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FULL RESEARCH ARTICLE

Advancing bird survey efforts through novel recorder technology and automated species identification

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Recent advances in acoustic recorder technology and automated species identification hold great promise for avian monitoring efforts. Assessing how these innovations compare to existing recorder models and traditional species identification techniques is vital to understanding their utility to researchers and managers. We carried out field trials in Monterey County, California, to compare bird detection among four acoustic recorder models (AudioMoth, Swift Recorder, and Wildlife Acoustics SM3BAT and SM Mini) and concurrent point counts, and to assess the ability of the artificial neural network BirdNET to correctly identify bird species from AudioMoth recordings. We found that the lowest-cost unit (AudioMoth) performed comparably to higher-cost units and that on average, species detections were higher for three of the five recorder models (range 9.8 to 14.0) than for point counts (12.8). In our assessment of BirdNET, we developed a subsetting process that enabled us to achieve a high rate of correctly identified species (96%). Using longer recordings from a single recorder model, BirdNET identified a mean of 8.5 verified species per recording and a mean of 16.4 verified species per location over a 5-day period (more than point counts conducted in similar habitats). We demonstrate that a combination of long recordings from low-cost recorders and a conservative method for subsetting automated identifications from BirdNET presents a process for sampling avian community composition with low misidentification rates and limited need for human vetting. These low-cost and automated tools may greatly improve efforts to survey bird communities and their ecosystems, and consequently, efforts to conserve threatened indigenous biodiversity.

Los recientes avances en la tecnología de grabación acústica y en la identificación automatizada de especies son muy prometedores para los esfuerzos de monitoreo aviar. Evaluar cómo estas innovaciones se comparan con los modelos de grabadora existentes y las técnicas tradicionales de identificación de especies es vital para entender su utilidad para investigadores y gerentes. Realizamos ensayos de campo en el condado de Monterey, California, para comparar la detección de aves entre cuatro modelos de grabadora acústica (AudioMoth, Swift Recorder y Wildlife Acoustics SM3BAT y SM Mini) y conteos por puntos simultáneos, y para evaluar la capacidad de la red neuronal artificial BirdNET en identificar correctamente las especies de aves de las grabaciones AudioMoth. Encontramos que la unidad de menor costo (AudioMoth) funcionaba de manera equiparable a unidades de mayor costo y que, en promedio, las detecciones de especies eran más altas para la mayoría de los grabadoras (rango 9.8 a 14.0) que para los conteos por puntos (12.8). En nuestra evaluación de BirdNET, desarrollamos un proceso de subconjuntos que nos permitió alcanzar una alta tasa de especies correctamente identificadas (96%). BirdNET identificó una media de 8.5 especies verificadas por registro y una media de 16.4 especies verificadas por ubicación (más que conteos por puntos realizados en hábitats similares). Demostramos que una combinación de grabaciones de larga duración con grabadoras de bajo costo y un método conservador para el subconjunto de identificaciones automatizadas de BirdNET presentan un proceso para tomar muestras de la composición de la comunidad aviar con bajas tasas de identificación errónea y necesidad limitada de verificación humana. Estas herramientas automatizadas y de bajo costo pueden facilitar en gran medida esfuerzos en examinar las comunidades de aves y sus ecosistemas y, en consecuencia, los esfuerzos para conservar la biodiversidad indígena amenazada.

Key words: acoustic monitoring, ARU, AudioMoth, autoclassification, BirdNET, birds, point count, species identification

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Acoustic monitoring is a non-invasive approach for surveying wildlife that uses remote acoustic technologies to record sounds emitted by vocalizing species (Blumstein et al. 2011). These autonomously triggered tools, also known as autonomous recording units (ARUs), hold many advantages over more traditional approaches like direct observations (e.g., point counts), given they allow scientists to collect information 24 hours per day and on multiple species from multiple taxa, all while minimizing the impacts of observer disturbance and bias during data collection (Brandes 2008; Heinicke et al. 2015; Sebastián-González et al. 2018; Shonfield and Bayne 2017). Further, all acoustic recordings can be permanently stored, allowing them to function as digital archives that can be revisited when new questions or technologies emerge (Chambert et al. 2018). Arrays of fixed acoustic sensors have been used to sample ecosystems (e.g., soundscapes in temperate forests and rainforests [Sethi et al. 2020]), taxonomic groups (Brandes 2008; Ribeiro et al. 2018; Walters et al. 2012; Wood et al. 2019), and individual species (Campos-Cerqueira and Aide 2016; Heinicke et al. 2015). They have also been used to help address questions regarding, for example, species distributions (Campos-Cerqueira and Aide 2016), spatial and temporal dynamics (Bader et al. 2015), phenology (Furnas and McGrann 2018), and spatial variation in habitat quality (Sethi et al. 2020).

