DEVELOPMENT OF NEW BIOACOUSTICS TOOLS TO MONITOR AND BETTER UNDERSTAND POPULATIONS OF TWO CRITICALLY ENDANGERED BIRD SPECIES ON MAUI

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Abstract

Bioacoustics monitoring using automated recording units (ARUs) offers an alternative method to monitor vocalizing wildlife with various improvements over traditional methods, including flexible scheduling, infinite replayability, and the ability to collect large datasets with minimal effort. Still, a drawback is the time-consuming nature of reviewing recordings for target species. Automatic detection algorithms can expedite ARU data analysis; however, automated detection algorithms are not well-developed for Hawaiian forest bird species. Here, I focused on using automated tools to improve monitoring protocols for two critically endangered Hawaiian forest birds: the kiwikiu (*Pseudonestor xanthophrys*) and the ʻākohekohe (*Palmeria dolei*). My first objective was to gather training data for the automatic detection algorithm BirdNET, then use it to examine the differences in vocalization characteristics of my target species in three distinct areas of their population. I deployed ARUs at The Nature Conservancy's Waikamoi Preserve, Manawainui, and upper Kīpahulu Valley in Haleakalā National Park.

For kiwikiu, I found significant differences in the mean length and frequency variability in songs between locations. For ʻākohekohe, I found a significant difference in the mean length of their "squirtle" calls. However, I did not find differences in repertoire sizes or diversity among locations in either species. I observed that shared syllables among different individual kiwikiu songs occurred most frequently in the same locations, suggesting variation in songs between the sub-populations of kiwikiu. ʻĀkohekohe vocalizations may also vary between sub-populations. These results demonstrate that some vocalizations vary by location may indicate the presence of dialects in these species. My second objective after the BirdNET algorithm was trained on Hawaiian species was to test the algorithm's accuracy for detecting kiwikiu and ʻākohekohe in soundscape recordings. This testing occurred in two phases, an efficacy phase, where the identifications BirdNET produced were compared to manually annotated files, and an expansion phase, where BirdNET identified vocalizations in unannotated files. Above a confidence score threshold of 0.5, BirdNET accurately identified ʻākohekohe 65.8% of the time and kiwikiu 27.4% of the time. My study demonstrates the potential for using BirdNET to analyze recording data for kiwikiu and ʻākohekohe and improve the tools available to conduct future bioacoustic research for these species.

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Introduction

Passive acoustic monitoring of animal sounds using autonomous recording units (ARU) is gaining popularity as bioacoustics technology develops (Teixeira et al. 2019). ARUs are easy to program and can record continuously or for specific time intervals depending on research needs (Celis-Murillo et al. 2009; Shonfield & Bayne 2017). These observations can occur day or night regardless of visibility, making them suitable for nocturnal or cryptic species that otherwise might be difficult for human observers to monitor (Steer 2010; Frommolt et al. 2014; Wrege et al. 2017; Pérez-Granados & Schuchmann 2020). Another benefit of passive acoustic monitoring is that ARU deployment in the field is expeditious and requires little training. The recordings obtained from an ARU can span months between servicing, making them attractive in remote areas that might be difficult or expensive to traverse for field staff. The ability to replay recordings an infinite number of times allows for the confirmation of vocalizations by multiple people, removing the necessity for trained observers of each species in the field, and reducing observer bias (Haselmayer et al. 2000; Aide et al. 2013).

Using sound analysis software, researchers can view recordings from the ARUs as spectrograms, which are two-dimension visual representations of the audio waveforms, with time on the x-axis and frequency along the y-axis. However, visually sorting these data is time-consuming and requires specialized training (Pérez-Granados et al. 2018). In a study that examined using acoustic monitoring techniques to determine species richness, researchers found that visually analyzing recordings took twice as long as field observations because observers tended to replay the data (Wimmer et al. 2013). In addition, automated recording units can generate immense amounts of data depending on their sampling schedule. For example, an ARU programmed to gather thirty ten-minute daily recordings for one month would result in 900 recordings, amounting to roughly 150 hours of recordings. Should a researcher choose to deploy more ARUs, the data that researchers must review proportionately grows and becomes impractical to analyze manually, especially when there is more than one focal species of interest.

Automated detection programs can expedite ARU data processing and analysis; however, they are often unreliable in many situations. In addition, automatic identification typically targets a single species, so monitoring large soundscapes may be more complex than targeted recordings

(Obrist et al. 2010). The quality of the recordings, external environmental noise, and overlap of other wildlife vocalizations create additional challenges with automatic detections. When vocalizations overlap, they are much more difficult for recognition algorithms to identify correctly, limiting the efficacy of the software (Rempel et al. 2005; Buxton & Jones 2012; Fristrup & Mennit 2012). Therefore, increasing the accuracy and effectiveness of automatic detection algorithms will improve our ability to recognize species and estimate their distribution and abundance (Brandes 2008).

In the last 30 years, the island of Maui has seen the extinction of several forest birds, including the Maui ʻakepa (*Loxops ochraceus*), the Maui nukupuʻu (*Hemignathus lucidus*), and the poʻouli (*Melamprosops phaeosoma*) (USFWS 2021). Native forest birds face several anthropogenically introduced threats, including habitat degradation via feral ungulates and invasive plants, predators, and avian disease (Paxton et al. 2018). Native forest birds are essential pollinators and seed dispersers in functioning Hawaiian forests (Carpenter 1976). The loss of these pollinators has likely played a role in the subsequent extinction of Campanulaceae plants (Cox & Elmqvist 2000), and the loss of native frugivores was linked with shifting functional traits in Hawaiian ecosystems (Case & Tarwater 2020). Similarly, insectivorous avifauna have experienced widespread extinctions (Boyer 2008).

Many Native Hawaiian moʻolelo, mele, and oli (stories, songs, and chants) feature birds (Gomes 2020). For example, "*ua ʻelepaio ʻia ka waʻa*," meaning "the ʻelepaio (*Chasiempsis* spp.) has marked the log," is an indication that a log would be poor for canoe-making as the ʻelepaio is insectivorous and prefers foraging on rotten logs (Pukui 1983). Aliʻi (chiefs) also prized these birds for their feathers for use in feathered regalia (Gomes 2016). These feathers were associated with the chief's power, with more extensive or intricate feather work equating to a more commanding aliʻi (Pratt et al. 2005). The extinction of these birds would be a tragic loss to the ecological and cultural foundation in Hawaiʻi.

Autonomous recording units offer an alternative method to improve spatial and temporal coverage for bird monitoring in Hawaiʻi. Statewide, Hawaiʻi Forest Bird Surveys occur approximately every one to five years, following established transects used since 1976 (Scott et al. 1986). Researchers survey birds using a point transect distance sampling method where trained observers record bird detections from survey stations during eight-minute counts (Camp et al. 2009). Until recently, forest bird monitoring within Haleakalā National Park (HALE) on

the island of Maui was inconsistent, mainly consisting of surveys along several point count transects once every five years, offering only tiny snapshots of the population trends of already elusive forest birds. Staffing, park priorities, and management of other critical resources have not always aligned with more intensive monitoring of forest birds. Researchers have concentrated efforts to monitor forest birds in other areas across Maui, but staffing limitations and site accessibility issues remain. As a result, researchers were left with an imprecise and incomplete knowledge of the status and distribution of forest birds within and outside the park.

The kiwikiu (Maui Parrotbill, *Pseudonestor xanthophrys*) is a critically endangered forest bird endemic to Maui and Molokaʻi. The current population is approximately 150 birds and is exclusively in native forest on the windward slopes of East Maui from The Nature Conservancy's (TNC) Waikamoi Preserve in the west to HALE in the east (Judge et al. 2019). The critically endangered ʻākohekohe (*Palmeria dolei*) is also endemic to Maui and Molokaʻi and shares a similar range to that of kiwikiu, with population estimates of approximately 1700 individuals (Judge et al. 2019). Other native forest birds such as Hawaiʻi ʻamakihi (*Chlorodrepanis virens*) and Maui ʻalauahio (*Paroreomyza montana*) are experiencing declines in part of their ranges. While ʻiʻiwi (*Drepanis coccinea*) and ʻapapane (*Himatione sanguinea*) are more abundant, they could face future population decline (Judge et al. 2019).

Bird songs are essential in communication between the singer and other birds. These songs can vary amongst individuals and populations. The local adaptation hypothesis states that females are more likely to select males who sing songs familiar to their locality; these males are more likely to possess traits leading to higher fitness in their local area (Podos & Warren 2007). Other hypotheses, like the epiphenomenon hypothesis, state that there is no functional purpose to forming dialects and that they may develop coincidentally due to diverging selections in non-continuous populations (Podos & Warren 2007). On Kauaʻi, researchers found that over 40 years, the complexity of the songs of three forest bird species decreased significantly as population abundance declined (Paxton et al. 2019). Further, they observed a concurrent convergence of those three birds' songs, likely due to the lack of appropriate conspecific tutors during the song-learning phase. Anecdotally, there appear to be differences in the repertoires of the kiwikiu and ʻākohekohe across their ranges on Maui. Field observations in different parts of their range indicate that kiwikiu may have developed dialects.

Before the onset of this project, researchers from Maui Forest Birds Recovery Project familiar with the kiwikiu noted some variation in song qualities between Hanawī Natural Area Reserve in the central portion of the kiwikiu range compared to those in The Nature Conservancy's Waikamoi Preserve at the western edge of the range. However, the differences in songs among these areas were not great and somewhat inconsistent, with similar-sounding songs in both locations. While in the field in the Manawainui region of HALE in March 2022, the park's Forest Bird Program Coordinator, Chris Warren, and I observed a male kiwikiu singing a highly atypical song, divergent even from kiwikiu songs heard from other areas of the park. These observations, as well as variations observed outside the park, sparked an interest in the further examination of kiwikiu songs. ʻĀkohekohe exhibit an extensive repertoire of distinct songs and calls. Anecdotal evidence suggests that the dominant vocalization type also seems to vary across the landscape, with the primary vocalization heard differing in each area. My field observations indicate that ʻākohekohe may sing certain songs preferentially; for example, the "wow" song is common in Manawainui but less so in Waikamoi.

The main objective of this project was to use manually annotated soundscapes from TNC's Waikamoi Preserve, Kīpahulu Valley, and Manawainui to provide the data necessary to train a recently developed deep artificial neural network (DNN) known as BirdNET (Kahl et al. 2021), to accurately detect the songs and calls of ʻākohekohe and kiwikiu and then test the algorithm's efficacy on naïve datasets. I hypothesized that once trained, BirdNET would successfully identify kiwikiu and ʻākohekohe in our soundscape recordings and predicted that adding BirdNET to our analysis repertoire would likely expedite the processing of our ARU recordings.

A second objective was to use the recordings to examine the variability in kiwikiu and ʻākohekohe vocalizations across the landscape. Because song learning is a culturally transmitted trait, I hypothesized that I would find more variability in the repertoires of kiwikiu and ʻākohekohe between populations than within populations. Following anecdotal evidence, I predicted the vocalizations of ʻākohekohe and kiwikiu would vary between different populations, both in the dominant vocalization type and the acoustic qualities of the vocalizations. Considering the current population status of both birds, gaining additional information about their vocal repertoires will likely be necessary for the future as it relates to a deeper understanding of their ecology. Divergent vocalization behavior may suggest similarly diverging

populations, perhaps influencing future monitoring and translocation efforts. In addition, understanding variability in the vocalizations of these two species may allow us to improve the efficacy of automated detection algorithms.

