

**US Department of Agriculture Forest Service  
Pacific Northwest Research Station  
and  
US Department of the Interior National Park Service  
Pacific West Region**

**Bioacoustics 2021 Annual Report  
February 28, 2022**

**1. Title**

Passive Acoustic Monitoring within the Northwest Forest Plan Area: 2021 Annual Report

**2. Research Team**

Damon B. Lesmeister<sup>1\*</sup>, Julianna M. A. Jenkins<sup>1</sup>, Zachary J. Ruff<sup>1</sup>, Raymond J. Davis<sup>2</sup>, Cara L. Appel<sup>1</sup>, Alaina D. Thomas<sup>1</sup>, Scott Gremel<sup>3</sup>, Dave Press<sup>3</sup>, Tara Chestnut<sup>3</sup>, James K. Swingle<sup>1</sup>, Todd Wilson<sup>1</sup>, David C. Culp<sup>1</sup>, Heather Lambert<sup>1</sup>, Christopher McCafferty<sup>1</sup>, Kirsten Wert<sup>1</sup>, Brandon Henson<sup>1</sup>, Laura Platt<sup>1</sup>, Dylan Rhea-Fournier<sup>3</sup>, and Steven Mitchell<sup>3</sup>

<sup>1</sup>USDA Forest Service, Pacific Northwest Research Station

<sup>2</sup>USDA Forest Service, Pacific Northwest Region

<sup>3</sup>USDI National Park Service, Pacific West Region

\*Email: damon.lesmeister@usda.gov

**3. Introduction**

Northern spotted owl (*Strix occidentalis caurina*; hereafter NSO) populations have been monitored as part of the Northwest Forest Plan Interagency Monitoring Program to assess effectiveness of the plan, and to inform management and conservation decisions. Two phases were envisioned in the establishment of the monitoring program (Lint et al. 1999). Phase I of NSO population monitoring would rely on demographic data and Phase II would be based on habitat monitoring if population change were found to follow trends in forests suitable for nesting and roosting (Lint et al. 1999). The study design for Phase I focused on call-back surveys to locate territorial owls on 8 study areas comprised primarily of federal lands, then capturing, marking, and resighting those birds to estimate vital rates and population change (Franklin et al. 1996, Lint et al. 1999). Phase I has revealed continued and increasing rates of population decline throughout the NSO geographic range, as well as identifying barred owls (*S. varia*) and available habitat as important factors associated with those trends (Lesmeister et al. 2018, Yackulic et al. 2019, Franklin et al. 2021).

Declining NSO populations and increasing effects of barred owls have greatly increased the amount of effort and costs required to accomplish NSO demographic studies. Furthermore, several NSO populations, especially in Washington, have declined to levels where few individuals occupy and reproduce in the monitored territories, thus increasing uncertainty in population status and trend estimates obtained from Phase I methods (Dugger et al. 2016, Gremel 2019, Lesmeister et al. 2019, Franklin et al. 2021, Lesmeister et al. 2021b). NSO have consistently and repeatedly been found to be highly associated and reliant on older forests (Forsman et al. 1984, Jenkins et al. 2019, Sovern et al. 2019, Yackulic et al. 2019), but competition with, and displacement by, barred owls have disrupted previous NSO population

dynamics including a consistent relationship between habitat availability and NSO demographic performance (Dugger et al. 2005, Jenkins et al. 2019, Yackulic et al. 2019, Jenkins et al. 2021). Therefore, Phase II of NSO monitoring will require, in addition to habitat monitoring, an analytical framework coupled with species survey data to assess trends in the populations (Lesmeister et al. 2021a).

Passive acoustic monitoring using autonomous recording units (ARUs) has been demonstrated to be effective for detecting NSO and barred presence (Duchac et al. 2020), distinguishing NSO sex (Dale et al. *In Press*), and detecting trends in NSO populations (Lesmeister et al. 2021a). Further, ARUs allow for extended-duration sessions, which greatly decreases technician effort in the field while increasing the quantity of data collected (Tegeler et al. 2012). Development of artificial intelligence models to automate detections results in rapid and effective data processing and analysis workflows for NSO and a wide range of other vocal wildlife species (Ruff et al. 2020, Ruff et al. 2021). In 2020, the Northwest Forest Plan Regional Interagency Executive Committee decided to discontinue Phase I and transition to Phase II based on habitat monitoring coupled with passive acoustic monitoring survey data.

Here we provide a progress report on passive acoustic monitoring conducted during 2018–2021 within the Northwest Forest Plan area using a combination of ARU surveys in 5 km<sup>2</sup> hexagons and automated detections of NSO and 35 other species. Our primary objectives were to 1) establish and refine a long-term passive acoustic monitoring design; 2) develop and improve automated detection models and data processing workflow; and 3) quantify weekly detections and proportion of hexagons used by each species. A secondary objective of the project was to develop methods and tools that could be utilized by land management agencies to survey for NSO and process passive acoustic monitoring data.