Despite the many advantages of acoustic monitoring, there are also several potential limitations. First, differences between acoustic recorders and traditional survey methods may complicate comparisons of data from acoustic recorders to results from established long-term population monitoring programs employing point counts. For example, while acoustic recorders tend to perform equally to humans conducting point counts in estimating bird species richness (Darras et al. 2018), they tend to underperform in estimating bird density or require a secondary source of information (Stevenson et al. 2015). Research focused on estimating avian density from acoustic recordings is a rapidly growing field, however, which has had success and will likely have even greater success as automated and open-source sound localization software is developed (Blumstein et al. 2011; Sebastián-González et al. 2018; Perez-Granados et al. 2019; Rhinehart et al. 2020; Stevenson et al. 2021). Additionally, researchers have successfully integrated avian survey data from point counts and acoustic recorders and have given specific recommendations on sampling birds with acoustic recorders to achieve results comparable to those from point counts (Darras et al. 2018). For example, Stewart et al. (2020) used statistical offsets, or correction factors, to integrate data from point counts and ARUs.

A second potential limitation is the high cost of acoustic recorders, which can restrict their usage in many contexts (Hill et al. 2019; Rhinehart et al. 2020). Wildlife Acoustics Recorders (Wildlife Acoustics, Maynard, MA, USA) can cost upwards of $1,000, for example, meaning a project with 100 survey locations would need a minimum budget of over $100,000. Recently, however, low-cost alternatives like the AudioMoth (Open Acoustic Devices 2020) have been developed. The AudioMoth is a full-spectrum recorder that fits in the palm of a hand and has a cost of approximately 60 USD per unit (Hill et al. 2019). AudioMoths have proven successful for a variety of wildlife monitoring and conservation projects (Prince et al. 2019) but for a full understanding of their utility, need to be directly compared to other acoustic recorder models.

A final challenge associated with acoustic monitoring is the terabytes of sound files that can be produced, within which the sound of interest must be located and correctly identified to species (Chambert et al. 2018; Wrege et al. 2017). Accomplishing the latter by manually reviewing the spectrograms of all recordings requires an immense amount of effort (Campos-Cerqueira and Aide 2016). Thus, many researchers now rely on custom designed algorithms or commercially available sound analysis software to automate species identification (Brandes 2008; Gibb et al. 2019; Heinicke et al. 2015; Kalan et al. 2015). One recently developed tool is BirdNET, an artificial neural network that can automatically identify over 900 bird species (Kahl 2020). In an initial assessment of 225 recordings, BirdNET was found to have an overall accuracy (i.e., correctly identified vocalizing bird species) of 91.5% (Arif et al. 2020). Additional assessments of the accuracy of BirdNET are needed, however, given it is an extremely new and evolving tool.

The goal of our study is to help address these research gaps by assessing the efficacy of several acoustic recorder models in detecting birds and one sound analysis tool in identifying birds. Specifically, we 1) compared species-level detection rates among the acoustic recorder models and concurrent point counts; and 2) evaluated BirdNET's ability to correctly identify bird species from acoustic recordings. Understanding the optimal way to collect and process acoustic recordings of birds will help inform the design and feasibility of future large-scale bird monitoring efforts and enable managers to combat challenges associated with acoustic monitoring head-on.

METHODS

Study Area

We conducted fieldwork within the Hastings Natural History Reservation in Monterey County, California, USA (36.380, -121.564). This reserve covers 950 ha, and vegetation at the study area is primarily oak (*Quercus* sp.) woodland and chaparral (Griffon 1990). Mean annual temperature is 13.4 °C, and mean annual precipitation is 522 mm (McMahon et al. 2015).