Methods

Study sites

I primarily conducted this study within The Nature Conservancy's Waikamoi Preserve and Haleakalā National Park. These two locations represent the eastern and western extremes of both species' ranges (Figure 1). The Nature Conservancy of Hawai‘i manages Waikamoi Preserve which covers 8,951 acres on the slopes of Haleakalā. Here I divided the preserve into eastern and western sections, with the Ko‘olau Gap separating the two sections. The western portion of Waikamoi is easily accessible via hiking. It is an area where kiwikiu and ‘ākohekohe are reliably detected (and relatively well studied), whereas the eastern portion of the preserve is accessible via helicopter only. Therefore, to maximize data collection, I prioritized western Waikamoi for recording data to train the algorithm. HALE manages over 30,000 acres on the slopes of eastern Maui Island. However, forest exists primarily within Kīpahulu Valley and Manawainui planeze, an area of approximately 12,000 acres, although the birds are restricted to a much smaller area within the valley and planeze (Smith 1978; Stein 2007). Within the park, I focused on the West Camp area of upper Kīpahulu Valley and Manawainui – two regions where kiwikiu and ‘ākohekohe have been documented historically within the park but had not been monitored regularly in recent years. Acoustic data were collected from the above locations in 2020 and 2021 (Table 1). I supplemented this dataset with previous years' data from other projects within the same areas.

Study species

I focused on two Maui endemic bird species in the family Fringillidae, the kiwikiu (*Pseudonestor xanthophrys*) and the ‘ākohekohe (*Palmeria dolei*). These two birds are federally listed as endangered, with the estimated populations of kiwikiu at 157 ± 67 birds and ‘ākohekohe

at 1,768 ± 315 birds (Judge et al. 2021). Both birds are now restricted to the upper-elevation rainforests on the slopes of Haleakalā (Pratt et al. 2001; Pyle & Pyle 2017). Other Hawaiian forest birds and non-native birds not examined during this project are present within the study area and could be used in the future for similar work focusing on other species.

Kiwikiu have four unique vocalizations: one song and three call variants (Table 2). Only male kiwikiu produce a song consisting of consecutive "chuey" notes that often descend slightly in pitch (Mountainspring 1987). These songs typically contain five to eight notes and are thought to reinforce territories and attract mates (Simon et al. 2020). The rates at which males sing are unknown, and songs are less common outside the breeding season. Both sexes produce three additional call variants, a "chip" note very similar to those produced by the Maui ʻalauahio and several other insectivores on other islands, a three-note whistled "do-a-weet," and a shorter upslurred or downslurred "pweet" or "teer" whistle (Carothers et al. 1983; Simon et al. 2020). These whistles and calls are likely used as contact calls (used to keep in touch with other birds) but could also be used in warning situations (Simon et al. 2020).

ʻĀkohekohe display a variety of songs and calls, including whistles and "guttural" calls (Table 2). The most common calls are whistles that rise in pitch or rise then fall. Other calls include "chirrup," "squirtle," and "guttural" calls. Songs vary but are typically hoarse and low-pitched (Berlin & Vangelder 2020). There is little research describing the function of these vocalizations, but it is believed that the upslurred whistle establishes pair bonds and territory. Higher-pitched guttural calls, such as the "squirtle" call, are often exhibited by juveniles and may be associated with parent-offspring communication (Wang et al. 2020).

ARUs

In this study, I used Wildlife Acoustics SM2, Wildlife Acoustics SM4, and Wildlife Acoustics Mini ARUs (Figure 1). ARUs were deployed at least 200 meters apart to minimize the chances of capturing the same vocalizations on multiple ARUs. The listening radius of the ARU is approximately 50 meters for each of these species, depending on local vegetation, geography, and abiotic conditions (C. Warren, personal communication, 2022). I selected locations where birds had been sighted previously or areas of preferential habitat for kiwikiu. ARUs were deployed in the field and securely fastened to trees, with care taken to ensure that foliage did not

impact microphones. As kiwikiu are low in number, I placed a significant emphasis on deploying recorders in TNC's Waikamoi Preserve, where kiwikiu are present and observed regularly. The Nature Conservancy's Waikamoi Preserve is also accessible via hiking, so reliance on helicopters would not be a limiting factor in servicing the ARUs. Between December 2020 and June 2021, nine ARUs were deployed in West Waikamoi, 18 in Eastern Waikamoi, and four in Kīpahulu Valley at HALE (Table 1). To supplement the HALE ARU data, I used recordings from ARUs deployed by HALE employees in 2019 and 2020 along bird transect T18 in Manawainui, which provided the bulk of the recordings from this area. Automated recording unit data from previous studies were also used when available, mainly if recorders were deployed within the study sites. I also used data from various locations within HALE obtained during the Pacific Island Landbird Monitoring surveys in 2017 and by the HALE Wildlife Management crew in 2018—2020. In addition, mobile ARUs were used opportunistically on two trips in June 2021 and August 2021 to obtain vocalizations of desired birds. This involved an observer holding an ARU and directing it toward a bird if encountered. However, these efforts were met with limited success due to the elusive nature of these birds and the limited time spent in the field.

All ARUs deployed explicitly for this project were programmed with a schedule of five minutes on and ten minutes off from approximately 06:00 AM to 11:00 AM. Some sites were programmed to collect additional recordings in the afternoon. Additional ARUs from previous monitoring projects mainly used schedules of eight minutes on, eight minutes off, or 15 minutes on the hour. Recordings were saved onto Secure Digital cards in .wav file format at a sampling rate of 44.1KHz. I stored recording data in the Listening Observatory for Hawaiian Ecosystems (LOHE) Lab cloud-based Dropbox and an external hard drive.

Bioacoustic and statistical analysis

First, a team of students in the LOHE Lab at the University of Hawai‘i at Hilo and I visually identified and selected vocalizations from our target species using spectrograms generated in Raven Pro 1.5 (Cornell Lab of Ornithology: K. Lisa Yang Center for Conservation Bioacoustics 2022) acoustic analysis software. For each selection, Raven Pro reported values for several different variables based on the time and frequency of the acoustic signal. For time,

parameters included begin time (s), end time (s), and delta time (s). Begin time and end time refers to the point in the recording where the selection begins and ends, and delta time is the difference between the two. For frequency, parameters included low frequency (Hz), high frequency (Hz), delta frequency (Hz), and peak frequency (Hz). Delta frequency is the difference between low and high frequencies of the selection, while peak frequency records where the bird puts the most energy into its vocalization. Observers then manually classified vocalizations into additional annotated columns: species (ʻākohekohe or kiwikiu), call type (call or song), overlap (a binary presence/absence of co-occurring acoustic signal recorded as 1 or 0), overlap details (other sounds overlapping/co-occurring with the target vocalization), quality (high, medium, low), and notes. Before analysis, I reviewed the work of the additional observers and corrected for species identification. If I was unsure about species identification, I consulted other forest bird biologists.

One-way ANOVA and non-parametric Kruskal-Wallis tests were conducted in R version 1.3.1073 (R Core Team 2021) to compare different vocalization characteristics between Upper Kīpahulu Valley, Manawainui, and Western Waikamoi. Additionally, I constructed standardized repertoire sizes for each species. This was done in Microsoft Excel by dividing the number of unique calls for each ARU by the total number of selections. I then combined those by location to surmise geographic differences. Therefore, the standardized repertoire size is the proportion of unique call types in one location in relation to all call types recorded in any location. I used Simpson's diversity index to examine if there were differences in the vocal repertoires between locations. This diversity index considers the number of call types and their relative abundance to other call types observed in the area (Simpson 1949). Simpson's diversity index value D ranges from 0 to 1, with 1 representing the greatest repertoire diversity. This was calculated in Microsoft Excel with the formula:

$$D = 1 - \left(\frac{n\,(n-1)}{N\,(N-1)} \right)$$

n = the total number of unique call types in a particular location

N = the total number of unique call types across all locations

For further analysis, I grouped vocalizations using Luscinia version 2.16.10.29.01, an open-source sound analysis program (Lachlan 2016). Luscinia allows for the mass classification of acoustic units, which helps quantify data similarities and dissimilarities. I extracted individual

songs from ARU .wav files in Raven Pro 1.5 and added each .wav file to the Luscinia database. Only medium or high-quality songs were selected, as poor-quality songs were too difficult to analyze in Luscinia. Next, I used Luscinia's trace function to highlight each element (note) in the kiwikiu song spectrograms with high precision using the 5-pixel brush tool (Figure 2). I initially separated songs into groups by ARU. Elements were classified as single continuous signals (lines) in the spectrogram and syllables as a set of repeating elements (Figure 3). When organizing syllables, I needed to group them with enough precision to separate one syllable from the next without capturing overlapping elements. To avoid overlapping elements, I used every other syllable in kiwikiu songs in the analysis. Luscinia was also used to calculate the hierarchical clustering of vocalizations and produce dendrograms in which syllables are grouped on dendrogram branches based on their similarities. Luscinia generated global silhouette indices to measure the goodness of fit in the dendrogram groupings, with 1 being a perfect grouping and 0 showing no relationship. These dendrograms assisted me in identifying whether there were natural groupings of syllables in different kiwikiu songs. After visually examining the dendrogram, I created a global silhouette index threshold (represented by a line on the dendrogram) above which syllables looked appropriately grouped (to the right of the line). Below the threshold (to the left of the line), the syllables were not accurately grouped (Figure 4). I used the dendrogram groupings above the global silhouette index threshold to construct 45 new groups with visually similar syllables. Observations in these groups were then scored on a scale from 1-4 (1: syllables from the same songs, 2: syllables from the same recordings but different songs, 3: syllables from the same ARU but different recordings, 4: syllables from different ARUs). I used the groupings of kiwikiu syllables in these dendrograms and redefined groups to address my hypothesis regarding variability in their songs across a geographic gradient.

BirdNET

Due to time constraints, I used a preliminary, unreleased, Hawai‘i-specific model of BirdNET to analyze my data. To investigate BirdNET's classification accuracy, soundscape files were uploaded into a LOHE lab high-speed computer and processed with the BirdNET algorithm by Acoustic Bioinformatics Specialist A. Navine following the publicly available protocol on GitHub (Kahl 2021). BirdNET makes species presence/absence predictions for each 3-second

segment of a soundscape and exports these predictions as a Raven Pro-compatible selection table. R scripts were then used to sort through BirdNET selections and create species, location, and identification confidence score summaries.

To examine the algorithm's efficacy, I compared BirdNET's analysis with a manual annotation analysis conducted by myself and members of the LOHE Lab. Using Microsoft Excel's RAND function; I randomly selected 30 files each from six ARUs covering Western Waikamoi, Upper Kīpahulu Valley, and Manawainui. BirdNET selections with confidence scores (a number between 0 and 1 representing the likelihood that the BirdNET prediction is correct) greater than 0.50 (an arbitrary value selected for comparison in this study that does not represent the ideal threshold for accuracy using BirdNET) were compared with manual annotations, taking note of the incorrectly identified or missed vocalizations. I then calculated the accuracy score for each location and the overall accuracy rate of BirdNET for these two species with a simple calculation of the number of correct identifications divided by the total number of identifications.

To assess BirdNET's performance, I identified all false positives, false negatives, true positives, and true negatives for recordings by species to calculate sensitivity, specificity, and predictive values. Sensitivity is the ability of a test to detect true positives, specificity is the test's ability to detect true negatives, and the predictive value is the proportion of times that the identified result was the actual result. Other Hawaiian honeycreeper species are also detectable by the BirdNET algorithm, but I did not examine BirdNET's success at identifying these additional species here.

I analyzed data from Eastern Waikamoi and unannotated files from Western Waikamoi and upper Kīpahulu Valley with BirdNET to determine if this approach could expand our understanding of kiwikiu and ʻākohekohe distribution outside of well-studied areas. Because of the massive data output, I focused only on BirdNET predictions with confidence scores greater than 0.50, representing a 50% chance that BirdNET's identifications were correct. Using the RAND function in Microsoft Excel, I examined up to 50 identifications. I then determined an overall positive predictive value for each species by location.