#### **4. Study Area**

We collected data within 10 historical NSO demographic study areas with lands that were primarily under federal ownership and administered by US Forest Service, US Bureau of Land Management, or National Park Service. Nine of the study areas (OLY = Olympic Peninsula, CLE = Cle Elum, RAI = Mt. Rainer National Park, COA = Oregon Coast Range, HJA = HJ Andrews Experimental Forest, TYE = Tyee, KLA = Klamath, CAS = South Cascades, NWC = Northwest California) were long-term demographic study areas for NSO monitoring under the Northwest Forest Plan (Franklin et al. 2021) and one study area (MAR = Marin County) was included due to long-term and ongoing NSO demographic monitoring (Fig. 1). In 2021, we collected data from 20 designated Wilderness Areas (Table 1).

#### **5. Methods**

##### *Sampling design*

We created a uniform layer of 5 km<sup>2</sup> hexagons that covered the entire range of the NSO (Lesmeister et al. 2021a) and is now publicly available for download (USFWS 2021). This hexagon size is approximately the size of a NSO territory core area (Glenn et al. 2004, Schilling et al. 2013) and approximates the home range size reported for barred owls in the Pacific Northwest (Hamer et al. 2007, Singleton et al. 2010, Wiens et al. 2014). Within study areas we randomly selected approximately 20% of hexagons that contained  $\geq 50\%$  forest capable lands and  $\geq 25\%$  federal ownership. Forest capable lands were those areas with suitable soil type, plant association, and elevation capable of developing into forest (Davis and Lint 2005). In KLA we also surveyed hexagons in areas that were included as treatment areas of the barred owl control

experiment (Wiens et al. 2021). In a subset of our study areas (OLY, COA, KLA), we surveyed non-adjacent hexagons to provide a buffer between territories and reduce the probability of detecting the same individual in multiple hexagons. Within each hexagon, we deployed 4–5 ARUs as our sampling stations.

We collected acoustic data using Song Meter SM4 (primary device with > 95% data collected), Song Meter Mini (Wildlife Acoustics, Maynard, MA), and SWIFT (Cornell Lab Center for Conservation Bioacoustics) ARUs. All devices were portable, weatherproof, and easily programmable. The SM4s had two built-in omni-directional microphones with signal-to-noise ratio of 80 dB typical at 1kHz, two SDHC/SDXC flash card slots, 350–400 h battery life, and a recording bandwidth of 20 Hz to 48 kHz at decibel levels of -33.5 dB to 122 dB. The Song Meter Mini recorded at the same bandwidth, signal-to-noise ratio of 78 dB, one omni-directional microphone, one SDHC/SDXC flash card slot, and 210-1040 h battery life depending on configuration. The SWIFT unit is also small, waterproof, and portable, but must be programmed from a computer. It accepts 3 D-cell batteries and one SDHC/SDXC flash card in FAT32 file system, and the battery life lasts approximately 5 weeks. The signal-to-noise ratio was 58db with -48dB microphone sensitivity. All these acoustic ARUs recorded sound with equivalent sensitivity to normal range of human hearing, and their effective listening radius may be affected by external factors such as terrain, vegetation, and weather events such as wind and rain. At each sampling station within a hexagon, we mounted ARUs to small trees (15–20 cm diameter at breast height) to allow microphones to extend past the bole for unobstructed recording ability. We deployed ARUs on federal land; mid-to-upper slope positions;  $\geq 50$  m from roads, trails, and streams to reduce vandalism and excessive noise; spaced  $\geq 500$  m apart; and located  $\geq 200$  m from edge of hexagon. The deployment of ARUs and data retrieval were the first two steps in our general workflow for collection, processing, and reporting findings (Appendix A).

### *2018 data collection*

During the 2018 NSO breeding season (March–August), we deployed ARUs at 1,012 randomly placed sampling stations (Appendix B) in 208 hexagons (5 sampling stations/hexagon) in COA and OLY (Table 2). We intended to deploy ARUs in 120 hexagons in each study area; however, due to poor road access early in the season (e.g., down trees, snow), only 88 hexagons were sampled in OLY. We programed ARUs to record from 1 h before sunset to 3 h after sunset and from 2 h before sunrise to 2 h after sunrise, producing 8 h of recordings per day focused on crepuscular diel periods. We programmed ARUs to record in stereo at a sampling rate of 32 kHz. Duchac et al. (2020) found robust detection probabilities for NSO of  $\sim 0.98$  in hexagons with six weeks of sampling; therefore, we surveyed hexagons for 6 weeks during 2018.

### *2019 data collection*

In 2019, we deployed ARUs in 289 hexagons in COA ( $n = 106$ ), OLY ( $n = 120$ ), and KLA ( $n = 63$ ), with a total of 1,136 sampling stations across all three study areas (Table 2). Most hexagons and sampling stations surveyed in COA and OLY were also surveyed in 2018. Based on preliminary analysis of 2018 data we found that surveying with four stations/hexagon for six weeks resulted in seasonal detection probabilities of  $> 0.95$  for NSO at the hexagon scale (C. Appel, unpublished data), thus we refined our sampling to match this design starting in 2019 (Appendix B). We programmed ARUs to record on the same crepuscular schedule as 2018 but additionally recorded for the first 10 min of every hour throughout the day and night, allowing for additional detections of diurnal and nocturnal species (Fig. 2). Further refining 2018 methods,

starting in 2019 we set ARUs to record in mono to produce approximately half the volume of data with no loss in species detections (Z. Ruff, unpublished data).