Field Methods

Comparison among acoustic recorder models and point counts.—At each of three survey locations, we installed five acoustic recorders between 24 June and 26 June 2020: one Song Meter SM3BAT (Wildlife Acoustics), one Song Meter Mini Acoustic Recorder (Wildlife Acoustics), one Swift Recorder (Cornell Lab of Ornithology Bioacoustics Research Program), and two AudioMoths (Open Acoustic Devices) that were programmed with different acoustic settings (Table 1). We attached recorders to securely placed T-posts approximately 2 m above the ground. While recorders did not all face the same direction, recorder directionality should not have led to any bias in the mean number of species detected by any one recorder type compared to the others. We programmed all acoustic recorders to record from 0500 to 0800 Pacific Daylight Time (PDT), capturing peak hours of avian vocal activity.

Table 1. Means and standard deviations for numbers of bird species identified using six methods employed during the same four survey events: field-based surveys (point counts) and five acoustic recorder types. Also included are the recorder settings used and the cost per unit of each recorder. We collected all data at Hastings Natural History Reservation in Monterey County, CA, USA, 2020.

Survey method	Mean (SD) species identified	Gain (dB)	Sample rate (kHz)	Cost per unit (USD)
Swift Recorder	9.8 (1.5)	38	48	250.00
AudioMoth 1	11.8 (1.5)	27.2	48	59.99
Point count	12.8 (1.5)	NA	NA	NA
AudioMoth 2	13.3 (1.7)	32	32	59.99
Song Meter Mini	13.5 (1.7)	24	48	499.00
Song Meter SM3BAT	14.0 (2.2)	24	48	1,265.00

An observer trained in the aural and visual identification of California birds conducted a concurrent 6-minute point count survey at each of the recorder locations between 0600 and 0800 PDT. We followed methods outlined in McLaren et al. (2019), where we collected information on every individual bird detected, including the species identification, minute of first detection, and estimated distance from observer. We repeated surveys (recordings and point counts) at one of the locations on a second date, for a total of four survey events at the three survey locations.

Assessment of BirdNET performance.—We deployed ten additional AudioMoths to evaluate BirdNET's ability to correctly identify bird species. Specifically, we installed a single AudioMoth approximately 2 m above the ground at each of ten locations spaced by a minimum of 500 m. We placed AudioMoths inside small, resealable plastic bags along with desiccant bags to protect them from moisture. We programmed AudioMoths (hardware version 1.1.0) using firmware version 1.4.0 and set them to record with a gain of Medium (30.6 dB), a sample rate of 48 kHz, and a recording period from 2000 to 0630 PDT (10.5 hr) for five consecutive days between 16 June and 26 June. Thus, we used fifty recordings for this analysis (five recordings from each of ten locations).

Data Processing and Analyses

Comparison among acoustic recorder models and point counts.—From each recording, we selected the 6-minute time span corresponding to the 6-minute point count for that date and location. We listened to each recording once, identifying the species audible in the recording. We calculated means and standard deviations for the numbers of bird species detected by the human observer (both from point counts and from recordings). We performed all data summaries and analyses in RStudio (RStudio 1.3.1073, www.rstudio.com, accessed 17 Aug 2020).