Results

Raven Pro (manually annotated data)

I manually reviewed 3,190 recordings from 14 ARUs, 740 of which had vocalizations from our target species, obtaining a total of 7,587 selections of kiwikiu and ʻākohekohe vocalizations. While 16 additional ARUs were deployed, they were not all reviewed in this project due to time constraints and data availability. Most selections were ʻākohekohe (7,247), while the remainder were kiwikiu (327), and most of the vocalizations (4,153) were obtained from Western Waikamoi (Table 3). Of the recordings with vocalizations from target species (n = 740), I noted an average and standard error of 9.98 ± 0.489 ʻākohekohe vocalizations per recording and 4.95 ± 0.525 kiwikiu vocalizations per recording. Only 49 recordings captured the presence of both species in the same recording.

Vocalization Variability

Manual annotation of soundscapes showed each ARU captured an average of 3.08 ± 0.625 unique ʻākohekohe call types and 1.23 ± 0.394 kiwikiu call types. For ʻākohekohe, the upslur whistle was the most common vocalization in Western Waikamoi (91% of selections), and the 3-note whistle was most common in upper Kīpahulu Valley (58%) and Manawainui (36%) (Table 4). For kiwikiu, songs were the most identified vocalization across upper Kīpahulu Valley (55%), Manawainui (77%), and Western Waikamoi (92%) (Table 5). A Kruskal-Wallis test showed no significant differences between Manawainui, upper Kīpahulu Valley, and Western Waikamoi for either species' repertoire size or diversity index ($p > 0.05$) (Figure 4, 5). I found a significant difference in the mean length of kiwikiu songs, the delta frequency of kiwikiu songs, and the mean length of ʻākohekohe squirtle calls between the upper Kīpahulu Valley, Western Waikamoi, and Manawainui locations (Table 8), however, no significant differences were observed for peak frequencies of kiwikiu songs or the number of syllables in kiwikiu songs (Table 8).

Luscinia produced a dendrogram of kiwikiu syllable groupings with low global silhouette indices. For all syllables, at a tree depth of 0.398, the highest global silhouette index (0.488)

occurred at two branches (a total of only two groups). All other global silhouette indices were negative for branches 3–349. By visually examining the syllables, 131 total observations from 40 recordings were manually assigned to 45 groupings (Table 9). Groups varied in the number of observations (average = 2.91, mode = 2, SD = 1.76). Syllables in each group were scored depending on their relationship to other syllables: similarly identified syllables belonging to the same song (54%), belonging to the same recording (20%), belonging to the same ARU (15%), and belonging from different ARUs (11%). 92.5% of recordings appeared in groups five or fewer times; however, three were particularly influential: two from upper Kīpahulu Valley (8 and 28 times) and Western Waikamoi (13 times).

BirdNET

Efficacy

One hundred eighty previously annotated soundscapes were analyzed using the BirdNET algorithm using the default confidence score threshold of 0.1 and a species list specific to the species found on Maui (eBird 2022). In sum, BirdNET identified 2,819 ʻākohekohe and 1,211 kiwikiu vocalizations within these soundscapes.

From the 180 soundscapes, I reviewed 57 soundscapes that contained ʻākohekohe identifications over a 0.50 confidence score threshold. Within these 57 soundscapes, BirdNET identified 1,793 total ʻākohekohe vocalizations (Table 10) and 266 ʻākohekohe vocalizations above the 0.50 confidence score threshold, 215 of which were correct (Table 11). Similarly, I reviewed 28 soundscapes containing confident kiwikiu identifications over the 0.50 threshold, in which BirdNET identified 657 total kiwikiu vocalizations (Table 10), where 58 detections had confidence scores over 0.50, 27 of which were true positives (Table 11). Using these files, I calculated each species' sensitivity, specificity, and predictive values (Table 12).

Expansion

To test whether BirdNET could detect the range expansion of the two target species, 1,606 files from ARU EWK10, 830 files from ARU WEST01, and 515 from ARU WWK01

were analyzed (Table 1). None of these files had been scanned by observers before BirdNET analysis. From these files, 1,664 kiwikiu and 68 ʻākohekohe were confidently identified by BirdNET. For the kiwikiu identifications, I reviewed a random sample of 50 identifications from both upper Kīpahulu Valley and Eastern Waikamoi and all 34 identifications from Western Waikamoi. I scored for definitively correct and provisionally correct identifications (Table 13). For ʻākohekohe, I reviewed 50 random identifications from EWK10, all six from upper Kīpahulu Valley, and all five from Western Waikamoi. I corroborated just 12 ʻākohekohe identifications (Table 13). Of the false positives, 24 were chip notes that ʻākohekohe do not produce. Because BirdNET selects a three-second increment of time that potentially contains the desired species, it is not always clear which sound in the clip BirdNET misidentified as ʻākohekohe. Still, it appeared that rain often produced a false positive, as well as other native and non-native bird species. I did not review false negatives for the expansion dataset.

Discussion

This study represents the first time BirdNET analyzed soundscapes for Hawaiian bird species vocalizations. Conservatively looking at only BirdNET's identifications over a 0.50 confidence score threshold, BirdNET correctly identified 65.8% of ʻākohekohe and 27.4% of kiwikiu. Other studies have found higher accuracy using BirdNET (91.5%); however, they encountered similar issues with song dialects and the training material being from a different geographic area than their recordings dataset (Arif et al. 2020). In addition, the 0.50 confidence score was arbitrarily selected and did not represent an acceptable threshold for detecting these birds. It is recommended that future research includes receiver operating characteristics to evaluate further the quality of BirdNET's diagnostic abilities in alignment with specific program needs. Overall, accuracy declined for both species from the efficacy dataset to the expansion dataset.

In a perfect system, BirdNET would minimize both false positives and negatives, but regarding the practicality of using BirdNET for resource management purposes, I am most concerned with the number of false negatives. Because kiwikiu and ʻākohekohe are so rare, it is crucial that we are not missing vocalizations in recordings if they are present. While BirdNET's positive predictive values were low, suggesting that many false positives were generated, the

negative predictive values for both species were high, indicating that BirdNET is not missing many vocalizations (Table 12). The current iteration of BirdNET may not yet be the best tool for detecting abundance; however, it appears to detect presence and absence adequately. As mentioned, an equal effort was not expended in sorting through our recordings. My findings suggesting variation in songs highlight the importance of obtaining data from all locations across a species range and capturing that variation to best train BirdNET.

The complexity of a soundscape recording offers challenges, as the cacophony of noises like rain, wind, and other birds may mask vocalizations from target species (Bobay et al. 2018). For example, many of the kiwikiu false positives were rain. Loud raindrops appear as a vertical band on a spectrogram (Brown et al. 2019), which resembles chip notes, perhaps eliciting confusion from BirdNET. It should be noted that identifications for other bird species have yet to be validated, and perhaps once they have been, BirdNET will further eliminate options from other species as misidentifications.

When I extracted training data for BirdNET, not all the ARUs received equal scanning effort. For example, I expended extra effort sorting through ARU WWK04 once I initially identified kiwikiu songs, as I knew it was a reliable ARU to continue obtaining training data. This led to a potential biasing of the training data to relatively few individuals. In comparison, most of the expansion dataset comprised files from Eastern Waikamoi, an area not reviewed prior; therefore, no vocalizations from either target species at this location were provided when BirdNET was being trained. Since kiwikiu songs exhibit variation by location, the variability of kiwikiu songs in Eastern Waikamoi still needs to be captured by BirdNET. All the kiwikiu identifications from Eastern Waikamoi were chip notes with no other vocalizations confidently identified. Kiwikiu and Maui ‘alauahio share nearly identical chip notes, so I did not feel confident in confirming kiwikiu presence with chip notes identified by BirdNET without the context of other vocalizations from kiwikiu. Upon a perfunctory scan, ten files had Maui ‘alauahio singing, making it more likely that the chips were not kiwikiu. Kiwikiu most actively breed and vocalize between February and June (Mounce et al. 2013), but the ARUs captured just over one month of this period in the EWK10 recordings. I suspect that if there were kiwikiu singing in the range of this ARU, they would have been identified by BirdNET.

In the efficacy test, there were only five false negatives where BirdNET missed annotated kiwikiu songs, suggesting that if kiwikiu songs were present, they likely would have been

identified by BirdNET. Although kiwikiu are cryptic, I suspect that the ARU would have captured even an infrequent song in the three months of recordings if the ARU was placed within the home range of a male kiwikiu. I also observed that several false positive kiwikiu identifications were ʻākohekohe whistle notes. There were 393 false negatives for ʻākohekohe, most of which seemed to be whistle notes. While I did not explicitly look at the accuracy rates of songs versus calls, my initial observations suggest that this preliminary model of BirdNET is less refined in identifying calls. In contrast, song identification seemed to be adequate. My findings support the efficacy of using BirdNET to locate kiwikiu and ʻākohekohe in recordings, particularly for songs.

I hypothesized that there would be distinct differences in the vocalizations of target species between regions. Therefore, I expected to see differences in the characteristics of the vocalizations and the repertoires. However, in examining each location's standardized repertoire sizes and diversity indices, I found no significant difference between the locations for either species. Our sample sizes were vastly different amongst the three locations (Table 3), as I emphasized sampling effort on ARUs with observations of kiwikiu. However, even if each ARU was sampled equally, there is no guarantee that the output of selections would be the same because of the rarity of these species. Further research could address these disparities with a larger and more even dataset.

In contrast, I found statistically significant differences in the mean length and change in frequency of kiwikiu songs. Average song length differed amongst all three locations, suggesting that song lengths significantly vary across the landscape, with the average song length in Manawainui being the longest of the three locations. However, the number of syllables in kiwikiu songs did not vary among locations. In some passerine species, the number of other vocalizing species in the environment influences the mean length of songs, with longer songs occurring in communities with fewer species competing for acoustic space (Sorjonen 1986). The 2017 Pacific Landbird Monitoring Annual Report showed differences in species detections and densities between the windward (including Waikamoi) and HALE regions of Maui (Judge et al. 2019). While these observations were not specific to the study areas within my project, future studies can elucidate these observations within the study areas and their relationship to each area's available acoustic niche space.

The initial dendrogram produced by Luscinia grouped the kiwikiu song syllables with extremely low confidence. After manually breaking the syllables down and organizing them, I found some common ones between locations. I found most of these syllable groupings in the same song, which I would expect, considering a kiwikiu song consists of repeated elements. In my groups, similar syllables were gathered from the same ARU 89% of the time. This suggests that the most similar syllables are likely found between the same individual kiwikiu but also indicates that I observed shared syllables between different areas in only two instances: between Western Waikamoi and Manawainui and between Western Waikamoi and Hanawī. The lack of shared syllables between locations suggests variation in songs between the sub-populations of kiwikiu.

Many songbirds demonstrate local dialects, and the presence of geographic dialects in bird songs has been documented in many species, including Black-capped Chickadees, Tree Pipits, and Eastern Whipbirds (Kroodsma et al. 1999; Mennil & Rogers 2006; Petrusková et al. 2010). In the tropics, song divergence has been shown to occur over shorter ranges, particularly if barriers between populations exist (Danner et al. 2011). The kiwikiu may have become isolated over a relatively small geographic range, leading to dialect formation. Further supporting this idea, (Mounce et al. 2015) suggest that the Koʻolau Gap serves as a dispersal barrier between populations of kiwikiu, disrupting gene flow between the kiwikiu populations to the east and west of Koʻolau Gap and resulting in significant differences in genetic structure. Similar geologic features, e.g., Kīpahulu Valley, also have the potential to serve as barriers to gene flow. If gene flow is restricted between populations, this would also likely occur with culturally transmitted traits like song structure.

