
Merlin	3	00:18	00:15	00:20
Mourning Dove	5	00:12	00:06	00:27
Mourning Warbler	7	00:23	00:17	00:38
Nashville Warbler	8	00:23	00:05	00:36
Nelson's Sparrow	4	00:22	00:07	00:44
Northern Bobwhite	6	00:17	00:06	00:25
Northern Cardinal	18	00:41	00:15	00:55
Northern Flicker	15	00:28	00:09	00:47
Northern Gannet	1	01:21	01:21	01:21
Northern Goshawk	2	00:18	00:11	00:25
Northern Harrier	6	00:19	00:06	00:28
Northern Mockingbird	14	00:39	00:15	00:50
Northern Parula	6	00:23	00:12	00:29
Northern Saw-whet Owl	19	00:26	00:04	01:00
Northern Shoveler	5	00:09	00:05	00:18
Northern Waterthrush	6	00:22	00:15	00:31
Olive-sided Flycatcher	6	00:40	00:14	00:49
Osprey	5	00:25	00:20	00:27
Ovenbird	7	00:41	00:16	00:54
Palm Warbler	10	00:24	00:08	00:33
Peregrine Falcon	2	00:41	00:32	00:50
Philadelphia Vireo	7	00:32	00:07	00:47
Pied-billed Grebe	4	00:10	00:04	00:14
Pileated Woodpecker	10	00:29	00:04	00:54
Pine Grosbeak	9	00:15	00:04	00:38
Pine Siskin	9	00:35	00:11	00:53
Pine Warbler	14	00:27	00:07	01:05
Purple Finch	19	00:36	00:07	00:57
Purple Martin	7	00:32	00:16	00:56
Razorbill	2	00:20	00:13	00:26
Red Crossbill	21	00:26	00:07	01:12

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Red-bellied Woodpecker	9	00:09	00:02	00:23
Red-breasted Merganser	2	00:15	00:06	00:23
Red-breasted Nuthatch	13	00:29	00:15	00:49
Red-eyed Vireo	8	00:39	00:16	00:48
Red-headed Woodpecker	4	00:16	00:10	00:24
Red-shouldered Hawk	9	00:28	00:09	01:00
Red-tailed Hawk	9	00:35	00:12	01:41
Red-tailed Tropicbird	3	00:16	00:11	00:21
Red-winged Blackbird	36	00:29	00:04	01:02
Ring-billed Gull	5	00:28	00:05	00:49
Ring-necked Duck	4	00:30	00:13	00:57
Ring-necked Pheasant	7	00:18	00:04	00:39
Rock Pigeon	3	00:22	00:08	00:36
Roseate Tern	6	00:17	00:04	00:36
Rose-breasted Grosbeak	12	00:33	00:03	00:55
Ruby-crowned Kinglet	23	00:37	00:05	01:03
Ruby-throated Hummingbird	4	00:36	00:23	00:46
Ruddy Duck	4	00:12	00:06	00:18
Ruffed Grouse	5	00:13	00:10	00:16
Rusty Blackbird	6	00:09	00:05	00:19
Sandhill Crane	8	00:24	00:09	00:45
Savannah Sparrow	13	00:45	00:12	01:18
Scarlet Tanager	13	00:31	00:09	00:50
Sedge Wren	5	00:52	00:46	00:59
Semipalmated Plover	7	00:18	00:08	00:27
Sharp-shinned Hawk	5	00:25	00:15	00:44
Sharp-tailed Grouse	6	00:26	00:16	00:56
Solitary Sandpiper	8	00:16	00:03	00:34
Song Sparrow	12	00:17	00:03	00:36
Sora	10	00:19	00:05	00:34
Spotted Sandpiper	6	00:26	00:04	00:43
Spruce Grouse	6	00:24	00:13	00:41
Swainson's Thrush	7	00:43	00:36	00:47
Swamp Sparrow	6	00:26	00:11	00:35
Tennessee Warbler	17	00:33	00:18	01:14
Tree Swallow	10	00:30	00:11	00:53
Tufted Titmouse	22	00:33	00:07	00:48

Species	Number of Recordings	Average Length (s)	Minimum Length (s)	Maximum Length (s)
Turkey Vulture	2	00:14	00:08	00:19
Upland Sandpiper	8	00:14	00:10	00:23
Veery	14	00:34	00:03	00:54
Vesper Sparrow	5	00:31	00:11	00:43
Virginia Rail	8	00:22	00:09	00:38
Warbling Vireo	10	00:42	00:16	00:52
White-breasted Nuthatch	6	00:27	00:16	00:41
White-throated Sparrow	18	00:55	00:28	01:19
White-winged Crossbill	20	00:36	00:07	01:13
Wild Turkey	5	00:43	00:17	00:59
Willet (Eastern)	3	00:20	00:15	00:29
Willow Flycatcher	8	00:31	00:09	00:58
Wilson's Phalarope	8	00:19	00:07	00:41
Wilson's Snipe	9	00:27	00:10	00:46
Winter Wren	8	00:39	00:22	01:03
Wood Duck	4	00:41	00:10	01:02
Wood Thrush	11	00:39	00:14	00:50
Yellow Rail	2	00:32	00:28	00:35
Yellow Warbler	14	00:22	00:10	00:34
Yellow-bellied Flycatcher	3	00:18	00:11	00:24
Yellow-bellied Sapsucker	13	00:25	00:05	01:11
Yellow-billed Cuckoo	8	00:19	00:09	00:28
Yellow-headed Blackbird	9	00:38	00:18	00:53
Yellow-rumped Warbler	10	00:25	00:06	00:38
Yellow-throated Vireo	8	00:37	00:21	00:49
Yellow-throated Warbler	6	00:44	00:23	01:01