#### *2020–2021 data collection*

In 2020, we surveyed 1,494 sampling stations in 381 hexagons across COA ( $n = 120$ ), OLY ( $n = 119$ ), KLA ( $n = 73$ ), and CLE ( $n = 69$ ; Table 2). In COA, OLY, and KLA we surveyed the same hexagons and sampling stations that were surveyed in 2019. In 2021 we surveyed a total of 2,538 sampling stations in 643 hexagons in OLY ( $n = 119$ ), CLE ( $n = 75$ ), RAI ( $n = 11$ ), COA ( $n = 120$ ), TYE ( $n = 40$ ), KLA ( $n = 73$ ), HJA ( $n = 70$ ), CAS ( $n = 98$ ), NWC ( $n = 30$ ), and MAR ( $n = 7$ ; Fig. 1; Table 2). In COA, OLY, KLA, and CLE we surveyed the same hexagons that were surveyed in 2020. Hexagons entering the sampling pool in 2020 and 2021 were sampled with four ARUs placed in a standard design with a central station and one in three alternating triangles (Appendix B). In 2021, 462 of our sampling stations were in designated Wilderness Areas administered by US National Park Service ( $n = 285$ ) or US Forest Service ( $n = 177$ ; Table 1).

#### Data processing

##### *Convolutional neural network (CNN) development for automated species identification*

We developed four versions of a convolutional neural network model to automate detections of vocal wildlife species, with each version attaining improved performance and greater number of species identified compared to each preceding version (Appendix C, D). Preceding our broadscale passive acoustic monitoring, Duchac et al. (2020) and Duchac et al. (2021) conducted passive acoustic monitoring in 2017 to estimate detection probabilities and occupancy for several owl species in or near three of our study areas (OLY, COA, KLA). From those survey data, Ruff et al. (2020) used the sound clips for six owl species (including NSO and barred owl) to train our first version of the convolutional neural network (PNW-Cnet v1) to automate species identifications. We did not use PNW-Cnet v1 for processing data presented here, but the model and process used was replicated and refined for successive PNW-Cnet versions that were used for data processing. Details on development and performance of PNW-Cnet v1 can be found in Ruff et al. (2020). Briefly, we located target species vocalizations in the 2017 data using the Simple Clustering feature of Kaleidoscope Pro software (version 5.0, Wildlife Acoustics) to generate training data. Given that convolutional neural network models are designed for image classification, we split all sound files (.wav) into 12 s segments and then converted those to spectrograms, which are image representations of sound (Fig. 3). We used a 12 s interval because it cleanly divides an hour-long field recording and is long enough to fully contain any of the owl calls. To reflect the variation found in field recordings, we generated multiple spectrograms with different parameters for each unique clip, producing several images for each unique sound clip (Ruff et al. 2020).

The final training dataset used by Ruff et al. (2020) included spectrograms for seven target classes: northern saw-whet owl (*Aegolius acadicus*;  $n = 10,003$ ), great horned owl (*Bubo virginianus*;  $n = 9,999$ ), northern pygmy-owl (*Glaucidium californicum*;  $n = 10,003$ ), western screech-owl (*Megascops kennicottii*;  $n = 10,004$ ), NSO ( $n = 22,373$ ), barred owl ( $n = 22,204$ ), and noise ( $n = 10,003$ ). We implemented the PNW-Cnet v1 model in Python using Keras, an application programming interface, to Google's TensorFlow software library (Abadi et al. 2015). We trained the PNW-Cnet v1 for 100 epochs on our 94,589 training images, of which 80% were used for training and 20% were set aside as a validation set. See Ruff et al. (2020) for details on

model performance for each species.

We found that PNW-Cnet model performance could be improved for target species (notably NSO) by increasing the size of the model training dataset and incorporating additional target classes, including vocalizations easily confused with the existing classes. From 2018–2021, we expanded and further developed the PNW-Cnet for processing data with important advancements and expansions occurring each year of the study (Appendix C, Appendix D). The PNW-Cnet v2 included automated identification of 16 target sound classes comprising calls and sounds of 14 species (Table 3) and was trained on 173,964 training images (Ruff et al. 2021). In addition to classes representing sounds produced by target species, PNW-Cnet v2 included a catch-all noise class that included any sound not specifically covered by one of the target classes. The PNW-Cnet v3 included 33 sound classes representing 25 species (Table 3) and included 194,524 training images. The PNW-Cnet v4 included 45 sound classes for 36 individual species (Table 3) and was trained on 426,605 training images. Due to changes in the structure of the neural network, PNW-Cnet v3 and PNW-Cnet v4 did not include a Noise class, but each included several “nuisance” classes covering specific noise sources (e.g., buzzing insects, logging equipment, etc.); more broadly, any clip to which the PNW-Cnet did not assign a high score for at least one target class would be considered noise.