When tracing the elements of kiwikiu songs in Luscinia, the possibility of human error certainly comes into question. I traced them as precisely as possible, but there are likely elements, and thus syllables, that are more similar/dissimilar than they appear in the analysis. Even with tracing medium to high-quality kiwikiu spectrograms, spectrograms can be inherently noisy, especially if there are overlapping signals, contributing to ambiguity in the tracing process. Differences in some syllables thus may reflect some human error. As I did not deploy ARUs in Hanawī and obtained very few kiwikiu songs in Manawainui, there is still room for this study to be expanded to encompass the entire range. Nevertheless, this study captured the differences in kiwikiu songs in different locations, adding to the current knowledge of kiwikiu

ecology. This will have implications for the future use of automatic detection algorithms for these species and reinforces the importance of obtaining training data that encompasses as much vocalization variability as possible to ensure all variation is recognizable.

Although not a goal of this project, I have effectively created a sizeable acoustic repository for two critically endangered birds, which may be valuable as their predicted extinctions (without interventions) looms ever nearer (Paxton et al. 2022). It is worth noting that testing occurred with a preliminary BirdNET model, and the ability to use BirdNET to identify ʻākohekohe and kiwikiu did not exist before the beginning of this project. Additionally, BirdNET developers will use the manual validation conducted as part of this study to improve accuracy and contribute to a future improved version of BirdNET. Using an accurate algorithm to process ARU recordings will allow us to obtain information expeditiously from soundscapes, enabling resource managers and researchers in Hawaiʻi to use the data quickly rather than waiting months or years for manual processing and detection. Using ARUs and BirdNET will also increase the opportunities for the future use of passive acoustic monitoring across the landscape to monitor trends in forest bird abundance.

Appendix A: Figures

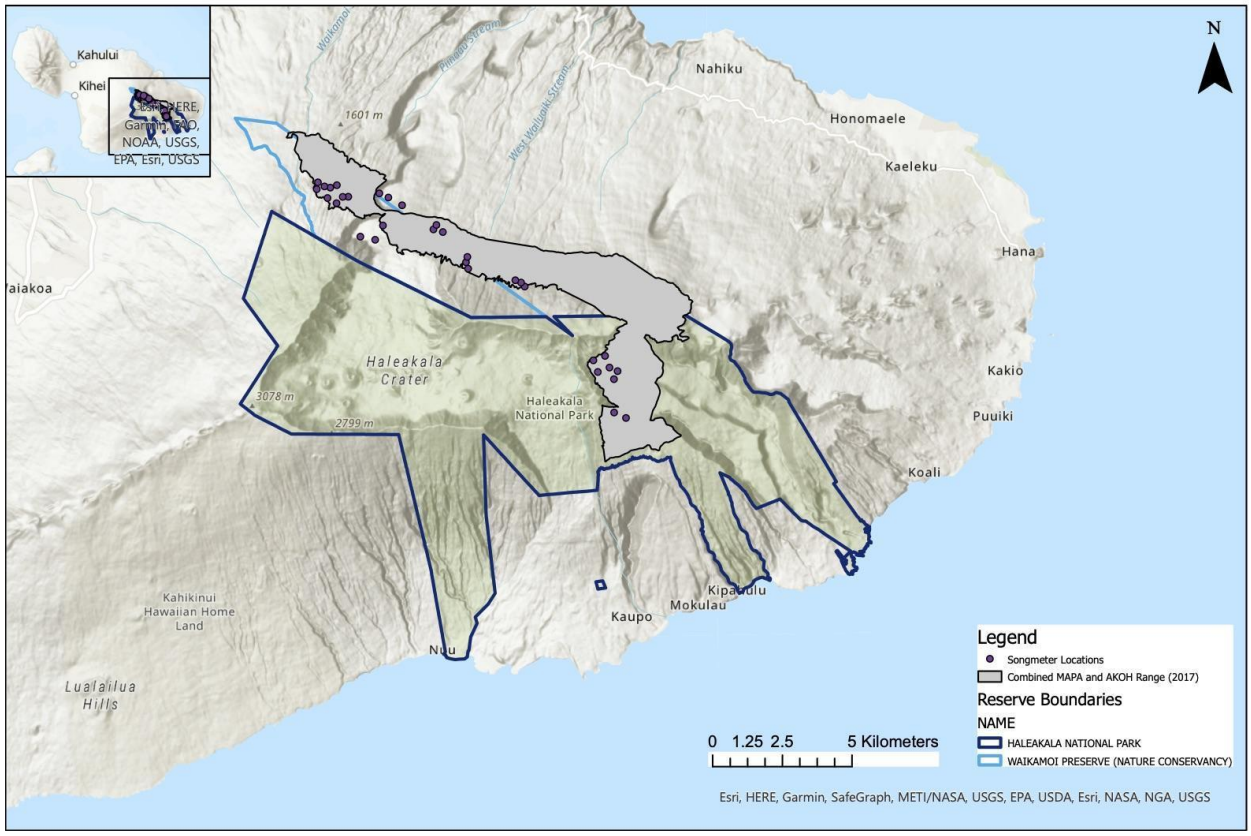


Figure 1. Map displaying ARU deployment locations within Haleakalā National Park and the Waikamoi Preserve. Also highlighted are the most recent kiwikiu and ʻākohekohe ranges, shown in grey.

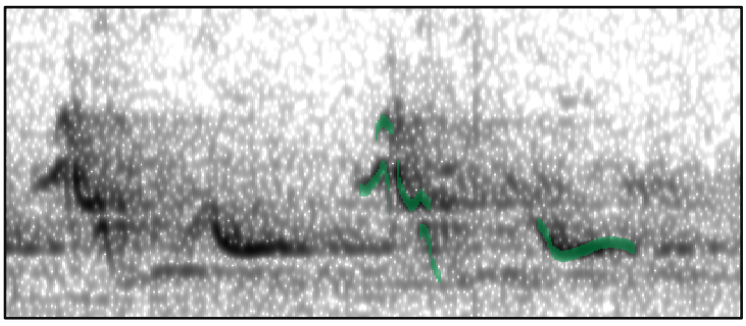


Figure 2. A spectrogram of a segment of a kiwikiu song showing two repeating syllables. The green outline shows how the elements would be traced in Luscinia.

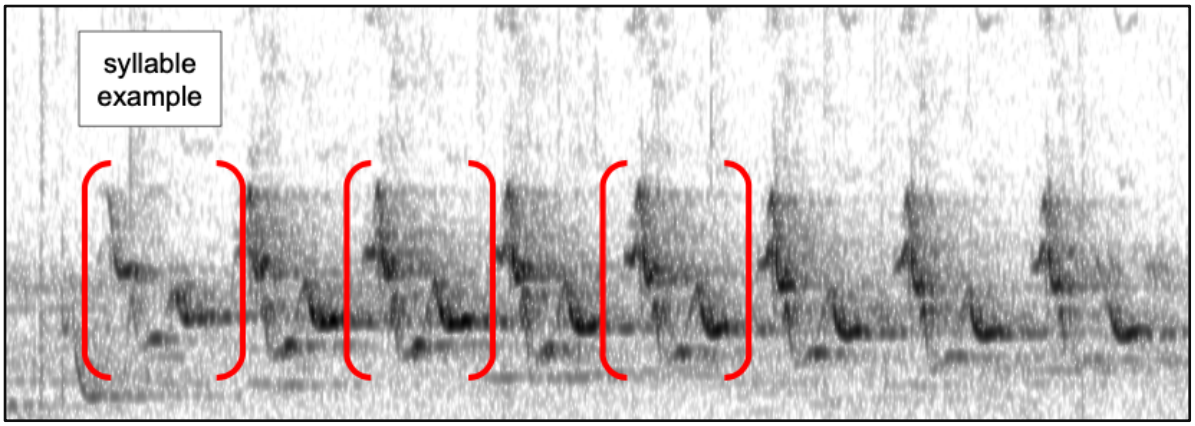


Figure 3. A spectrogram of a kiwikiu song with repeating syllables. The red represents how syllables were defined in Luscinia. Note that alternating syllables were selected to avoid capturing elements from the previous syllable.

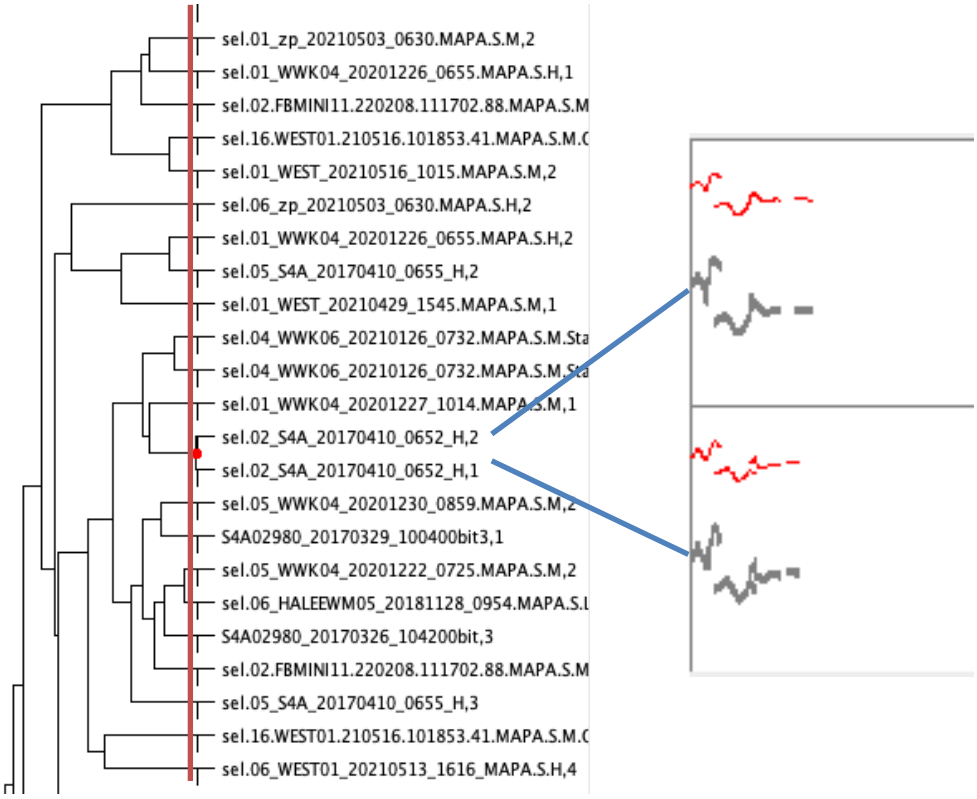


Figure 4. An example of how the Luscinia-generated dendrogram was regrouped. Syllables on the righthand of the line were appropriately grouped, and syllables on the left were incorrectly grouped.