Table A 4: An overview of the recordings contained within the testing dataset, obtained from the Xeno-Canto Database (Xeno Canto Database, 2019) 'A' quality recordings were those which the recordist identified the targeted species as recorded 'Loud and Clear'. In B quality the species was 'Clear, but bird a bit distant, or some interference with other sound sources', and C quality recordings the bird was recorded 'Moderately clear, or quite some interference'.

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
A Quality Recordings	**10256**	**1:05**	**0:00**	**15:14**
Alder Flycatcher	50	1:17	0:01	6:26
American Bittern	20	0:32	0:04	2:30
American Black Duck	6	0:17	0:06	0:49
American Coot	36	0:41	0:03	4:00
American Crow	102	1:01	0:01	5:00
American Goldfinch	40	1:15	0:08	7:21
American Kestrel	15	0:36	0:06	2:23
American Redstart	76	1:09	0:04	4:11
American Robin	141	1:13	0:00	8:51
American Wigeon	10	0:22	0:01	1:49
American Woodcock	31	1:06	0:04	4:25
Bald Eagle	10	0:17	0:07	0:35
Baltimore Oriole	35	1:02	0:10	3:12
Barn Swallow	193	1:33	0:01	4:00
Bay-breasted Warbler	27	1:22	0:08	6:00
Belted Kingfisher	11	0:28	0:04	1:43
Bicknell's Thrush	26	1:14	0:07	5:28
Black Guillemot	8	0:34	0:00	1:18
Black-and-white Warbler	42	1:10	0:03	6:47
Black-backed Woodpecker	20	1:22	0:05	5:48
Black-billed Cuckoo	6	1:11	0:39	1:47
Blackburnian Warbler	35	1:12	0:01	6:02
Black-capped Chickadee	67	0:58	0:05	6:48
Blackpoll Warbler	62	1:15	0:03	8:16
Black-throated Blue Warbler	30	1:08	0:08	2:52
Black-throated Green Warbler	40	0:48	0:02	2:27

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Blue Jay	108	0:39	0:00	3:55
Blue-grey Gnatcatcher	86	1:09	0:04	10:00
Blue-headed Vireo	52	1:12	0:07	6:08
Blue-winged Teal	17	0:25	0:02	1:26
Blue-winged Warbler	26	1:24	0:04	7:07
Bobolink	42	1:18	0:04	4:58
Bonaparte's Gull	19	0:35	0:05	2:07
Boreal Chickadee	29	1:00	0:07	3:22
Boreal Owl	87	1:20	0:00	7:34
Broad-winged Hawk	31	0:53	0:03	3:30
Brown Creeper	76	1:03	0:03	3:33
Brown Thrasher	56	2:08	0:14	9:56
Brown-headed Cowbird	49	1:10	0:03	6:50
Canada Goose	95	0:48	0:06	10:25
Canada Warbler	38	1:01	0:12	3:45
Cape May Warbler	29	1:14	0:02	3:07
Carolina Wren	118	0:55	0:03	5:59
Cedar Waxwing	18	0:36	0:02	1:45
Chestnut-sided Warbler	49	1:12	0:04	5:16
Chimney Swift	6	0:55	0:17	3:08
Chipping Sparrow	75	1:07	0:05	9:08
Chuck-will's-widow	30	1:00	0:01	7:37
Clay-colored Sparrow	31	1:36	0:08	10:54
Common Eider	24	0:56	0:05	2:08
Common Gallinule	74	0:39	0:04	4:37
Common Goldeneye	41	0:41	0:03	3:23
Common Grackle	39	1:00	0:06	4:29
Common Merganser	18	0:55	0:10	4:18
Common Murre	17	1:50	0:06	7:45
Common Nighthawk	11	0:44	0:12	1:53
Common Pheasant	64	0:43	0:02	4:12
Common Starling	191	1:30	0:01	15:14
Common Yellowthroat	117	0:55	0:02	5:00
Cooper's Hawk	29	0:45	0:07	3:38
Dark-eyed Junco	137	0:54	0:03	4:10
Double-crested Cormorant	9	0:40	0:05	2:01
Downy Woodpecker	35	0:55	0:04	5:33
Eastern Bluebird	25	1:39	0:04	13:17
Eastern Kingbird	20	0:56	0:03	3:40