To determine the performance of each version of the PNW-Cnet to correctly classify each sound class, we calculated precision and recall, generated from a test set of clips that were fully tagged by human technicians (Table 3). Precision is the rate of true positives among apparent detections (clips with an output prediction  $\geq 0.95$ ). Recall is the proportion of calls in the dataset that were detected and correctly identified. The performance metrics given for PNW-Cnet v2 differ from those published in Ruff et al. (2021), as they were calculated using a different test dataset. We initially developed this test dataset in 2021 to assess the performance of PNW-Cnet v3 by taking a random sample of the clips that were assigned a score  $\geq 0.95$  by PNW-Cnet v3 for any of that version’s target classes. For each class, the percentage of apparent detections included in the test set ranged from 0.1–100.0% due to large differences in the number of apparent detections available for review; the final test dataset included 120,269 images with known labels. To have comparable metrics, we used the same test set to generate all the performance metrics given for PNW-Cnet v2, v3 and v4.

### *2018–2021 data processing*

We followed a multi-step workflow that integrated the latest version of PNW-Cnet to efficiently process large volumes of audio data, combining automated identification and human validation (Ruff et al. 2021). This workflow reduced the necessary human effort by  $> 99\%$  compared to full manual review of the data while producing detection/non-detection data based only on human-confirmed detections. We used PNW-Cnet v2 to process data collected in 2018 and 2019, PNW-Cnet v3 to process data collected in 2020, and PNW-Cnet v4 to process data collected in 2021 (Appendix C). Each version of the PNW-Cnet generated predictions (interpretable as probabilities between 0–1) for each sound class for each 12 s clip. We used a prediction threshold of  $\geq 0.95$  for most sound classes to determine the predicted number of detections of each sound class for each study area (Tables 4–6). To ensure we identified as many NSO calls as possible, we selected a prediction threshold of 0.25 for NSO location call class, which resulted in lower precision but higher recall (Table 3; Ruff et al. 2021) and operationally resulted in the need to manually review a greater number of sound clips during validation but increased the overall number of NSO detections (Tables 4–6). For each year of the study, we calculated the number of estimated detections (i.e., number of clips with score exceeding the score threshold) for each target sound class by study area and associated recall and precision

from a test dataset (Tables 4–6).

#### *Data validation and sex predictions*

Output from PNW-Cnet v2 (2018 and 2019 data), PNW-Cnet v3 (2020 data), and PNW-Cnet v4 (2021 data) was validated through a process of review by trained human technicians (Appendix C). The human validation process consisted of reviewing 12 s clips that met our model prediction threshold ( $> 0.25$  for NSO location call,  $> 0.95$  for other sound classes). We used the program Kaleidoscope Pro for validating PNW-Cnet output (i.e., prediction score  $> 0.95$ ) by examining the audio and spectrogram to confirm correct output or apply corrected sound class tags. In addition to producing a validated final dataset, the corrected sound class tags can be used for successive training datasets and for establishing new target classes. Depending on species-specific objectives and need to generate training data for future versions of the PNW-Cnet, we reviewed sound classes at one of four intensities:

- 1) Fully review all clips,
- 2) Confirm species detection/non-detection for each ARU during each week of survey,
- 3) Confirm annual detection/non-detection at each ARU,
- 4) Confirm annual detection/non-detection within each hexagon (detection on any ARU).

We considered confirmation of species detection as  $\geq 3$  true detections. We fully reviewed all PNW-Cnet output that scored at or above a 0.25 probability threshold for NSO location call class. The validation intensity for non-NSO sound classes each year varied due to PNW-Cnet model development sample needs, PNW-Cnet model performance, and collaborator requirements.

For 2018–2020 data, we calculated the proportion of surveyed ARU stations and hexagons with validated detections. For those species with multiple sound classes, we combined those detections as estimates for the species. Full validation of 2021 data is ongoing so not reported here. After identifying validated NSO calls in 2018 data, we further classified high quality NSO four-note location calls as female, male, or unknown based on frequency and call length measurements using a logistic regression model developed by Dale et al. (*In Press*). NSO sex predictions are ongoing for 2019–2021 datasets.