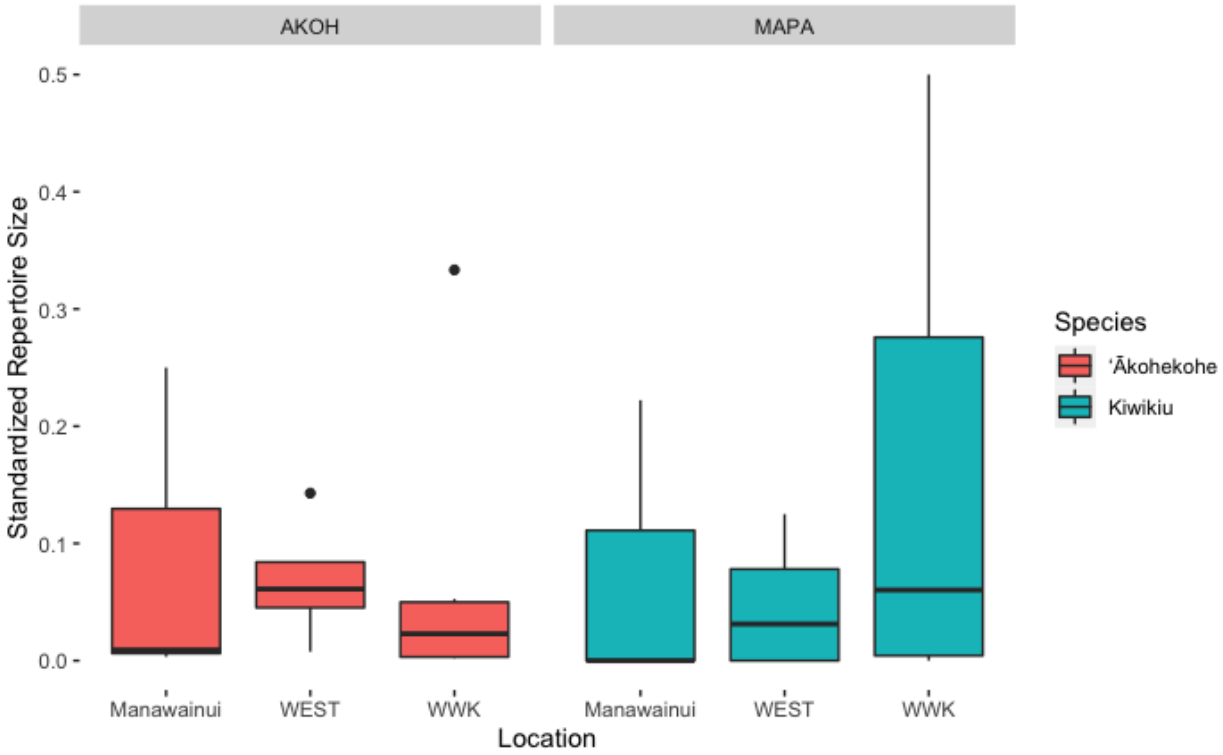


Figure 5. The repertoire size of ʻākohekohe (left) and kiwikiu (right) in three different locations. The boxplot represents each location's median, interquartile range, and outliers.

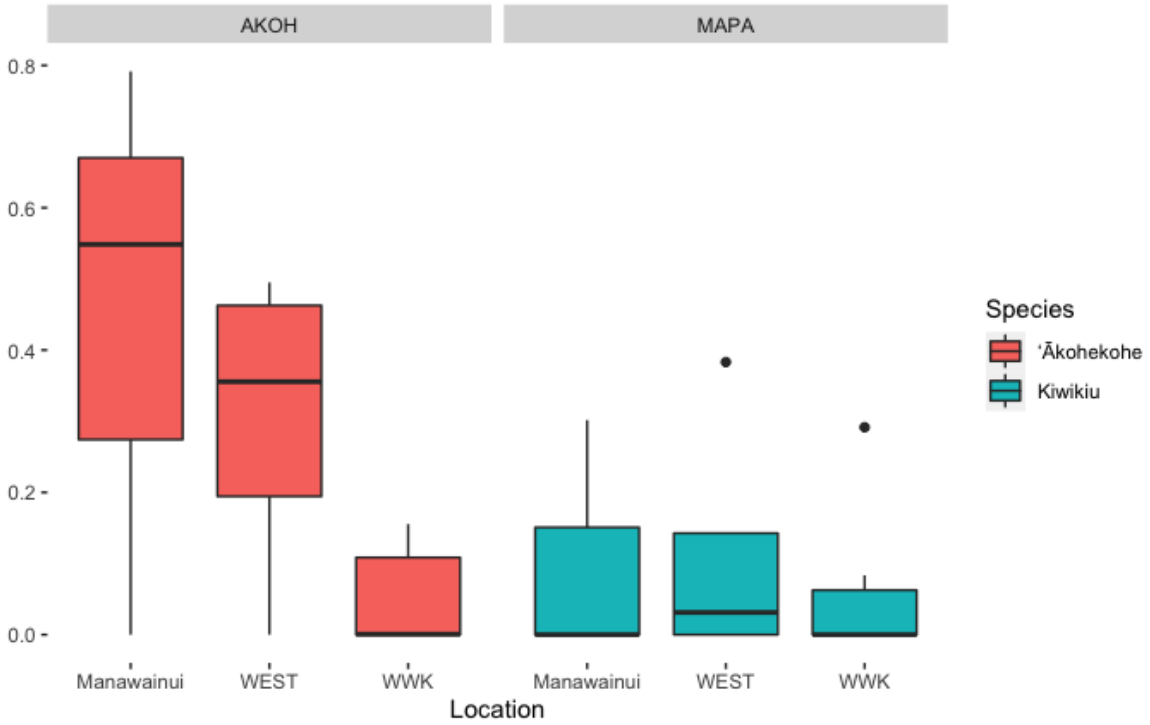


Figure 6. Simpson's Diversity indices of ʻākohekohe (left) and kiwikiu (right) vocal repertoires in three different locations. The boxplot represents each location's median, interquartile range, and outliers.

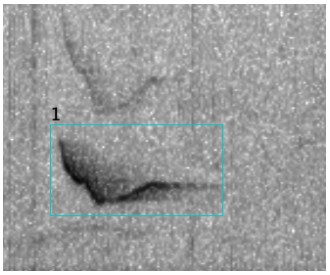
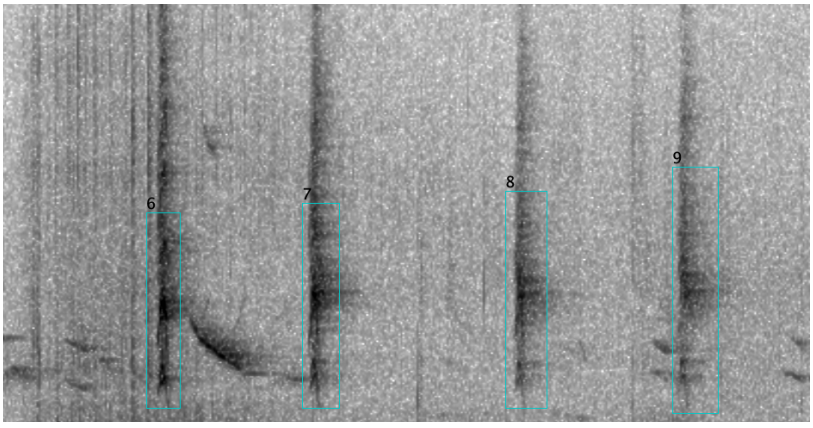
Appendix B: Tables

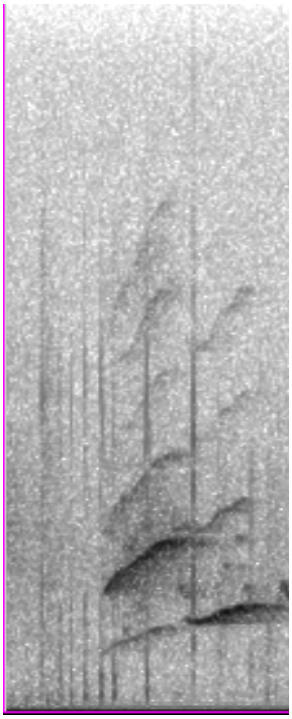
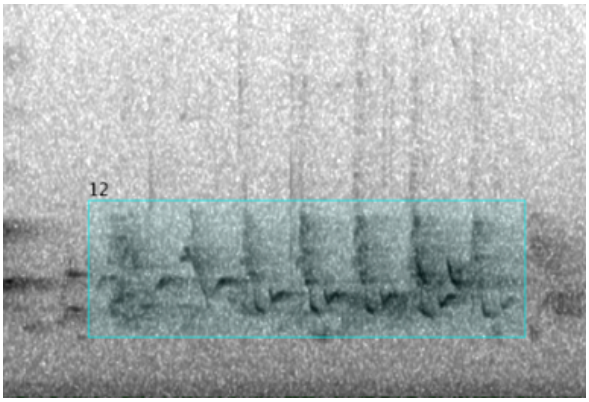
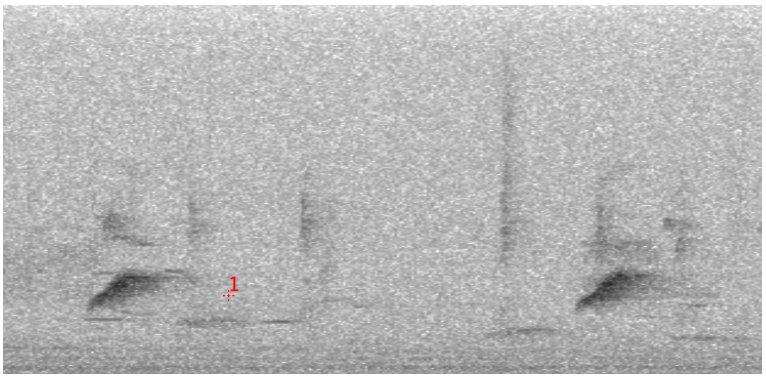
Table 1. Deployed ARUs that were partially manually reviewed, including deployment dates, the days of sampling, and the total number of minutes of recordings obtained.

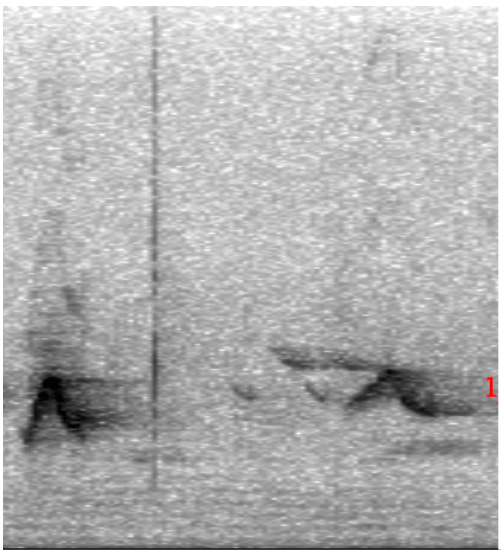
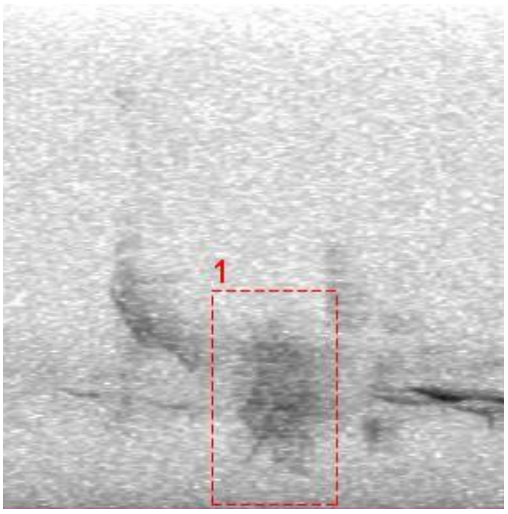
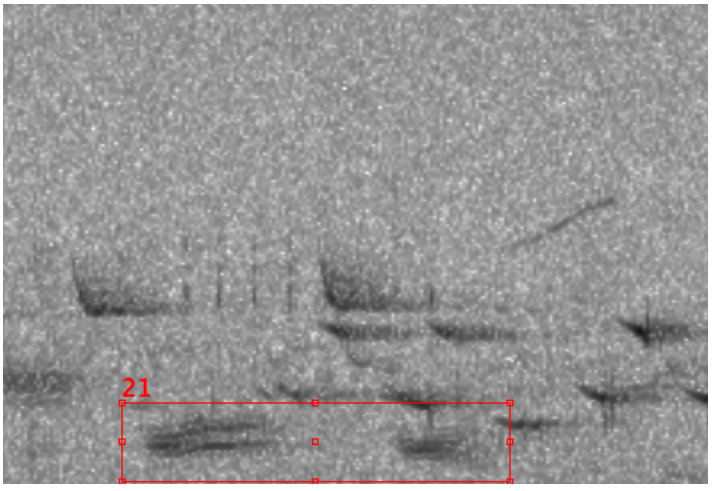
Location	File Prefix	Files	Dates	Sample Days	Total Hours
Eastern Waikamoi	EWK01	1714	1/8/21 - 5/1/21	114	228.53
Eastern Waikamoi	EWK02	187	1/8/21 - 1/25/21	18	24.93
Eastern Waikamoi	EWK03	529	3/20/21 - 4/20/21	32	70.53
Eastern Waikamoi	EWK06	1178	4/17/21 - 5/24/21	37	157.07
Eastern Waikamoi	EWK10	1606	5/24/21- 9/2/21	101	214.13
Eastern Waikamoi	EWK11	730	5/25/21 - 8/19/21	86	97.33
Eastern Waikamoi	EWK12	1587	5/25/21 - 9/7/21	105	211.6
Kīpahulu Valley	WEST01	4085	4/21/21 - 9/30/21	159	340.08
Kīpahulu Valley	WEST02	4298	6/21/21 - 11/22/21	215	358.17