Assessment of BirdNET performance.—To evaluate BirdNET's ability to correctly identify bird species from acoustic recordings, we processed the 10.5-hour AudioMoth recordings using BirdNET (version available at https://github.com/kahst/BirdNET) run through Python version 3.8.2 in Ubuntu 20.04.1. We supplied BirdNET with the week of the year, latitude, and longitude corresponding to the recording location. We left all other BirdNET settings as defaults. To limit the number of false positive species records (i.e., instances when BirdNET identified species in a recording that were not actually audible), we used several parameters to subset species detections from BirdNET. First, we removed species that only had a single detection across all five recordings for the location since these were more likely to represent misidentifications or species flying over but not occupying the location. Second, we subsetted BirdNET output based on two parameters that it assigns for every identification: 1) confidence, indicating the degree of confidence BirdNET has in each species identification (on a scale where 0 represents lowest confidence and 1 represents highest confidence); and 2) rank, which indicates the species with the highest confidence value when BirdNET identifies multiple possible species. We chose to only include detections if BirdNET assigned them a Rank of 1 and a Confidence value of 0.95 or higher so that we would retain only the highest confidence detections. Finally, we excluded purported detections of diurnal species if they were detected during the nighttime (2100 to 0430 PDT). We did this to correct for BirdNET's tendency to produce high-confidence false positive detections at higher rates during this period (often due to apparent misidentifications of rustling vegetation or vocalizations from nocturnal animals). We believe that excluding these purported detections reduced false positive identifications without compromising our ability to detect these species because any diurnal species acoustically active at a location should be more active outside nighttime hours.

Following the subsetting process, we listened to select portions of the sound files to confirm whether the species BirdNET identified were audible in each recording. We did not listen to all 10.5 hours of each recording, but rather skipped to the times of the recording for which BirdNET had produced detections. We calculated the mean and standard deviation for the number of species identified per recording, including the number of species identified but not confirmed to be audible by the human observer (false positives) and the number of species identified and confirmed to be audible (true positives). We also calculated the mean and standard deviation for the number of species identified (including true and false positives) at the survey location level, by determining the cumulative total number of species identified across the five recordings from each location.

RESULTS

Comparison of Acoustic Recorder Models

We identified 26 bird species across the concurrent point counts and recordings (Table 2). Steller's Jay (*Cyanocitta stelleri*, n = 24) and warbling vireo (*Vireo gilvus*, n = 24) were detected by all methods during all survey events. We identified two species on point counts but not on recordings: white-breasted nuthatch (*Sitta carolinensis*) and house wren (*Troglodytes aedon*), although we detected calls from an unidentified wren species on all recordings. We identified three species on recordings but not on point counts: Black-headed grosbeak (*Pheucticus melanocephalus*), bushtit (*Psaltriparus minimus*), and house finch (*Haemorhous mexicanus*). The highest mean number of species was identified via the Song Meter SM3BAT and the lowest via the Swift Recorder (Table 1). While the mean number of species identified during point counts was higher than that of two recorders, we found that on average, AudioMoths (with higher gain and lower sampling rate programming) and both Wildlife Acoustics recorders resulted in higher mean numbers of species identifications than point counts (Table 1).

Assessment of BirdNET Performance

Across the ten locations, BirdNET identified 42 species that we confirmed to be audible in the 10.5-hr AudioMoth recordings (Appendix I). The species identified from the most recordings were Pacific-slope flycatcher (*Empidonax difficilis,* n = 25), California scrub-jay (*Aphelocoma californica*, n = 24), and California towhee (*Melozone crissalis*, n = 24). The mean number of species detected by BirdNET and subsequently confirmed was 8.5 per recording (range 3–15, SD = 3.5). The mean number of false positive species records was 0.3 per recording (range 0–2, SD = 0.6), which equated to a false positive (misidentification) rate of 3.8% of species records. Cumulative species totals from the five recordings at each location showed that BirdNET correctly identified a mean of 16.4 species per location (range 8–23, SD = 5.3; Table 3) and misidentified 1.6 species per location (range 0–3, SD = 1.0; Table 3).

For two species identified by BirdNET, we removed detections from our results because we could not distinguish sounds to the species level. These species were chestnut-backed chickadee (*Poecile rufescens*), detected in 5 recordings, where call notes were indistinguishable from those of oak titmouse (*Baeolophus inornatus*), and white-crowned sparrow (*Zonotrichia leucophrys*), with a single unidentifiable call note from one recording. BirdNET identified six species that were not detected by the human observer in any recording, with five of these misidentified in a single recording each (Appendix II).

Table 2. Bird species identified using six methods employed at the same locations and times: field-based surveys (point counts) and five acoustic recorder types. For each method, we list the number of surveys (n = 4) during which the species was identified. We collected all data at Hastings Natural History Reservation in Monterey County, CA, USA, 2020.