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Eastern Meadowlark	98	1:04	0:03	4:06
Eastern Osprey	3	0:17	0:05	0:28
Eastern Phoebe	29	0:45	0:05	2:41
Eastern Screech Owl	7	2:27	0:36	4:48
Eastern Whip-poor-will	26	1:16	0:12	9:06
Eastern Wood Pewee	27	0:53	0:10	4:16
European Herring Gull	77	0:40	0:02	4:42
Evening Grosbeak	13	1:14	0:28	2:46
Field Sparrow	46	1:05	0:02	4:42
Fox Sparrow	270	1:21	0:03	7:49
Gadwall	41	0:39	0:02	6:02
Golden-crowned Kinglet	75	0:51	0:02	5:08
Great Black-backed Gull	31	0:28	0:04	2:00
Great Blue Heron	26	0:35	0:04	1:59
Great Crested Flycatcher	46	1:15	0:02	7:39
Great Horned Owl	70	1:08	0:02	8:37
Great Northern Loon	17	0:43	0:05	2:42
Greater Scaup	5	0:39	0:11	1:05
Greater Yellowlegs	21	0:33	0:04	2:03
Green-winged Teal	11	0:44	0:05	2:20
Grey Catbird	86	1:15	0:00	5:05
Grey Jay	23	0:38	0:02	3:24
Grey-cheeked Thrush	30	0:54	0:03	7:18
Hairy Woodpecker	57	0:39	0:01	1:49
Hermit Thrush	112	1:51	0:07	14:34
Hooded Merganser	5	1:09	0:08	2:57
Horned Lark	52	0:49	0:05	3:06
House Finch	75	1:09	0:05	6:48
House Sparrow	172	1:04	0:05	14:30
House Wren	379	0:47	0:01	6:49
Indigo Bunting	62	0:58	0:03	4:11
Killdeer	57	0:54	0:02	10:02
King Rail	24	0:57	0:04	9:02
Least Bittern	17	0:46	0:03	4:30
Least Flycatcher	33	1:06	0:07	3:56
Least Sandpiper	18	0:27	0:04	1:36
Lincoln's Sparrow	81	1:11	0:01	5:50
Magnolia Warbler	62	1:02	0:07	3:27
Mallard	98	0:49	0:03	10:41

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Mangrove Warbler	47	0:31	0:01	1:35
Marsh Wren	96	1:16	0:03	7:16
Merlin	19	1:11	0:05	5:51
Mourning Dove	27	1:21	0:09	3:48
Mourning Warbler	52	1:18	0:02	6:32
Myrtle Warbler	58	1:01	0:03	4:08
Nashville Warbler	48	1:08	0:04	3:49
Nelson's Sparrow	17	1:01	0:03	2:31
Northern Barred Owl	34	1:26	0:07	4:55
Northern Bobwhite	32	1:19	0:01	8:14
Northern Cardinal	130	1:02	0:03	9:36
Northern Flicker	69	0:51	0:03	5:48
Northern Gannet	14	1:35	0:03	4:10
Northern Goshawk	57	1:04	0:00	7:56
Northern Harrier	9	0:59	0:03	4:05
Northern Mockingbird	114	1:56	0:05	9:53
Northern Parula	48	0:59	0:01	6:11
Northern Raven	358	1:16	0:02	14:03
Northern Saw-whet Owl	33	0:45	0:02	2:16
Northern Shoveler	23	0:23	0:05	0:59
Northern Waterthrush	60	1:05	0:02	5:01
Olive-sided Flycatcher	32	1:09	0:02	4:36
Ovenbird	76	1:17	0:04	5:01
Palm Warbler	21	1:11	0:15	2:49
Peregrine Falcon	54	0:35	0:03	3:13
Philadelphia Vireo	24	1:32	0:06	4:17
Pied-billed Grebe	26	0:40	0:02	7:28
Pileated Woodpecker	25	1:22	0:03	6:40
Pine Grosbeak	24	1:00	0:07	3:20
Pine Siskin	59	1:10	0:04	9:05
Pine Warbler	35	1:08	0:03	5:08
Purple Finch	25	0:57	0:02	2:21
Purple Martin	29	1:46	0:03	13:45
Razorbill	4	0:52	0:09	2:35
Red Crossbill	380	0:48	0:00	9:12
Red-bellied Woodpecker	56	0:54	0:04	6:45
Red-breasted Merganser	11	0:25	0:05	1:15
Red-breasted Nuthatch	52	1:00	0:04	5:12
Red-eyed Vireo	149	1:01	0:06	5:58