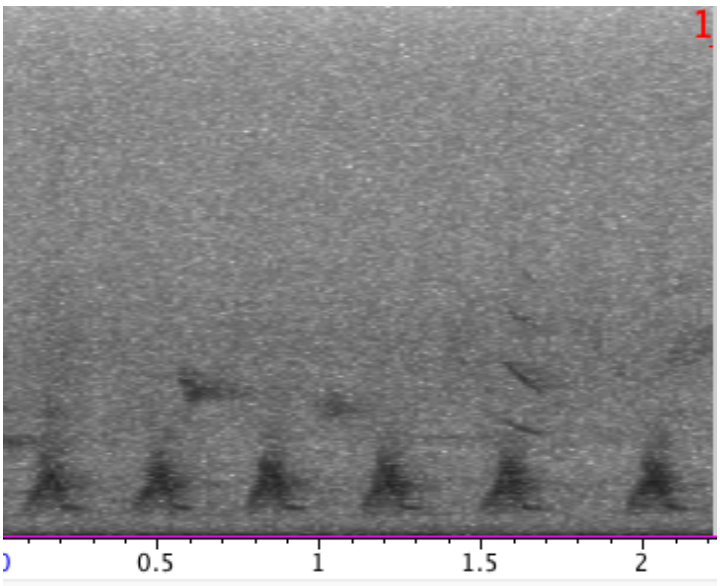
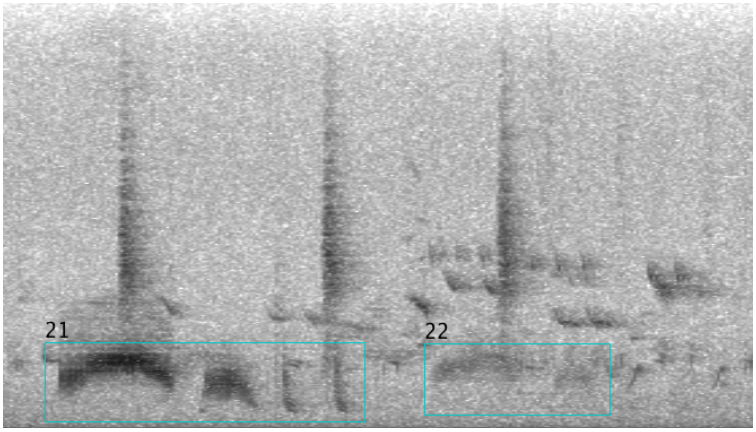
Kīpahulu Valley	WEST03	4069	6/1/21 - 10/9/21	171	339.08
Manawainui	RMOFFICE	1382	3/26/19-6/11/19	78	184.27
Manawainui	KUIKI2020	739	1/29/20-3/22/20	54	184.75
Manawainui (mobile)	WWK2021	17	9/2/21	1	
Western Waikamoi	WWK03	1144	12/20/20 - 02/19/21	60	95.33
Western Waikamoi	WWK04	1144	12/20/20 - 02/19/21	60	95.33
Western Waikamoi	WWK05	1144	12/21/20 - 02/19/21	60	95.33
Western Waikamoi	WWK06	1144	12/21/20 - 02/19/21	60	95.33
Western Waikamoi	WWK07	1605	12/21/20 - 03/02/21	71	133.75
Western Waikamoi	WWK08	1144	12/21/20 - 03/01/21	70	95.33
Western Waikamoi	WWK09	1781	12/21/20 - 10/03/21	286	148.42

Table 2. Vocalization library for both species showing the type of vocalization, the name of the vocalization, and a spectrogram example of each vocalization.

Species	Call Type	Name	Spectrogram
Kiwikiu	Call	Contact Call	
		Chip	

		Upslur	
	Song	Song	
ʻĀkohekohe	Call	Upslur	

		3-note whistle	
		“Squirtle”	
		Long call	

	Song	Wow song	
		Growl song	

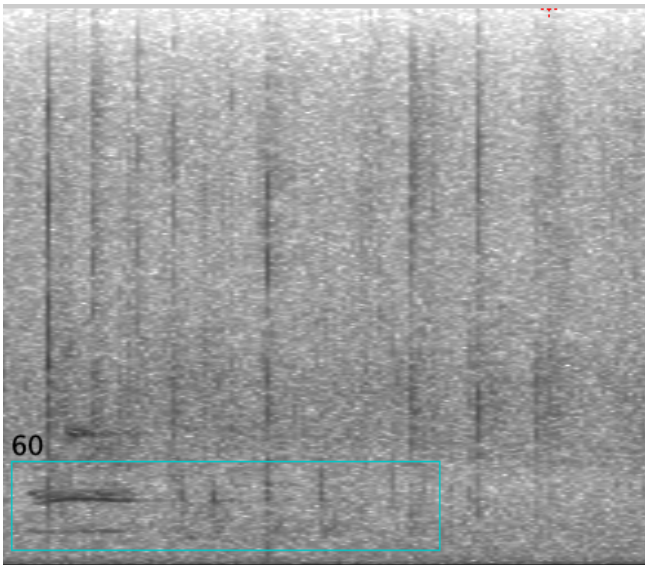
		Type II song	

Table 3. Number of selections obtained from 14 ARUs, divided by species. ARUs are also grouped by location, showing each location's total selections. 54.8% of the total selections were obtained from West Waikamoi, demonstrating a sampling bias towards that location.

Location	ARU	Number of selections		Total Selections
		ʻĀkohekohe	**Kiwikiu**	
Manawainui	HALEEWM05	4	9	13
	KUIKI2020	766	0	766
	RMOFFICE	1832	0	1832
	subtotal	**2602**	**9**	**2611**
Upper Kīpahulu Valley	WEST01	657	48	705
	WEST02	52	15	67
	WEST03	7	0	7
	WESTMINI	31	0	31
	subtotal	**747**	**63**	**810**
West Waikamoi	WWK01	0	0	0
	WWK02	24	0	24
	WWK04	1212	222	1434
	WWK05	722	2	724
	WWK06	1918	28	1946
	WWK08	3	3	6
	WWK09	19	0	19
	subtotal	**3898**	**255**	**4153**
Totals		**7247**	**327**	**7574**

Table 4. Repertoire of vocalizations obtained at each ARU for ‘ākohekohe, as well as the number of files reviewed for each ARU.

‘Ākohekohe									
ARU	**Files reviewed**	**3-note whistle**	**Upslur**	**Squirtle**	**Short call**	**Wow song**	**Growl song**	**Type 2 song**	**Other**
HALEEWM05	1	X							
KUIKI2020	35	X	X	X		X	X	X	X
RMOFFICE	46	X	X	X		X	X	X	
WEST01	1138	X	X	X		X			
WEST02	187	X	X						
WEST03	9	X							
WESTMINI	4	X	X						
WWK02	60		X						
WWK04	326		X	X	X		X	X	X
WWK05	1144		X	X					
WWK06	227		X	X	X			X	X
WWK08	2		X						
WWK09	13		X						

Table 5. Repertoire of vocalizations obtained at each ARU for kiwikiu and the number of files reviewed for each ARU.

Kiwikiu						
ARU	**Files reviewed**	**Contact call**	**Chip**	**Upslur**	**Song**	**Unsure**
HALEEWM05	1		X		X	
KUIKI2020	35					
RMOFFICE	46					
WEST01	1138		X	X	X	
WEST02	187		X		X	
WEST03	9					
WESTMINI	4					
WWK02	60					
WWK04	326	X	X	X	X	X
WWK05	1144				X	
WWK06	227	X		X	X	
WWK08	2				X	
WWK09	13					

Table 6. Summary of the unique vocalizations obtained at each location for ‘ākohekohe.

‘Ākohekohe								
Location	**3-note whistle**	**Upslur**	**Squirtle**	**Short call**	**Wow song**	**Growl song**	**Type 2 song**	**Other**
Manawainui	X	X	X		X	X	X	X
Upper Kīpahulu Valley	X	X	X		X		X	
West Waikamoi		X	X	X		X	X	X

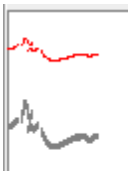
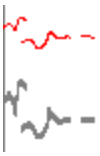
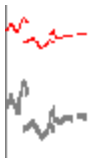
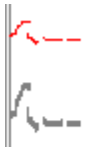
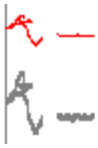
Table 7. Summary of the unique vocalizations obtained in each location for kiwikiu.

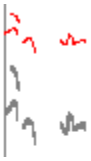
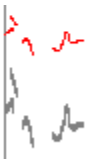
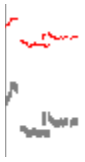
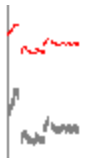
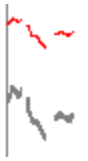
Kiwikiu					
Location	**Contact call**	**Chip**	**Upslur**	**Song**	**Unsure**
Manawainui		X		X	
Upper Kīpahulu Valley		X	X	X	
West Waikamoi	X	X	X	X	X

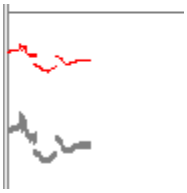
Table 8. Statistical analyses of vocalization properties of kiwikiu songs and ‘ākohekohe squirtle vocalizations.

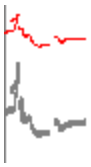
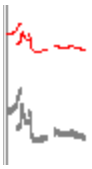
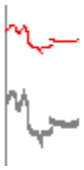
	ANOVA	**Post hoc Tukey's HSD Test**			**Kruskal-Wallis**	**Post hoc Mann-Whitney**		
	Overall	Upper Kīpahulu Valley and Manawainui	Western Waikamoi and Manawainui	Western Waikamoi and upper Kīpahulu Valley	Overall	Upper Kīpahulu Valley and Manawainui	Upper Kīpahulu Valley and Western Waikamoi	Western Waikamoi and Manawainui
Mean length of kiwikiu songs	$F_{2,290} = 19.026$ $p < 0.001$	95% C.I. = (-0.458, -0.0787) $p = 0.0028$	95% C.I. = (-0.568, -0.215) $p < 0.001$	95% C.I = -0.204, -0.0421). $p = 0.0012$				
Peak frequency of kiwikiu songs					chi-square = 2.567 df = 2 p = 0.2771			
Delta frequency of kiwikiu songs					chi-square = 17.536, df = 2 $p < 0.001$	$p > 0.05$	$p < 0.001$	$p = 0.0412$
Mean length of ‘ākohekohe squirtle vocalizations	$F_{2,542} = 81.691$ $p < 0.001$	$p > 0.05$	$p < 0.001$	$p < 0.001$				
Syllables in kiwikiu songs					chi-square = 6.337 df = 3 p = 0.0845			

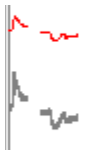
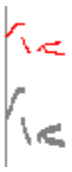
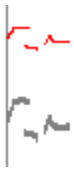
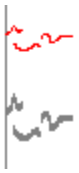
Table 9. Groupings of shared syllables of kiwikiu songs, made in Luscinia.