Species	Swift Recorder	Audio-Moth 1	Audio-Moth 2	Song Meter Mini	Song Meter SM3BAT	Point count
acorn woodpecker	2	3	4	4	4	4
American robin	1	1	2	3	4	2
band-tailed pigeon	0	0	2	2	3	2
black-headed grosbeak	1	1	1	1	1	0
Bullock's oriole	1	1	1	1	1	1
bushtit	0	0	1	1	0	0
California towhee	2	2	2	2	2	2
hairy woodpecker	0	1	1	1	1	1
house finch	0	0	1	0	0	0
house wren	0	0	0	0	0	1
Hutton's vireo	2	4	4	4	3	2
lesser goldfinch	1	1	1	1	1	2
mourning dove	2	3	2	3	3	2
northern flicker	2	2	2	2	2	2
Nuttall's woodpecker	1	0	0	0	1	1
oak titmouse	3	4	4	4	4	4
Pacific-slope flycatcher	3	3	3	2	3	3
purple finch	0	2	3	4	3	3
red-shouldered hawk	0	0	0	0	1	1
song sparrow	3	2	3	3	3	2
spotted towhee	2	3	2	2	2	3
Steller's jay	4	4	4	4	4	4
warbling vireo	4	4	4	4	4	4
western bluebird	1	1	1	1	1	1
white-breasted nuthatch	0	0	0	0	0	1
wrentit	2	3	3	3	3	3
Total	39	47	53	54	56	51

DISCUSSION

The use of passive acoustic monitoring methods in terrestrial systems has been increasing exponentially since the 1990s (Sugai et al. 2019). Balancing the trade-off between high-quality recordings and costs is vital for researchers and managers considering these methods. In our comparison of four acoustic recorder models and concurrent point counts, we found that the lowest-cost units, AudioMoths, performed comparably to higher-cost

Table 3. Cumulative numbers of bird species identified by BirdNET, an artificial neural network, from AudioMoth acoustic recordings from ten locations in Hastings Natural History Reservation, Monterey County, CA, USA, 2020. Numbers represent cumulative totals across five 10.5-hr recordings (52.5 total hours) taken at each location. True positive species are those that a human observer confirmed to be audible in recordings, while false positive species are those that the observer could not confirm.

Site ID	True positive species	False positive species
1	17	2
2	20	3
3	13	2
4	8	2
5	15	0
6	23	1
7	21	1
8	23	1
9	10	1
10	14	3
Mean	16.4	1.6

units as measured by the number of species identified by a human listener. Specifically, we found that Wildlife Acoustics SM3BAT and SM Mini, the highest cost recorders we tested, had the highest quality recordings with means of 14 and 13.8 species detected, respectively, compared to 13.3 for the AudioMoth. In some cases, however, the mean number of species identified using AudioMoths exceeded that of the higher cost units, as well as point counts. Researchers and managers with diverse project needs must decide if these small differences in the mean numbers of species detected are worth an eight- to 21-fold increase in equipment costs. For large-scale acoustic monitoring or assessment projects requiring many recorders, our results suggest that the low-cost AudioMoth can provide acoustic data of sufficient quality to justify trade-offs demanded by factors such as budget constraints and the risk of recorder loss or damage.

We recognize that the results of our comparison among acoustic recorders and point counts are based upon a small sample size. It was also not possible to program all recorders with the exact same gain and sample rate settings, which would have provided a more standardized comparison among recorder models. We encourage larger scale studies that further examine the relative performance of acoustic recorder models, especially as new models rapidly become available.

Like costs, the time required to process sound files (i.e., identifying vocalizing animals to species) has been identified as a challenge associated with acoustic monitoring (Campos-Cerqueira and Aide 2016; Chambert et al. 2018; Wrege et al. 2017). We found that by subsetting results from BirdNET, a freely available tool that automates species identifications, we achieved a high rate of true positive species identifications and a misidentification rate of less than 4%, which is lower than that reported for humans in other studies. For example, Campbell and Francis (2011) found that across experienced observers listening to recordings, bird species reported by observers but not present on recordings accounted for a mean of 14% of reported species records. Farmer et al. (2012) also examined performance of humans listening to recordings for bird species designated as common or rare and observers with skills ranked from moderate to expert. Across those categories, they reported false positive rates ranging from 6% to 22%. These results demonstrate BirdNET's promise for providing efficient, automated, and accurate bird identification, reducing reliance on human observers with variable identification abilities.