#### *Removal of data affected by call-back surveys*

Call-back surveys for NSO and barred owl were commonly used in our study areas by other biologists working on other research projects (e.g., Franklin et al. 2021, Wiens et al. 2021). These surveys broadcast recorded calls of NSO or barred owl to elicit a territorial response by NSO or barred owl. The broadcast calls were typically a NSO 4-note location call or barred owl 8-note location call. To remove the clips of call-back survey recordings and NSO or barred owl response to those surveys, we developed a process to identify and remove those data from our passive acoustic monitoring datasets. After validating data, we summarized the number of validated NSO and barred owl clips (i.e., species detections) at each ARU sampling station and hexagon and removed any detections (surveys and species call) that overlapped spatially and temporally with broadcast call-back surveys. We requested broadcast survey information from surveyors at the end of each field season. In 2018–2020 there were both NSO and barred owl surveys which needed to be removed from 3 study areas (COA, KLA, CLE). In 2021, barred owl call-back surveys were conducted only on NWC, so for all other study areas we only removed NSO data potentially affected by NSO call-back surveys. We removed any validated detections if there was a call-back survey (or barred owl removal visit by Wiens et al. 2021) in the hexagon on the same night, or if we could identify that the detection was a call-back survey. Beginning in

2021, we distributed a recording consisting of a brief series of pure tones (1 s at 0.5, 1.5 and 1.0 kHz) for call-back surveyors to voluntarily play at the same volume directly before or after NSO call-back surveys (USFWS 2021). When used, these tones made call-back surveys more easily identifiable when we processed the 2021 acoustic monitoring.

### *Background noise analysis*

Background noise has consistently been found to be an important predictor of detection probabilities in species occurrence models (Duchac et al. 2020, Duchac et al. 2021). Therefore, we used the sound pressure level analysis feature in Kaleidoscope Pro to quantify background noise levels at each ARU sampling station. We created weekly estimates of average background noise for each sampling station.

## **6. Results**

Here we present the most up to date results at the writing of this annual report but should be considered preliminary with need for further validation and quality assurance/quality control before formal analyses can be conducted. The amount of data collected and area surveyed has increased each year over the four years of passive acoustic monitoring (Table 2; Appendix D). In 2018, we surveyed 208 hexagons with approximately 350,000 h of recordings processed and in 2021 we surveyed 643 hexagons with nearly 1.2 million h of recordings processed with automated species identification (Table 2). Each year we experienced some degree of data loss by various sources such as wildlife, theft, animal damage, firmware issues, and corrupted data cards. With each new version of the PNW-Cnet we found a consistent improvement in overall performance (i.e., balance of precision and recall) for automated identification of each species, and the number of species detected automatically has increased from 14 to 36 species (Table 3).

Among the owls, northern pygmy-owls were the most vocally active on COA and OLY in 2018 and 2019 (Table 4). On KLA in 2019, we detected northern saw-whet owls more than other owls, and we observed a relatively even distribution of calling activity between barred owls, western screech-owls, and northern pygmy-owls (Table 4). Of the non-owl birds detected in 2018 and 2019, Steller's jay (*Cyanocitta stelleri*), common raven (*Corvus corax*), and band-tailed pigeon (*Patagionenas fasciata*) were the most vocally active (Table 4). Douglas' squirrels (*Tamiasciurus douglasii*) were commonly detected in all study areas (Table 4).

In 2020, thrushes, nuthatches, corvids, and sooty grouse (*Dendragapus fuliginus*) were the most detected species (Table 5). We observed similar patterns in calling activity of owls in 2020 as observed in 2018 and 2019. Western screech-owls were detected most often on KLA, and among the least detected species on OLY and CLE (Table 5). Marbled murrelets (*Brachyramphus marmoratus*) were included for automated identification starting in 2020 with PNW-Cnet v3, and were most frequently detected in COA and OLY (Table 5). We also observed many apparent detections of marbled murrelets on CLE and KLA, but those study areas are mostly outside the geographic range and human validation cleared those as "false positives" before calculating proportion of stations and hexagons with confirmed detections (Tables 7–8).

We observed similar pre-validated results in 2021 for the species and study areas included in previous years but we surveyed an additional 5 study areas and 11 additional species (Table 6). Western screech-owls were most vocally active in three Oregon study areas (COA, TYE, KLA) and NWC, but were not commonly detected in the two study areas of the Washington Cascades (CLE, RAI; Table 6). Some apparent detections of marbled murrelets with PNW-Cnet v4 were observed outside the geographic range (Table 6), but the rate of false

positives improved from PNW-Cnet v3, suggesting benefits of our process for improving model performance. Further, we will use human validation to confirm detections on all study areas. Flammulated owls (*Psiloscoptes flammeolus*) were one of the new sound classes included in PNW-Cnet v4 with potential detections (i.e., prior to full validation to clear false positives) on all study areas except RAI (Table 6). Some of these study areas are outside the known range of flammulated owls, so human validation will likely confirm these as false positives.

Our data processing and validation had progressed far enough to estimate proportion of stations and hexagons with species detections through the 2020 field season (Tables 7–8). Barred owls were the most widespread owl species with a high proportion of stations and hexagons with validated detections. The proportion of stations and hexagons with western screech-owl detections followed a similar trend as the number of detections by study area, with lowest naïve occupancy in Washington and highest in Oregon study areas (Tables 7–8). The year-to-year station and hexagon naïve occupancy was most variable for northern saw-whet owls (Tables 7–8). We observed no verified marbled murrelet detections on CLE and KLA, so documented 0.0 proportion of stations and hexagons with detections (Tables 7–8).