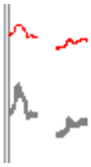
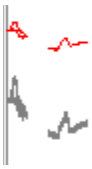
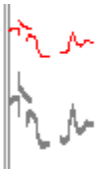
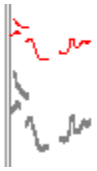
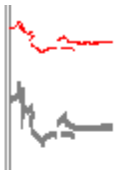
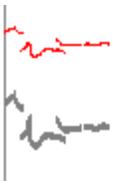
Group	Selection	Recording	ARU	Location	Image
1	16	WEST_20210516_1015.wav	WEST01	Upper Kīpahulu	
1	1	WEST_20210516_1015.wav	WEST01	Upper Kīpahulu	
2	4	WWK06_20210126_0732.wav	WWK06	WWK	
2	4	WWK06_20210126_0732.wav	WWK06	WWK	
3	2	S4A_20170410_0652.wav	S4A	WWK	
3	2	S4A_20170410_0652.wav	S4A	WWK	
4	5	WWK04_20201222_0725.wav	WWK04	WWK	
4	6	HALEEWM05_20181128_0954.wav	HALEEWM05	Manawainui	

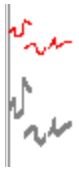
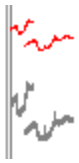
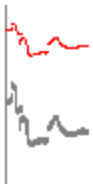
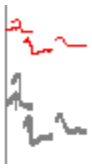
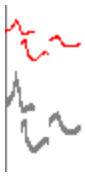
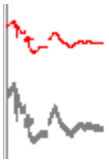
5	1	WWK04_20201225_0940.wav	WWK04	WWK	
5	1	WWK04_20201225_0940.wav	WWK04	WWK	
6	3	WWK04_20201225_0940.wav	ZP	WWK	
6	2	WWK04_20201225_0940.wav	ZP	WWK	
7	2	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
7	3	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
8	1	WWK04_20210121_0817.wav	WWK04	WWK	
8	2	HANAWI_20201221_0846.wav	HANAWI	Hanawī	

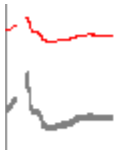
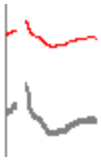
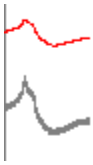
9	1	WEST_20210429_1545.wav	WEST01	Upper Kīpahulu	
9	4	S4A02980_20170404_100400.bit4.wav	S4A02980	Upper Kīpahulu	
10	6	WEST01_20210503_1531.wav	WEST01	Upper Kīpahulu	
10	6	WEST01_20210503_1531.wav	WEST01	Upper Kīpahulu	
11	2	WWK04_20201224_0940.wav	WWK04	WWK	
11	3	WWK04_20201225_0941.wav	WWK04	WWK	
12	24	WWK04_20201226_1014.wav	WWK04	WWK	
12	24	WWK04_20201226_1014.wav	WWK04	WWK	
13	24	WWK04_20201226_1014.wav	WWK04	WWK	

13	24	WWK04_20201226_1014.wav	WWK04	WWK	
13	6	WEST_20210503_1531.wav	WEST01	Upper Kīpahulu	
14	14	WEST02_20210707_091500.wav	WEST02	Upper Kīpahulu	
14	1	S4A02980_20170404_100400.bit1.wav	S402980	Upper Kīpahulu	
14	2	FBMINI11_220208_111702.wav	FBMINI11	Upper Kīpahulu	
14	1	S4A02980_20170404_100400.bit1.wav	S4A02980	Upper Kīpahulu	
15	2	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
15	1	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
16	1	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	

16	2	WWK04_20210121_0817.wav	WWK04	WWK	
16	2	WWK04_20210121_0817.wav	WWK04	WWK	
17	3	zp_20210503_0630.wav	ZP	WWK	
17	3	zp_20210503_0630.wav	ZP	WWK	
18	3	WWK04_20201222_0909.wav	WWK04	WWK	
18	1	WWK04_20210121_0817.wav	WWK04	WWK	
19	5	WWK06_20210126_0731.wav	WWK06	WWK	
19	3	WWK04_20201230_0859.wav	WWK04	WWK	
19	24	WWK04_20201226_1014.wav	WWK04	WWK	

20	3	FBMINI11.220208.111713.wav	FBMINI11	Upper Kīpahulu	
20	3	FBMINI11.220208.111713.wav	FBMINI11	Upper Kīpahulu	
20	3	FBMINI11.220208.111713.wav	FBMINI11	Upper Kīpahulu	
21	3	WWK04_20201224_0940.wav	WWK04	WWK	
21	1	WWK04_20201227_1014.wav	WWK04	WWK	
22	2	S4A02980_20170329_100400bit 2.wav	S4A02980	Upper Kīpahulu	
22	1	S4A02980_20170326_104200bit .wav	S4A02980	Upper Kīpahulu	
22	1	S4A02980_20170326_104200bit .wav	S4A02980	Upper Kīpahulu	

23	3	WWK04_20210121_0749.wav	WWK04	WWK	
23	3	WWK04_20210121_0749.wav	WWK04	WWK	
23	3	WWK04_20210121_0749.wav	WWK04	WWK	
24	4	WEST_20210503_1531.wav	WEST01	Upper Kīpahulu	
24	3	WEST_20210503_1530.wav	WEST01	Upper Kīpahulu	
24	5	WEST_20210501_0634.wav	WEST01	Upper Kīpahulu	
24	4	WEST_20210501_0634.wav	WEST01	Upper Kīpahulu	
24	4	WEST_20210503_1531.wav	WEST01	Upper Kīpahulu	
24	3	S4A02980_20170329_100400bit 3.wav	S4A02980	Upper Kīpahulu	

25	11	WEST01_210516_1015.wav	WEST01	Upper Kīpahulu	
25	2	WEST01_210516_1015.wav	WEST01	Upper Kīpahulu	
25	2	WEST01_210516_1015.wav	WEST01	Upper Kīpahulu	
26	3	WWK04_20201225_0941.wav	WWK04	WWK	
26	2	WWK04_20210121_0817.wav	WWK04	WWK	
26	1	WWK04_20201228_0711.wav	WWK04	WWK	
26	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
26	6	WEST_20210501_0634.wav	WEST01	Upper Kīpahulu	
26	3	WEST_20210501_0634.wav	WEST01	Upper Kīpahulu	

26	6	WEST_20210501_0634.wav	WEST01	Upper Kīpahulu	
26	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
27	3	zp_20210503_0630.wav	ZP	WWK	
27	2	zp_20210503_0630.wav	ZP	WWK	
28	5	zp_20210503_0630.wav	ZP	WWK	
28	5	zp_20210503_0630.wav	ZP	WWK	
29	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
29	4	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
30	6	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	

30	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
30	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
31	26	WWK06_20210126_0733.wav	WWK06	WWK	
31	5	WWK04_20201222_0725.wav	WWK04	WWK	
31	5	WWK04_20201222_0725.wav	WWK04	WWK	
32	26	WWK06_20210126_0733.wav	WWK06	WWK	
32	26	WWK06_20210126_0733.wav	WWK06	WWK	
33	3	zp_20210503_0630.wav	ZP	WWK	
33	3	zp_20210503_0630.wav	ZP	WWK	

33	3	zp_20210503_0630.wav	ZP	WWK	
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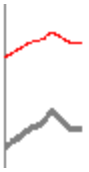
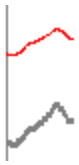
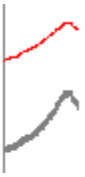
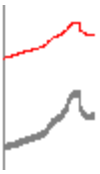
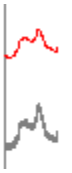
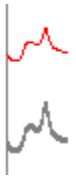
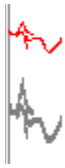
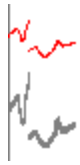
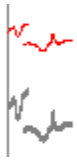
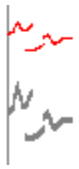
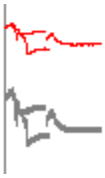
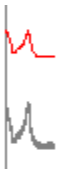
34	6	WEST01_20210513_1616.wav	WEST01	Upper Kīpahulu	
34	6	WEST01_20210513_1616.wav	WEST01	Upper Kīpahulu	
34	3	WEST_20210501_0633.wav	WEST01	Upper Kīpahulu	
35	13	HALEEWM05_20181128_0955.wav	HALEEWM05	Upper Kīpahulu	
35	13	HALEEWM05_20181128_0955.wav	HALEEWM05	Upper Kīpahulu	
36	1	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
36	1	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	

37	3	MANAWAINUI_20220301_1500.wav	Vid	Manawainui	
37	1	MANAWAINUI_20220301_1500.wav	vid	Manawainui	
38	4	MANAWAINUI_20220301_1500.wav	Vid	Manawainui	
38	4	MANAWAINUI_20220301_1500.wav	Vid	Manawainui	
38	2	MANAWAINUI_20220301_1500.wav	vid	Manawainui	
39	5	zp_20210503_0630.wav	ZP	WWK	
39	3	WWK04_20201228_0712.wav	WWK04	WWK	
40	1	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	

40	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
40	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
40	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
40	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
40	1	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
40	6	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
40	4	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
41	6	WWK04_20201224_0941.wav	WWK04	WWK	
41	5	WWK04_20201224_0941.wav	WWK04	WWK	

41	3	WWK04_20201230_0859.wav	WWK04	WWK	
42	2	S4A02980_20170329_100400bit 2.wav	S4A02980	Upper Kīpahulu	
42	2	S4A02980_20170329_100400bit 2.wav	S4A02980	Upper Kīpahulu	
42	2	S4A02980_20170329_100400bit 2.wav	S4A02980	Upper Kīpahulu	
43	1	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
43	1	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
44	2	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	
44	1	WEST_20210423_0630.wav	WEST01	Upper Kīpahulu	

44	6	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	4	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	5	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	4	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	6	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
44	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	
45	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	

45	2	WEST_20210423_0930.wav	WEST01	Upper Kīpahulu	

Table 10. Total identifications from BirdNET in the efficacy test by species in the reviewed files.

Species	Total identifications	True positives	False positives	True negatives	False negatives
Kiwikiu	657	53 40 chips	564	2054	5
ʻĀkohekohe	1793	859	922	3195	376

Table 11. True and false positives of BirdNET's confident identifications from the reviewed files for both species.

Species	Total confident identifications	True positives	False positives
Kiwikiu	58	27 7 chips	24
ʻĀkohekohe	266	215	51

Table 12. Sensitivity, specificity, positive predictive values, and negative predictive values for both species.

Species	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Kiwikiu	94.9%	78.5%	14.2%	99.8%
ʻĀkohekohe	69.6%	77.6%	48.2%	89.5%

Table 13. Confident identifications from BirdNET and the number of correct identifications found in the expansion phase.

Species	Location	Confident BirdNET Identifications	Correct	Chips
Kiwikiu	Upper Kīpahulu	50	36	1
	WWK	50	3	14
	EWK	34	0	40
ʻĀkohekohe	Upper Kīpahulu	6	2	-
	WWK	5	5	-
	EWK	50	5	-

Table 14. Accuracy scores for BirdNET identifications over a confidence score threshold of 0.50. Scores are divided by species, dataset, and location. Highlighted numbers represent possible kiwikiu accuracy scores, considering chips observed that could be kiwikiu but likely are Maui ʻalauahio.

	Kiwikiu				**ʻĀkohekohe**			
	Upper Kīpahulu	WWK	EWK	Manawainui	Upper Kīpahulu	EWK	WWK	Manawainui
Efficacy	*	0.5625 0.583	-	0 0.60	0.714	-	1.00	0.798
Expansion	0.72 0.74	0.0882 0.50	0 0.80	-	0.333	0.100	1.00	-

Works Cited

Arif M., R. Hedley, and E. Bayne. 2020. Testing the Accuracy of a birdNET, Automatic bird song Classifier. University of Alberta, DOI: 10:7939/r3-6khb-kz18.