The few sounds that BirdNET misidentified were generally sounds that a human observer would also have difficulty identifying, such as confusing non-avian sounds and brief call notes that are very similar among species. Examining BirdNET results can reveal certain species that are more likely to be false positives. For example, BirdNET appeared to misidentify rustling vegetation as calls of hooded oriole (*Icterus cucullatus*) on more than one occasion. We recommend that researchers initially vet identifications from subsetted data to establish study area-specific lists of problematic species that should be vetted (i.e., reviewed by a human observer to confirm or correct species identification), further limiting the need to vet across all recordings and species.

It is important to note that we were unable to assess how our subsetting process affected the proportion of false negatives (i.e., instances where our process failed to detect species audible in the recordings). Our conservative approach, which produced a low rate of misidentifications (false positives), likely also produced an elevated rate of missed species (false negatives). However, based on the mean number of true positive species detected per location (16.4), we are confident that our methods enabled BirdNET to produce both low misidentification rates and rigorous samples of avian community composition matching or exceeding those typically produced by more traditional methods. For example, the mean number of confirmed species per location recorded by AudioMoths and identified by BirdNET was higher than our mean number of species from point counts (12.8), which were done in very similar habitats using the protocol of one of North America's largest-scale bird monitoring programs. In addition, the longer species lists from AudioMoths/BirdNET often included species that traditional point count protocols have difficulty sampling, such as nocturnal species (e.g., barn owl [*Tyto alba*] and great horned owl [*Bubo virginianus*]). A growing body of research demonstrates that sound recording systems can match and even outperform point counts in their ability to sample birds (Darras et al. 2018; Darras et al. 2019; Wimmer et al. 2013), but to our knowledge this is the first published work to document this comparison for the AudioMoth.

Our study also elucidated several approaches that will likely enhance the number of true positive species detections produced by acoustic recorders and BirdNET. First, we recorded for less than one hour after local sunrise, but recorders could be set to record for more time, especially during the morning hours when avian acoustic activity peaks. Second, logistical constraints prevented us from collecting recordings during the seasonal peak of avian acoustic activity at our study area. Recording during the seasonal peaks of acoustic activity for as many species as possible should increase the number of species that are recorded and subsequently detected by BirdNET. Recording after this peak, as we did, may also increase error in BirdNET by increasing detection of individuals likely to present sound-based identification challenges, such as fledglings. On the other hand, researchers should be cautious about recording early in the breeding season when migrating or unpaired (nonbreeding) individuals are more likely to be present. Finally, we used a single conservative confidence threshold to subset detections across all species, eliminating the majority of BirdNET's detections, including all detections for several species in some of our recordings. Approaches that use species-specific confidence thresholds may optimize the balance between high true positive and low false negative identification rates. Kahl (2020) provided optimal species-specific confidence thresholds in BirdNET, but we found that they resulted in high numbers of false positive identifications from our recordings. BirdNET's utility for avian acoustic monitoring may benefit greatly from further exploration of optimal species-specific confidence thresholds, especially if these thresholds are established for specific geographic regions. Researchers may also consider establishing lower confidence thresholds for species of special interest, which are often rare species that may be missed by a single, conservative threshold.

The results of this study provide critical information to researchers and managers considering the use of acoustic methods for surveying bird communities. By using a combination of long recordings from low-cost recorders and conservative subsetting of BirdNET's automated identifications, we have honed a process that shows great promise for sampling avian community composition with low misidentification rates and limited need for human vetting. Together, these tools may greatly improve efforts to survey bird communities and their ecosystems, and consequently, efforts to conserve threatened indigenous biodiversity.

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APPENDIX I: BIRD SPECIES CORRECTLY IDENTIFIED BY BIRDNET

Common and scientific names of species correctly identified (verified by a human observer) by the artificial neural network BirdNET following the authors' subsetting process. Also included is the number of recordings in which each species was detected and confirmed by the observer (out of a total of 50 recordings).