### *NSO detections*

We detected NSO in each study area but were consistently among the species with fewest detections (Tables 4–6), despite the lower prediction threshold used for validating detections of this species. For study areas surveyed during 2018–2020, NSO were detected in the highest proportion of hexagons (0.53 in 2020) and stations (0.34 in 2020) in KLA (Tables 7–8). The COA, OLY, and CLE study areas had similar naïve detection rates at the hexagon and station level (Tables 7–8). For the 2018 dataset, we classified 372 calls as male and 87 calls as female in COA, and 168 calls as male and 25 calls as female in OLY. At the time of this report writing, data collected in 2021 were not fully validated so not included in naïve occupancy estimates.

### *Call broadcast surveys*

In 2018 data, we removed 4,071 barred owl detections and 788 NSO detections in COA and 214 potential NSO detections in OLY due to concurrent call-back broadcast surveys. In 2019 data, we removed 500 NSO detections and 1,609 barred owl detections in COA, 1,360 NSO detections and 1,163 barred owl detections from KLA and 14 NSO detections in OLY. In 2020 data, NSO call-back surveys have mostly been removed but a few remaining locations in OLY need final quality assurance/quality control to ensure no false positives are included in the final dataset for formal analysis. So far, we removed 1,159 barred owl detections and 567 NSO detections in CLE, 1,152 barred owl detections and 372 NSO detections from COA, and 658 barred owl detections and 1,738 NSO detections from KLA. Barred owl detections were due to barred owl removal/surveys (Wiens et al. 2021). We have not yet fully removed all NSO call-backs in 2021 data, but we are collecting survey information from collaborators to complete validation in 2022 (Appendix C).

## **7. Discussion**

### *Status of Acoustic Monitoring program*

In 2020, the Northwest Forest Plan Regional Interagency Executive Committee decided to transition to Phase II, consisting of habitat monitoring coupled with passive acoustic monitoring on 20% of hexagons in former demographic study areas and 2% of all other hexagons in federal forests within the range of the NSO. As of 2021, we expanded passive



acoustic monitoring to all former NSO demography sites at approximately 20% sampling density with an overlap of demography and bioacoustics of at least 1 year on most study areas (Lesmeister et al. 2021a). In 2022, we will pilot test various strategies to conduct the 2% sampling of matrix between study areas, with the goal of sampling the full 2% range-wide forest sample beginning in 2023.

We designed range-wide templates for our hexagon sampling design that can be expanded and used for sampling design anywhere within the range of NSOs (USFWS 2021). Additionally, our flexible ARU placement design, with 4 ARUs per hexagon placed either randomly or in a stratified design (Appendix B) on forested land (following the rule set for available areas within a hexagon) could easily be adapted to accomplish surveys with diverse objectives while enabling collaborators to potentially contribute to the larger monitoring network.

Over the last 4 years, we have improved our ability to process and validate increasingly large volumes of acoustic data (Table 2, Appendix D). This is due to a range of improvements in data processing workflows, PNW-Cnet performance, recent increases in field and validation staff stability, and protocols have shifted from a testing to implementation phase. Clearing bioacoustics data of NSO call-back surveys is a primary factor constraining workflow speed in producing final datasets for NSO analyses, but surveyors are increasingly aware of the passive acoustic monitoring program and processes are in place to expedite call-back survey information sharing. We expect continued improvement in the speed at which we provide final hexagon and station naïve occupancy results for all species included in our automated identification list.

#### *NSO acoustic data*

We do not have enough years of data to evaluate trends in NSO populations, but our naïve occupancy estimates align well with occupancy estimates from other studies (Dugger et al. 2016, Yackulic et al. 2019, Franklin et al. 2021, Wiens et al. 2021). Barred owls are nearly ubiquitous throughout all study areas, so few locations remain for NSO to establish territories without harassment by barred owls. The ability of the automated detection model (PNW-Cnet) to identify potential NSO vocalizations has improved. At a score threshold of 0.25, recall for PNW-Cnet v2 was > 75% and in v3 and v4 it is > 90% for the NSO location call class. By using a low score threshold combined with full manual review of all potential detections for this class, we are confident we maximized detections of NSO. Although the low score threshold entails lower precision and hence yields a greater number of false positives, reviewing these potential detections is still a reasonable investment of effort for this ESA-listed species. Precision has also increased even at the 0.25 score threshold, yielding fewer false positives for NSO classes.

The biggest challenge to producing occupancy estimates for NSO has been identifying calls originating from human surveyors using broadcast play-back surveys. Broadcast surveys have been the primary method of determining NSO occupancy for the last 40 years and are widely used by private, state, tribal, and federal entities. The use of a three-note tone (USFWS 2021) by some NSO call-back surveyors in Oregon and Washington (e.g., Bureau of Land Management, Forest Service, State agencies) has greatly enhanced our ability to screen out and identify call-back surveys during human review and should expedite occupancy estimates for those overlapping survey areas.