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Red-headed Woodpecker	19	1:00	0:07	3:24
Red-shouldered Hawk	24	1:20	0:04	7:54
Red-tailed Hawk	31	0:40	0:03	3:44
Red-winged Blackbird	145	1:07	0:01	8:30
Ring-billed Gull	18	0:16	0:05	0:45
Ring-necked Duck	4	0:52	0:12	2:01
Rock Dove	17	1:20	0:10	8:33
Rose-breasted Grosbeak	32	1:01	0:09	2:49
Rough-legged Buzzard	14	0:48	0:05	2:03
Ruby-crowned Kinglet	62	1:03	0:03	4:54
Ruby-throated Hummingbird	7	0:23	0:01	1:11
Ruddy Duck	3	0:27	0:10	0:53
Ruffed Grouse	2	0:08	0:05	0:12
Rusty Blackbird	32	1:05	0:09	5:36
Sand Martin	55	1:49	0:02	10:00
Sandhill Crane	59	1:42	0:07	20:43
Savannah Sparrow	79	1:09	0:01	6:26
Scarlet Tanager	34	1:36	0:03	9:49
Sedge Wren	125	1:04	0:03	11:51
Semipalmated Plover	21	0:26	0:08	1:08
Sharp-shinned Hawk	2	1:33	1:00	2:06
Sharp-tailed Grouse	20	3:44	0:09	10:57
Solitary Sandpiper	20	0:41	0:02	3:10
Song Sparrow	254	1:03	0:03	13:06
Sora	36	0:45	0:03	5:50
Spotted Sandpiper	13	0:23	0:02	1:30
Spruce Grouse	8	0:38	0:04	2:22
Swainson's Thrush	132	1:14	0:04	5:11
Swamp Sparrow	37	0:56	0:04	4:49
Tennessee Warbler	59	1:00	0:03	2:39
Tree Swallow	28	1:23	0:09	8:57
Tufted Titmouse	56	0:47	0:06	4:25
Turkey Vulture	1	2:32	2:32	2:32
Two-barred Crossbill	36	1:12	0:01	3:02
Upland Sandpiper	12	0:36	0:11	1:25
Veery	44	0:59	0:11	4:00
Vesper Sparrow	42	1:57	0:05	7:07
Virginia Rail	34	0:51	0:02	6:10
Warbling Vireo	102	1:28	0:03	7:06

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Western Osprey	36	0:48	0:04	2:20
White-breasted Nuthatch	56	1:18	0:04	6:06
White-throated Sparrow	75	1:18	0:02	6:47
Wild Turkey	18	1:33	0:03	4:19
Willet	36	0:38	0:03	2:07
Willow Flycatcher	33	1:02	0:05	4:21
Wilson's Phalarope	2	1:09	0:10	2:09
Wilson's Snipe	27	0:40	0:05	5:25
Winter Wren	44	1:18	0:05	5:03
Wood Duck	8	0:33	0:07	1:15
Wood Thrush	72	1:14	0:01	9:36
Yellow Rail	8	1:52	0:08	5:00
Yellow-bellied Flycatcher	33	1:09	0:09	6:40
Yellow-bellied Sapsucker	24	0:29	0:01	1:36
Yellow-billed Cuckoo	21	0:31	0:06	3:53
Yellow-headed Blackbird	38	1:19	0:03	4:29
Yellow-throated Vireo	40	0:51	0:02	2:37
B Quality Recordings	**14442**	**0:53**	**0:00**	**23:24**
Alder Flycatcher	65	0:46	0:05	3:08
American Bittern	21	1:47	0:05	6:59
American Black Duck	4	1:18	0:06	4:36
American Coot	45	0:18	0:03	2:47
American Crow	70	0:53	0:03	9:00
American Goldfinch	91	0:56	0:03	5:36
American Kestrel	34	0:27	0:04	2:06
American Redstart	142	0:54	0:01	4:58
American Robin	206	1:07	0:01	15:26
American Wigeon	25	0:35	0:01	2:33
American Woodcock	35	1:50	0:04	9:52
Bald Eagle	25	0:46	0:02	4:25
Baltimore Oriole	115	0:51	0:02	3:30
Barn Swallow	306	1:18	0:02	20:04
Bay-breasted Warbler	25	1:07	0:02	3:42
Belted Kingfisher	41	0:46	0:00	6:12
Bicknell's Thrush	10	0:54	0:05	2:23
Black Guillemot	1	0:02	0:02	0:02
Black-and-white Warbler	94	0:39	0:02	2:55
Black-backed Woodpecker	11	0:55	0:10	3:18
Black-billed Cuckoo	22	0:32	0:01	2:13

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Blackburnian Warbler	71	0:52	0:01	3:37
Black-capped Chickadee	77	0:42	0:01	3:46
Blackpoll Warbler	82	0:54	0:01	4:08
Black-throated Blue Warbler	47	0:40	0:01	2:33
Black-throated Green Warbler	67	0:43	0:01	4:10
Blue Jay	111	0:41	0:00	2:57
Blue-grey Gnatcatcher	108	0:46	0:02	4:54
Blue-headed Vireo	67	0:55	0:05	4:14
Blue-winged Teal	30	0:24	0:01	2:01
Blue-winged Warbler	47	0:45	0:02	2:42
Bobolink	78	0:51	0:03	5:00
Bonaparte's Gull	11	0:35	0:04	3:25
Boreal Chickadee	18	0:44	0:07	1:53
Boreal Owl	77	1:05	0:01	5:17
Broad-winged Hawk	26	0:42	0:03	3:18
Brown Creeper	107	0:47	0:01	3:41
Brown Thrasher	53	1:24	0:01	9:11
Brown-headed Cowbird	104	0:49	0:01	7:10
Canada Goose	69	0:49	0:04	4:47
Canada Warbler	73	1:03	0:02	5:24
Cape May Warbler	38	0:51	0:02	4:38
Carolina Wren	175	0:49	0:02	9:16
Cedar Waxwing	49	0:49	0:04	4:32
Chestnut-sided Warbler	73	0:46	0:02	5:26
Chimney Swift	21	0:33	0:03	2:57
Chipping Sparrow	114	0:40	0:03	4:51
Chuck-will's-widow	25	0:54	0:02	2:32
Clay-colored Sparrow	40	1:23	0:02	8:59
Common Eider	17	0:42	0:08	1:33
Common Gallinule	74	0:27	0:03	4:21
Common Goldeneye	34	0:31	0:01	2:43
Common Grackle	56	0:49	0:01	4:35
Common Merganser	38	0:25	0:00	2:06
Common Murre	15	2:56	0:06	23:24
Common Nighthawk	12	0:47	0:08	1:47
Common Pheasant	78	0:43	0:01	5:59
Common Starling	186	1:13	0:02	16:00
Common Yellowthroat	164	0:40	0:02	4:56
Cooper's Hawk	36	0:40	0:02	5:08