Common name	Scientific name	Number of recordings
acorn woodpecker	*Melanerpes formicivorus*	12
American crow	*Corvus brachyrhynchos*	5
American kestrel	*Falco sparverius*	1
American robin	*Turdus migratorius*	2
ash-throated flycatcher	*Myiarchus cinerascens*	15
band-tailed pigeon	*Patagioenas fasciata*	5
barn owl	*Tyto alba*	10
Bewick's wren	*Thryomanes bewickii*	10
black-headed grosbeak	*Pheucticus melanocephalus*	10
black phoebe	*Sayornis nigricans*	10
blue-gray gnatcatcher	*Polioptila caerulea*	16
brown creeper	*Certhia americana*	5
Bullock's oriole	*Icterus bullockii*	1
bushtit	*Psaltriparus minimus*	20
California scrub-jay	*Aphelocoma californica*	24
California thrasher	*Toxostoma redivivum*	4
California towhee	*Melozone crissalis*	24
Cooper's hawk	*Accipiter cooperii*	1
dark-eyed junco	*Junco hyemalis*	15
great horned owl	*Bubo virginianus*	10
hairy woodpecker	*Dryobates villosus*	6
house finch	*Haemorhous mexicanus*	3
Hutton's vireo	*Vireo huttoni*	6
lark sparrow	*Chondestes grammacus*	1
Lawrence's goldfinch	*Spinus lawrencei*	3
lesser goldfinch	*Spinus psaltria*	11
mourning dove	*Zenaida macroura*	9
northern flicker	*Colaptes auratus*	4
Nuttall's woodpecker	*Dryobates nuttallii*	7
oak titmouse	*Baeolophus inornatus*	21
orange-crowned warbler	*Leiothlypis celata*	1
Pacific-slope flycatcher	*Empidonax difficilis*	25
purple finch	*Haemorhous purpureus*	9

APPENDIX I continued

Common name	Scientific name	Number of recordings
red-shouldered hawk	*Buteo lineatus*	3
red-tailed hawk	*Buteo jamaicensis*	6
spotted towhee	*Pipilo maculatus*	23
Steller's jay	*Cyanocitta stelleri*	23
violet-green swallow	*Tachycineta thalassina*	18
warbling vireo	*Vireo gilvus*	4
western bluebird	*Sialia Mexicana*	5
white-breasted nuthatch	*Sitta carolinensis*	13
wrentit	*Chamaea fasciata*	24

APPENDIX II: BIRD SPECIES MISIDENTIFIED BY BIRDNET

Common and scientific names of species apparently misidentified by the artificial neural network BirdNET following the authors' subsetting process. Also included are the number of recordings in which BirdNET was known to have misidentified the species, as well as the apparent true source of the misidentified sound. Six of these species (in bold) were not confirmed to be present in any of the recordings at the study area.

Common name	Scientific name	Apparent true sound source	Number of recordings
acorn woodpecker	*Melanerpes formicivorus*	Unknown	1
American avocet	***Recurvirostra americana***	Female wrentit	1
American coot	***Fulica americana***	**Unknown**	**1**
band-tailed pigeon	*Patagioenas fasciata*	great horned owl	1
band-tailed pigeon	*Patagioenas fasciata*	Unknown	1
belted kingfisher	***Megaceryle alcyon***	**Unknown**	**1**
Bewick's wren	*Thryomanes bewickii*	blue-gray gnatcatcher	1
black phoebe	*Sayornis nigricans*	Unknown	1
Bullock's oriole	*Icterus bullockii*	California thrasher call	1
downy woodpecker	***Dryobates pubescens***	Unknown	1
hooded oriole	***Icterus cucullatus***	**Rustling vegetation**	**2**
Lawrence's goldfinch	*Spinus lawrencei*	California towhee call	1
lesser goldfinch	*Spinus psaltria*	Unknown	1
Savannah sparrow	***Passerculus sandwichensis***	**Unknown bird call**	**1**
white-breasted nuthatch	*Sitta carolinensis*	acorn woodpecker	1