#### *Non-NSO acoustic data*

The extraction of non-NSO target class detections has demonstrated the robustness of

passive bioacoustics for multi-species monitoring and community-level analyses and has helped to improve model predictions for NSO. The number of species and sound classes has increased from 17 sound classes in 2018 to 51 sound classes in 2021. Although some of the additional sound classes have not been of immediate interest (e.g., dog barking and chickadee calls), the inclusion of these classes improves the PNW-Cnet performance for other sound classes and provides opportunities for wildlife community-level analysis or other collaborative projects. We have also incorporated sound classes for species of interest to collaborators and other population monitoring teams, including the marbled murrelet, gray wolf (*Canis lupus*), and sooty grouse.

As the geographical scope of sampling increases, PNW-Cnet sound class predictive performance is expected to initially be lower in new regions. This is due to variation in background noise and vocal community composition at new sites that are not yet encompassed by model training sets. With expansion to new locations, we may encounter species not yet incorporated as a PNW-Cnet class but have similar vocalizations as other target classes. For example, PNW-Cnet v3 predicted >2,500 clips as containing possible marbled murrelet flight calls in CLE and KLA study areas, which are largely outside of the range of the species. PNW-Cnet v4 predicted < 500 clips in those same areas for marbled murrelet, indicating improved model performance and discrimination from other sounds. We also have PNW-Cnet v4 predicted flammulated owl detections outside the geographic range that will be cleared through validation, and we expect fewer of these “false positives” with further trainings of the model. Beyond these examples, we will continue to expand and improve our training sets and performance of future PNW-Cnet versions. Manual review and confirmation of sound class presence will continue to be important as new sites and sound classes are added to the monitoring program. Manual review of apparent detections by humans ensures that our hexagon occupancy status for each target class is accurate and has the secondary benefit of producing additional training data which can be added to the next versions of the PNW-Cnet.

One of our goals has been to increase benefits of passive acoustic monitoring by making the methods more accessible to landowners, wildlife biologists and others interested in monitoring wildlife activity. Therefore, we developed and published a desktop application which performs the same audio processing and PNW-Cnet classification following our protocols (Ruff et al. 2021). This application is freely available and can be run using only open-source software including RStudio, Keras / TensorFlow, and SoX. Users can process large volumes of audio data at a reasonable speed on consumer-grade desktop computers and review and extract apparent detections. Results will be directly comparable to those obtained through the monitoring program; to the extent that the sampling regime is similar, and the results are shared publicly, this effectively expands the spatial extent of the monitoring program.

## **8. Acknowledgments**

Funding and support for this program was provided by:

USDI Bureau of Land Management *and* National Park Service

USDA Forest Service Pacific Northwest Region, Pacific Northwest Research Station, *and*  
Western Wildland Environmental Threat Assessment Center, *and*

Oregon State University

We thank T. Levi, C. Sullivan, J. Koning, B. Padmaraju, M. Samaduroff, and A. Subramanian for assistance in PNW-Cnet development and data processing. We are deeply indebted to the dedicated field and lab technicians that collected and processed millions of hours of bioacoustics: 2018 field and lab crew: D. Culp, C. Cardillo, A. Ingrassia, D. Jacobsma, K. McLaughlin, P.

Papajcik, R. Justice, T. Garrido, A. Froelich. Z. Farrand, A. Munes, Z. Ruff.  
 2019 field and lab crew: L. Duchac, S. Nuss, M. Peterman, T. Young, H. Lambert, S. Dale, T. Munger, J. Runjaic, A.M. Doss, L.S Bartholomew, E.S. Eber, J.R. Garrido, E.M. Guzman, T.J. Kay, P.M. Loafman, M.H. McConnell, P.S. Papaczik.  
 2020 field and lab crew: A. Thomas, O. Hardy, H. Lambert, K. Nelson, V. Berdecia, H. Hester, E. Janasov, T. Munger, A. Nino de Rivera, J. Witteman, J. Runjaic, Z. Farrand, A. Munes, L. Kufta-Christie, K. Wert, N. Rugg, A.M. Doss, E.S. Eber, E.H. Graham, E.M. Guzman, P.M. Loafman, N.M. Starling, and C.J. Urnes.  
 2021 field and lab crew: H. Lambert, M. Ruggiero, T. Kohler, M. Parker, B. Henson, S. Reffler, A. Miera, T. Munger, N. Rugg, K. Nelson, A. Thomas, J. Witteman, K. Wright, C. McCafferty, A. Henderson, J. Hurd, K. Wert, D. Culp, J. Fry, N. Murphy, E. Sutphin, L. Platt, E. Tevini, U. Briggs, O. Awbrey, H. Hester, L. Kufta-Christie, R. Neil, J. Runjaic, C. Woods, T. Darling, C. Zeller-Edmonds, A. Doss, E. Eber, E. Graham, E. Guzman, P. Loafman, H. Nay, and C. Urnes.