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Dark-eyed Junco	150	0:51	0:02	10:35
Double-crested Cormorant	21	0:37	0:06	2:37
Downy Woodpecker	86	0:38	0:01	5:42
Eastern Bluebird	40	0:43	0:06	2:53
Eastern Kingbird	38	0:56	0:02	6:47
Eastern Meadowlark	110	0:38	0:00	2:54
Eastern Osprey	2	0:46	0:10	1:22
Eastern Phoebe	35	0:38	0:03	2:37
Eastern Screech Owl	24	1:14	0:06	7:05
Eastern Whip-poor-will	26	0:45	0:03	5:00
Eastern Wood Pewee	78	0:50	0:03	9:11
European Herring Gull	46	0:31	0:01	2:19
Evening Grosbeak	59	0:48	0:06	4:32
Field Sparrow	62	0:48	0:04	3:21
Fox Sparrow	153	0:57	0:02	6:16
Gadwall	42	0:35	0:02	2:48
Golden-crowned Kinglet	69	1:04	0:02	5:02
Great Black-backed Gull	24	0:36	0:04	2:33
Great Blue Heron	28	0:49	0:01	6:05
Great Crested Flycatcher	90	0:45	0:02	5:17
Great Horned Owl	89	1:09	0:03	5:57
Great Northern Loon	19	1:01	0:03	3:09
Greater Scaup	6	0:17	0:07	0:51
Greater Yellowlegs	69	0:21	0:01	2:39
Green-winged Teal	20	0:29	0:04	1:59
Grey Catbird	158	1:02	0:01	6:33
Grey Jay	61	0:57	0:05	5:44
Grey-cheeked Thrush	31	0:56	0:00	6:51
Hairy Woodpecker	106	0:38	0:01	4:48
Hermit Thrush	110	1:05	0:04	6:18
Hooded Merganser	13	0:34	0:01	1:35
Horned Lark	100	0:30	0:01	3:35
House Finch	118	0:44	0:01	4:03
House Sparrow	342	1:15	0:01	14:30
House Wren	469	0:43	0:01	6:20
Indigo Bunting	93	0:47	0:01	3:25
Killdeer	73	0:33	0:03	4:38
King Rail	16	0:55	0:07	2:21
Least Bittern	36	0:32	0:04	2:39

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Least Flycatcher	88	1:01	0:02	5:00
Least Sandpiper	40	0:15	0:01	2:57
Lesser Scaup	3	0:11	0:06	0:19
Lincoln's Sparrow	79	0:42	0:01	6:20
Magnolia Warbler	72	1:01	0:00	5:44
Mallard	119	0:29	0:00	4:23
Mangrove Warbler	28	0:30	0:03	2:35
Marsh Wren	151	0:58	0:03	6:44
Merlin	23	0:33	0:02	2:04
Mourning Dove	55	0:54	0:03	7:23
Mourning Warbler	65	1:21	0:03	7:12
Myrtle Warbler	76	0:47	0:02	4:18
Nashville Warbler	63	0:55	0:06	5:30
Nelson's Sparrow	11	1:08	0:04	5:00
Northern Barred Owl	37	1:15	0:06	4:31
Northern Bobwhite	43	0:59	0:02	6:01
Northern Cardinal	187	0:59	0:03	15:14
Northern Flicker	102	0:37	0:01	5:09
Northern Gannet	15	2:37	0:10	4:11
Northern Goshawk	71	1:02	0:03	10:17
Northern Harrier	14	0:42	0:04	3:32
Northern Mockingbird	98	1:30	0:00	10:47
Northern Parula	96	0:50	0:02	7:12
Northern Raven	316	0:56	0:01	16:10
Northern Saw-whet Owl	103	0:47	0:03	3:05
Northern Shoveler	30	0:33	0:01	3:25
Northern Waterthrush	109	0:50	0:02	6:54
Olive-sided Flycatcher	59	0:55	0:02	6:31
Ovenbird	85	0:43	0:01	3:04
Palm Warbler	21	0:40	0:01	2:46
Peregrine Falcon	36	0:28	0:02	2:17
Philadelphia Vireo	15	1:43	0:52	4:13
Pied-billed Grebe	62	0:26	0:04	7:25
Pileated Woodpecker	53	0:33	0:02	3:00
Pine Grosbeak	28	0:32	0:01	2:21
Pine Siskin	87	0:52	0:03	5:10
Pine Warbler	54	0:55	0:02	8:38
Piping Plover	5	0:21	0:03	0:47
Purple Finch	93	0:53	0:02	5:15