Aslan C. E., E. S. Zavaleta, B. Tershy, D. O. N. Croll, and R. H. Robichaux. 2014. Imperfect replacement of native species by non-native species as pollinators of endemic Hawaiian plants. Conservation Biology, **28**(2):478-488.

Berlin K. E. and E. M. Vangelder. 2020. Akohekohe (*Palmeria dolei*), version 1.0. In Birds of the World (A. F. Poole and F. B. Gill, Editors). Cornell Lab of Ornithology, Ithaca, NY, USA. DOI: 10.2173/bow.crehon.01

Bioacoustics Research Program. 2014. Raven Pro: interactive sound analysis software (Version 1.5). *The Cornell Lab of Ornithology*.

Bobay L. R., P. J. Taillie, and C. E. Moorman. 2018. Use of autonomous recording units increased detection of a secretive marsh bird. Journal of Field Ornithology, **89**(4):384-392.

Brenowitz E. A., D. Margoliash, and K. W. Nordeen. 1997. An introduction to birdsong and the avian song system. Journal of Neurobiology, **33**(5):495-500.

Brown A., S. Garg, and J. Montgomery. 2019. Automatic rain and cicada chorus filtering of bird acoustic data. Applied Soft Computing, **81** DOI: 10.1016/j.asoc.2019.105501.

Buxton R. T. and I. L. Jones. 2012. Measuring nocturnal seabird activity and status using acoustic recording devices: applications for island restoration. Journal of Field Ornithology **83**:47-60.

Camp R. J., P.M Gorresen, T. K. Pratt, and B. L. Woodworth. 2009. Population trends of native Hawaiian forest birds, 1976–2008: the data and statistical analyses. Hawaii Cooperative Studies Unit Technical Report HCSU-012. University of Hawaii at Hilo, Hilo, HI.

Carothers S. J., H. S. R. Sabo, and R. B. Hansen. 1983. Ecological observations on an endangered species: the Maui Parrotbill, Pseudonestor xanthophrys. A.M. Birds, **37**:820-821.

Cox P. A. and T. Elmqvist. 2000. Pollinator Extinction in the Pacific Islands. Conservation Biology, **14**(5):1237–1239.

Danner J. E., R. M. Danner, F. Bonier, P. R. Martin, T. W. Small, and I. T. Moore. 2011. Female, but not Male, Tropical Sparrows Respond More Strongly to the Local Song Dialect: Implications for Population Divergence. The American Naturalist, **178**(1):53-63.

eBird. 2021. eBird: An online database of bird distribution and abundance. [Online]. eBird, Cornell Lab of Ornithology, Ithaca, New York. Available: http://www.ebird.org

Fristrup K. M. and D. Mennit. Bioacoustical monitoring in terrestrial environments. 2012. Acoustics Today **8**:16-24.

Frommolt K. and K. Tauchert. 2014. Applying bioacoustic methods for long-term monitoring of a nocturnal wetland bird. Ecological Informatics, **21** DOI: 10.1016/j.ecoinf.2013.12.009.

Gomes, N. 2016. Some traditional native Hawaiian bird hunting practices on Hawai‘i Island. Hawaiian Journal of History, **50**(50):33-51.

Gomes, N. 2020. Reclaiming Native Hawaiian Knowledge Represented in Bird Taxonomies. Ethnobiology Letters, **11**(2):30-43.

Haselmayer J. and J.S. Quinn. 2000. A comparison of point counts and sound recording as bird survey methods in Amazonian Southeast Peru. The Condor **102**:887-893.

Hutto R. L. and R. R. Hutto. 2020. Does the presence of an observer affect a bird's occurrence rate or singing rate during a point count? Journal of Field Ornithology **91**:214–223.

Judge S. W., R. J. Camp, C. C. Warren, L. K. Berthold, H. L. Mounce, P. J. Hart, and R. J. Monello. 2019. Pacific Island Landbird Monitoring Annual Report, Haleakalā National Park and East Maui Island, 2017. Natural Resource Report NPS/PACN/NRR—2019/1949. National Park Service, Fort Collins, Colorado.

Judge S. W., C. C. Warren, R. J. Camp, L. K. Berthold, H. L. Mounce, P. J. Hart, and R. J. Monello. Population estimates and trends of three Maui Island-endemic Hawaiian Honeycreepers. Journal of Field Ornithology **92**(2):115-126.

Kahl S., T. Wilhelm-Stein, H. Klinck, D. Kowerko, and M. Eibl. 2018. Recognizing birds from sound - The 2018 BirdCLEF Baseline System. DOI: 10.48550/arXiv.1804.07177

Kahl S., C. M. Wood, M. Eibl, and H. Klinck. BirdNET: A deep learning solution for avian diversity monitoring. Ecological Informatics **61** DOI: 10.1016/j.ecoinf.2021.101236

Kroodsma D. E. and B. E. Byers. 1991. The function (s) of bird song. American Zoologist, **31**(2):318-328.

Kroodsma D. E., B. E. Byers, S. L. Halkin, C. Hill, D. Minis, J. R. Bolsinger, and K. Wilda. 1999. Geographic variation in black-capped chickadee songs and singing behavior. The Auk, **116**(2):387-402.

Lachlan R., Luscinia software. [Online]. Available: http: //rflachlan.github.io/Luscinia

Marler P. and M. Tamura. 1962. Song "dialects" in three populations of White-crowned Sparrows. The Condor, **64**(5):368-377.

Mennill D. J. and A. C. Rogers. 2006. Whip it good! Geographic consistency in male songs and variability in female songs of the duetting eastern whipbird Psophodes olivaceus. Journal of Avian Biology, **37**(1):93-100.

Mounce H. L., C. Raisin, D. L. Leonard, H. Wickenden, K. J. Swinnerton, and J. J. Groombridge. 2015. Spatial genetic architecture of the critically-endangered Maui Parrotbill (Pseudonestor xanthophrys): management considerations for reintroduction strategies. Conservation Genetics, **16** DOI: 10.1007/s10592-014-0641-9.

Mounce H. L., D. L. Leonard, K. J. Swinnerton, C. D. Becker, L. K. Berthold, K. J. Iknayan, and J. J. Groombridge. 2013. Determining productivity of Maui Parrotbills, an endangered Hawaiian honeycreeper. Journal of Field Ornithology, **84**(1):32-39.

Mcloughlin M. P., R. Stewart, and A. G. McElligott. 2019. Automated bioacoustics: methods in ecology and conservation and their potential for animal welfare monitoring. Journal of the Royal Society **16** DOI: 10.1098/rsif.2019.0225.

Obrist M. K., G. Pavan, J. Sueur, K. Riede, D. Llusia, and R. Marquez. 2010. Bioacoustic approaches in biodiversity inventories. Abc Taxa, **8:**68-99

Paxton E. H., M. Laut, J. P. Vetter, and S. J. Kendall. 2018. Research and management priorities for Hawaiian forest birds. The Condor: Ornithological Applications, **120**(3):557-565.

Paxton E. H., M. Laut, S. Enomoto, and M. Bogardus. 2022. Hawaiian forest bird conservation strategies for minimizing the risk of extinction: biological and biocultural considerations. Hawaii Cooperative Studies Unit Technical Report HCSU-103. University of Hawaii at Hilo, Hilo, HI.

Paxton K. L., E. Sebastián-González, J. M. Hite, L. H. Crampton, D. Kuhn, and P. J. Hart. 2019. Loss of cultural song diversity and the convergence of songs in a declining Hawaiian forest bird community. Royal Society Open Science **6** DOI: 10.1098/rsos.190719.

Pérez-Granados C., G. Bota, D. Giralt, and J. Traba. 2018. A cost-effective protocol for monitoring birds using autonomous recording units: a case study with a night-time singing passerine. Bird study, **65**(3):338-345.

Pérez-Granados C. and K. L. Schuchmann. 2020. Monitoring the annual vocal activity of two enigmatic nocturnal Neotropical birds: the Common Potoo (*Nyctibius griseus*) and the Great Potoo (*Nyctibius grandis*). Journal of Ornithology **161**:1129–1141.

Petrusková T., T. S. Osiejuk, and A. Petrusek 2010. Geographic variation in songs of the tree pipit (Anthus trivialis) at two spatial scales. The Auk, **127**(2):274-282.

Podos J. and P. S. Warren. 2007. The evolution of geographic variation in birdsong. Advances in the Study of Behavior, **37**:403-458.

Pratt H. et al. The Hawaiian Honeycreepers: Drepanidinae, Oxford University Press, 2005. Available from http://ebookcentral.proquest.com/lib/uhm/detail.action?docID=422384

Pukui M. K. 1983. ‘Olelo No‘eau: Hawaiian proverbs & poetical sayings. Vol. 71. Bishop Museum Press, Hawai‘i.

R Core Team. 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [Online]. Available https://www.R-project.org/

Rempel R. S., K. A. Hobson, G. Holborn, S. L. Van Wilgenburg, and J. Elliot. Bioacoustic monitoring of forest songbirds: interpreter variability and effects of configuration and digital processing methods in the laboratory. Journal of Field Ornithology **76**:1-11.

Riebel K., K. J. Odom, N. E. Langmore, and M. L. Hall. 2019. New insights from female bird song: Towards an integrated approach to studying male and female communication roles. Biology letters, **15** DOI 10.1098/rsbl.2019.0059.

Sebastián-González E., J. Pang-Ching, J. M. Barbosa, P. J. Hart. 2015. Bioacoustics for species management: Two case studies with a Hawaiian forest bird. Ecology and Evolution **5**:4696–4705.

Simon J. C., P. E. Baker, and H. Baker. 2020. Maui Parrotbill (*Pseudonestor xanthophrys*), version 1.0. In Birds of the World (A. F. Poole and F. B. Gill, Editors). Cornell Lab of Ornithology, Ithaca, NY, USA. DOI 10.2173/bow.maupar.01

Simpson, E.H. 1949. Measurement of diversity. Nature **163** DOI: 10.1038/163688a0

Smith, C. W. 1978. Kīpahulu Valley Research Plan. Technical Report 22, Cooperative National Park Resources Studies Unit, Honolulu, Hawai‘i.

Sorjonen J. 1986. Factors affecting the structure of the song and the singing behaviour of some northern European passerine birds. Behaviour, **98**(1-4):286-304.

Steer J. 2010. Bioacoustic monitoring of New Zealand birds. Notornis **57**:75-80.

Stein V. Critical assessment of habitat for release of Maui Parrotbill. Technical report 146. Pacific Cooperative Studies Unit, Honolulu, Hawai‘i.

Sugai L. S. M. and D. Llusia. 2019. Bioacoustic time capsules: Using acoustic monitoring to document biodiversity. Ecological Indicators **99**:149-152.

Teixeira D., M. Maron, and B. J. van Rensburg. 2019. Bioacoustic monitoring of animal vocal behavior for conservation. Conservation Science and Practice **1** DOI: 10.1111/csp2.72.

Wang, A. X., E. B. Paxton, H. L. Mounce, and P. J. Hart. Divergent movement patterns of adult and juvenile ‘Akohekohe, an endangered Hawaiian Honeycreeper. Journal of Field Ornithology **91**(4):346-353.

Wheeldon A., H. L. Mossman, M. J. P. Sullivan, J. Mathenge, and S. R. de Kort. 2018. Comparison of acoustic and traditional point count methods to assess bird diversity and composition in the Aberdare National Park, Kenya. African Journal of Ecology **57**:168-176.

Williams H. 2004. Birdsong and singing behavior. Annals of the New York Academy of Sciences, **1016**(1):1-30.

Wimmer J., M. Towsey, P. Roe, and I. Williamson. 2013. Sampling environmental acoustic recordings to determine bird species richness. Ecological Applications **23**:1419-1428.

Wrege P. H., E. D. Rowland, S. Keen, and Y. Shiu. 2017. Acoustic monitoring for conservation in tropical forests: examples from forest elephants. Methods in Ecology and Evolution **8**:1292-1301.