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Purple Martin	49	0:52	0:04	7:20
Razorbill	2	0:19	0:18	0:20
Red Crossbill	766	0:47	0:01	12:13
Red-bellied Woodpecker	56	0:38	0:02	3:25
Red-breasted Merganser	10	0:14	0:05	0:34
Red-breasted Nuthatch	83	0:55	0:02	3:44
Red-eyed Vireo	163	0:44	0:03	7:05
Red-headed Woodpecker	35	1:02	0:01	4:27
Red-shouldered Hawk	32	0:36	0:03	3:14
Red-tailed Hawk	39	0:50	0:03	3:54
Red-winged Blackbird	257	0:55	0:02	14:30
Ring-billed Gull	23	0:32	0:03	1:45
Ring-necked Duck	15	0:24	0:05	1:14
Rock Dove	35	0:29	0:04	2:11
Rose-breasted Grosbeak	63	0:57	0:01	2:53
Rough-legged Buzzard	2	0:20	0:20	0:20
Ruby-crowned Kinglet	119	1:05	0:02	6:04
Ruby-throated Hummingbird	14	0:16	0:04	1:05
Ruddy Duck	9	0:53	0:10	4:13
Ruffed Grouse	16	0:52	0:07	3:35
Rusty Blackbird	23	0:34	0:04	1:54
Sand Martin	60	0:38	0:01	3:26
Sandhill Crane	46	0:49	0:01	5:32
Savannah Sparrow	76	0:46	0:01	4:10
Scarlet Tanager	58	0:49	0:00	2:26
Sedge Wren	137	1:02	0:02	9:35
Semipalmated Plover	37	0:17	0:01	1:16
Sharp-shinned Hawk	8	0:55	0:03	3:11
Sharp-tailed Grouse	12	2:42	0:22	6:00
Solitary Sandpiper	45	0:21	0:01	2:43
Song Sparrow	246	0:50	0:02	4:38
Sora	67	0:54	0:02	9:24
Spotted Sandpiper	40	0:36	0:01	5:24
Spruce Grouse	3	1:05	0:37	1:28
Swainson's Thrush	189	0:57	0:00	6:56
Swamp Sparrow	65	0:52	0:03	14:40
Tennessee Warbler	75	0:42	0:02	3:20
Tree Swallow	44	0:32	0:04	2:42
Tufted Titmouse	122	0:47	0:02	9:56

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Two-barred Crossbill	69	0:56	0:05	7:26
Upland Sandpiper	21	0:52	0:02	5:42
Veery	77	0:50	0:01	3:49
Vesper Sparrow	50	0:56	0:02	3:22
Virginia Rail	61	0:59	0:03	5:56
Warbling Vireo	162	0:57	0:00	7:00
Western Osprey	47	0:49	0:03	3:59
White-breasted Nuthatch	158	1:00	0:02	9:26
White-throated Sparrow	205	2:21	0:02	15:06
Wild Turkey	20	0:49	0:01	2:44
Willet	48	0:24	0:01	1:56
Willow Flycatcher	89	0:34	0:01	3:20
Wilson's Phalarope	8	0:41	0:04	3:34
Wilson's Snipe	69	1:12	0:04	5:00
Winter Wren	81	1:02	0:01	8:23
Wood Duck	25	0:37	0:02	4:06
Wood Thrush	120	0:56	0:00	8:24
Yellow Rail	11	1:21	0:02	5:00
Yellow-bellied Flycatcher	61	0:40	0:08	2:21
Yellow-bellied Sapsucker	21	0:54	0:03	4:03
Yellow-billed Cuckoo	60	1:05	0:03	9:03
Yellow-headed Blackbird	27	1:19	0:02	4:12
Yellow-throated Vireo	51	0:46	0:02	3:04
C Quality Recordings	**6882**	**0:51**	**0:00**	**17:47**
Alder Flycatcher	89	0:34	0:01	5:00
American Bittern	14	0:37	0:00	3:51
American Black Duck	1	0:21	0:21	0:21
American Coot	41	0:56	0:03	5:00
American Crow	27	0:40	0:01	3:14
American Goldfinch	32	0:59	0:02	6:23
American Kestrel	15	0:19	0:06	0:56
American Redstart	66	0:30	0:01	2:49
American Robin	76	1:29	0:02	10:22
American Wigeon	7	0:15	0:02	0:31
American Woodcock	15	1:16	0:03	9:14
Bald Eagle	9	0:48	0:03	4:58
Baltimore Oriole	37	0:55	0:02	3:14
Barn Swallow	219	1:26	0:02	8:18
Bay-breasted Warbler	12	0:21	0:02	0:48

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Belted Kingfisher	9	0:13	0:03	0:24
Bicknell's Thrush	6	0:27	0:16	0:48
Black-and-white Warbler	35	0:28	0:04	2:00
Black-backed Woodpecker	3	0:32	0:05	1:26
Black-billed Cuckoo	13	0:25	0:03	1:54
Blackburnian Warbler	26	0:32	0:01	1:47
Black-capped Chickadee	47	0:52	0:02	4:34
Blackpoll Warbler	26	0:38	0:02	2:12
Black-throated Blue Warbler	24	0:33	0:02	3:37
Black-throated Green Warbler	16	0:45	0:01	3:32
Blue Jay	32	0:53	0:00	4:45
Blue-grey Gnatcatcher	28	0:57	0:03	3:48
Blue-headed Vireo	30	0:49	0:03	2:52
Blue-winged Teal	18	0:31	0:02	4:18
Blue-winged Warbler	25	0:35	0:01	2:10
Bobolink	15	0:38	0:01	4:19
Bonaparte's Gull	6	0:29	0:17	0:47
Boreal Chickadee	10	0:31	0:16	1:00
Boreal Owl	25	1:09	0:08	2:49
Broad-winged Hawk	14	0:38	0:02	4:21
Brown Creeper	38	0:59	0:01	9:14
Brown Thrasher	24	0:57	0:04	4:11
Brown-headed Cowbird	36	0:27	0:01	3:00
Canada Goose	49	0:54	0:04	4:43
Canada Warbler	21	0:44	0:01	3:52
Cape May Warbler	8	0:35	0:07	2:38
Carolina Wren	72	0:40	0:01	9:17
Cedar Waxwing	23	0:34	0:11	2:08
Chestnut-sided Warbler	21	0:29	0:03	2:00
Chimney Swift	6	1:05	0:04	2:47
Chipping Sparrow	43	0:47	0:01	2:28
Chuck-will's-widow	22	0:24	0:06	0:58
Clay-colored Sparrow	36	0:55	0:02	5:00
Common Eider	9	1:47	0:12	8:20
Common Gallinule	28	0:18	0:02	1:24
Common Goldeneye	14	0:17	0:01	1:20
Common Grackle	26	1:00	0:02	4:54
Common Merganser	27	0:31	0:01	2:54
Common Murre	11	3:54	0:12	8:18

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Common Nighthawk	17	1:18	0:07	6:23
Common Pheasant	73	1:08	0:00	8:17
Common Starling	151	1:14	0:01	8:17
Common Yellowthroat	55	0:39	0:01	4:41
Cooper's Hawk	18	0:42	0:03	3:43
Dark-eyed Junco	69	0:44	0:04	3:40
Double-crested Cormorant	7	0:16	0:07	0:52
Downy Woodpecker	37	0:24	0:02	1:47
Eastern Bluebird	20	0:27	0:03	1:35
Eastern Kingbird	20	0:54	0:03	4:12
Eastern Meadowlark	47	0:22	0:01	2:50
Eastern Osprey	1	0:20	0:20	0:20
Eastern Phoebe	19	0:51	0:04	3:31
Eastern Screech Owl	26	1:12	0:01	4:14
Eastern Whip-poor-will	13	0:26	0:13	1:14
Eastern Wood Pewee	45	0:30	0:01	3:32
European Herring Gull	16	0:36	0:08	1:37
Evening Grosbeak	21	0:22	0:02	0:57
Field Sparrow	35	0:33	0:00	2:26
Fox Sparrow	59	0:49	0:02	3:18
Gadwall	23	0:29	0:01	1:44
Golden-crowned Kinglet	23	0:52	0:04	4:07
Great Black-backed Gull	30	0:47	0:00	2:33
Great Blue Heron	5	0:14	0:05	0:37
Great Crested Flycatcher	32	0:26	0:03	1:15
Great Horned Owl	42	1:07	0:02	5:41
Great Northern Loon	16	0:41	0:03	2:46
Greater Scaup	1	0:51	0:51	0:51
Greater Yellowlegs	25	0:29	0:02	3:05
Green-winged Teal	8	0:22	0:04	1:01
Grey Catbird	63	0:52	0:02	3:32
Grey Jay	19	0:36	0:05	1:53
Grey-cheeked Thrush	15	0:35	0:01	2:29
Hairy Woodpecker	49	0:46	0:02	2:39
Hermit Thrush	38	1:26	0:03	7:38
Hooded Merganser	6	0:31	0:03	1:25
Horned Lark	30	0:31	0:01	4:36
House Finch	31	0:46	0:03	10:36
House Sparrow	393	2:16	0:01	14:30

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
House Wren	157	0:37	0:01	6:00
Indigo Bunting	20	0:16	0:02	0:37
Killdeer	19	0:30	0:00	4:33
King Rail	7	0:26	0:06	1:13
Least Bittern	24	0:25	0:03	1:10
Least Flycatcher	55	0:42	0:02	2:33
Least Sandpiper	26	0:13	0:01	0:46
Lesser Scaup	2	0:28	0:01	0:55
Lincoln's Sparrow	12	0:34	0:02	1:12
Magnolia Warbler	42	0:38	0:01	2:30
Mallard	59	0:28	0:01	6:26
Mangrove Warbler	11	0:23	0:02	0:41
Marsh Wren	34	0:47	0:04	5:00
Merlin	5	1:01	0:10	1:56
Mourning Dove	24	0:34	0:02	1:39
Mourning Warbler	25	0:40	0:03	2:40
Myrtle Warbler	29	0:29	0:02	1:44
Nashville Warbler	22	0:32	0:03	2:55
Nelson's Sparrow	6	1:47	0:47	4:56
Northern Barred Owl	26	0:56	0:02	6:40
Northern Bobwhite	7	0:12	0:02	0:55
Northern Cardinal	72	0:55	0:05	8:32
Northern Flicker	40	0:38	0:00	4:16
Northern Gannet	16	6:06	0:06	14:40
Northern Goshawk	58	0:32	0:01	3:36
Northern Harrier	6	0:22	0:05	0:34
Northern Mockingbird	49	1:27	0:03	8:15
Northern Parula	39	0:30	0:00	2:45
Northern Raven	118	0:44	0:02	3:11
Northern Saw-whet Owl	38	0:40	0:03	3:10
Northern Shoveler	14	0:13	0:02	0:42
Northern Waterthrush	47	0:36	0:02	3:07
Olive-sided Flycatcher	13	0:44	0:13	2:25
Ovenbird	21	0:29	0:00	2:30
Palm Warbler	12	0:20	0:02	0:54
Peregrine Falcon	17	0:30	0:05	1:37
Philadelphia Vireo	9	0:24	0:02	1:06
Pied-billed Grebe	32	0:18	0:04	1:48
Pileated Woodpecker	29	0:19	0:02	1:03

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Pine Grosbeak	25	1:30	0:03	10:42
Pine Siskin	25	0:38	0:02	2:20
Pine Warbler	25	1:02	0:02	8:33
Piping Plover	9	0:21	0:04	1:19
Purple Finch	77	0:51	0:02	5:14
Purple Martin	13	0:32	0:01	1:40
Razorbill	5	3:04	0:06	8:10
Red Crossbill	481	0:40	0:01	10:46
Red-bellied Woodpecker	30	0:20	0:02	1:23
Red-breasted Merganser	3	0:41	0:15	1:11
Red-breasted Nuthatch	30	0:34	0:02	2:10
Red-eyed Vireo	65	0:41	0:02	5:00
Red-headed Woodpecker	7	0:30	0:02	1:13
Red-shouldered Hawk	2	0:24	0:07	0:41
Red-tailed Hawk	18	0:26	0:02	1:32
Red-winged Blackbird	88	0:46	0:01	4:30
Ring-billed Gull	14	0:28	0:03	1:26
Ring-necked Duck	7	0:32	0:01	1:30
Rock Dove	17	0:40	0:01	2:18
Rose-breasted Grosbeak	39	0:41	0:02	2:44
Ruby-crowned Kinglet	79	0:48	0:03	4:09
Ruby-throated Hummingbird	16	0:18	0:05	1:17
Ruddy Duck	7	0:26	0:02	1:22
Ruffed Grouse	5	0:32	0:12	1:07
Rusty Blackbird	10	0:23	0:05	1:05
Sand Martin	28	0:30	0:03	3:23
Sandhill Crane	9	0:34	0:06	2:06
Savannah Sparrow	33	0:45	0:01	4:13
Scarlet Tanager	32	0:37	0:00	2:51
Sedge Wren	78	0:45	0:02	9:57
Semipalmated Plover	18	0:09	0:01	0:23
Sharp-shinned Hawk	6	0:16	0:07	0:37
Sharp-tailed Grouse	4	0:23	0:03	0:44
Solitary Sandpiper	21	0:14	0:02	1:02
Song Sparrow	117	0:48	0:01	17:47
Sora	26	0:42	0:01	3:22
Spotted Sandpiper	24	0:15	0:02	2:01
Spruce Grouse	2	3:01	0:11	5:51
Swainson's Thrush	90	0:41	0:00	5:30

Species	Number of Recordings	Average Length of Recordings	Minimum Recording Length	Maximum Recording Length
Swamp Sparrow	30	0:18	0:02	2:00
Tennessee Warbler	30	0:37	0:04	3:05
Tree Swallow	11	0:40	0:03	3:17
Tufted Titmouse	31	0:46	0:01	4:32
Turkey Vulture	1	0:15	0:15	0:15
Two-barred Crossbill	40	0:41	0:05	2:10
Upland Sandpiper	16	0:11	0:03	0:24
Veery	57	0:38	0:00	2:57
Vesper Sparrow	16	0:51	0:05	2:41
Virginia Rail	47	0:50	0:03	4:52
Warbling Vireo	96	1:12	0:01	6:16
Western Osprey	46	0:30	0:01	5:57
White-breasted Nuthatch	55	0:33	0:01	3:01
White-throated Sparrow	57	1:01	0:01	6:00
Wild Turkey	13	0:38	0:01	3:17
Willet	13	0:26	0:00	2:03
Willow Flycatcher	53	0:34	0:01	3:02
Wilson's Phalarope	4	0:31	0:06	1:12
Wilson's Snipe	25	0:34	0:03	4:46
Winter Wren	61	0:34	0:03	2:47
Wood Duck	11	0:40	0:02	2:42
Wood Thrush	38	0:59	0:02	8:48
Yellow Rail	9	0:54	0:02	5:00
Yellow-bellied Flycatcher	26	0:31	0:00	1:58
Yellow-bellied Sapsucker	17	0:43	0:03	3:34
Yellow-billed Cuckoo	48	0:41	0:04	4:47
Yellow-headed Blackbird	5	0:37	0:05	1:10
Yellow-throated Vireo	19	0:23	0:01	1:08

Curriculum Vitae

Candidate’s full name: Jeff Hines

Universities attended: University of New Brunswick, Bachelor of Science with Honours, 2018

Publications: None

Conference Presentations: None