## 9. Literature Cited

- Abadi, M., P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D. G. Murray, B. T. Steiner, P., V. Vasudevan, P. Warden, M. Wicke, Y. Yu, X. Zheng, and Google Brain. 2015. TensorFlow: A System for Large-Scale Machine Learning. Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI '16).
- Dale, S. S., J. M. A. Jenkins, Z. J. Ruff, L. S. Duchac, C. E. McCafferty, and D. B. Lesmeister. *In Press*. Quantifying vocal variation in pitch to distinguish female and male Northern Spotted Owls. *Journal of Raptor Research* 00:000-000.
- Davis, R. J., and J. Lint. 2005. Habitat status and trends. Pages 21-82 in J. Lint, editor. Status and Trends of Northern Spotted Owl Populations and Habitat. PNW-GTR-648. USDA Forest Service, Pacific Northwest Research Station, Portland, OR.
- Duchac, L. S., D. B. Lesmeister, K. M. Dugger, and R. J. Davis. 2021. Differential landscape use by forest owls two years after a mixed-severity wildfire. *Ecosphere* 12:e03770.
- Duchac, L. S., D. B. Lesmeister, K. M. Dugger, Z. J. Ruff, and R. J. Davis. 2020. Passive acoustic monitoring effectively detects Northern Spotted Owls and Barred Owls over a range of forest conditions. *The Condor* 122:1-22.
- Dugger, K. M., E. D. Forsman, A. B. Franklin, R. J. Davis, G. C. White, C. J. Schwarz, K. P. Burnham, J. D. Nichols, J. E. Hines, C. B. Yackulic, P. F. Doherty Jr., L. L. Bailey, D. A. Clark, S. H. Ackers, L. S. Andrews, B. Augustine, B. L. Biswell, J. A. Blakesley, P. C. Carlson, M. J. Clement, L. V. Diller, E. M. Glenn, A. Green, S. A. Gremel, D. R. Herter, J. M. Higley, J. Hobson, R. B. Horn, K. P. Huyvaert, C. McCafferty, T. L. McDonald, K. McDonnell, G. S. Olson, J. A. Reid, J. Rockweit, V. Ruiz, J. Saenz, and S. G. Sovern. 2016. The effects of habitat, climate and Barred Owls on the long-term population demographics of Northern Spotted Owls. *Condor* 118:57-116.
- Dugger, K. M., F. Wagner, R. G. Anthony, and G. S. Olson. 2005. The relationship between habitat characteristics and demographic performance of Northern Spotted Owls in Southern Oregon. *Condor* 107:863-878.
- Forsman, E. D., E. C. Meslow, and H. M. Wight. 1984. Distribution and biology of the spotted owl in Oregon. *Wildlife Monographs* 48:1-64.
- Franklin, A. B., D. R. Anderson, E. D. Forsman, K. P. Burnham, and F. W. Wagner. 1996. Methods for collecting and analyzing demographic data on the Northern Spotted Owl.

- Franklin, A. B., K. M. Dugger, D. B. Lesmeister, R. J. Davis, J. D. Wiens, G. C. White, J. D. Nichols, J. E. Hines, C. B. Yackulic, C. J. Schwarz, S. H. Ackers, L. S. Andrews, L. L. Bailey, R. Bown, J. Burgher, K. P. Burnham, P. C. Carlson, T. Chestnut, M. M. Conner, K. E. Dillione, E. D. Forsman, E. M. Glenn, S. A. Gremel, K. A. Hamm, D. R. Herter, J. M. Higley, R. B. Horn, J. M. Jenkins, W. L. Kendall, D. W. Lamphear, C. McCafferty, T. L. McDonald, J. A. Reid, J. T. Rockweit, D. C. Simon, S. G. Sovern, J. K. Swingle, and H. Wise. 2021. Range-wide declines of northern spotted owl populations in the Pacific Northwest: A meta-analysis. *Biological Conservation* 259:109168.
- Glenn, E. M., M. C. Hansen, and R. G. Anthony. 2004. Spotted owl home-range and habitat use in young forests of western Oregon. *Journal of Wildlife Management* 68:33-50.
- Gremel, S. A. 2019. Spotted Owl Monitoring in Olympic National Park: 1992-2018. National Park Service. Report Report NPS/OLYM/NRR—2017/XXX.
- Hamer, T. E., E. D. Forsman, and E. M. Glenn. 2007. Home range attributes and habitat selection of Barred Owls and Spotted Owls in an area of sympatry. *Condor* 109:750-768.
- Jenkins, J. M. A., D. B. Lesmeister, E. D. Forsman, K. M. Dugger, S. H. Ackers, L. S. Andrews, S. A. Gremel, B. Hollen, C. E. McCafferty, M. S. Pruett, J. A. Reid, S. G. Sovern, and J. D. Wiens. 2021. Conspecific and congeneric interactions shape increasing rates of breeding dispersal of northern spotted owls. *Ecological Applications* 31:e02398.
- Jenkins, J. M. A., D. B. Lesmeister, J. D. Wiens, J. T. Kane, V. R. Kane, and J. Verschuyt. 2019. Three-dimensional partitioning of resources by congeneric forest predators with recent sympatry. *Scientific Reports* 9:6036.
- Lesmeister, D. B., C. L. Appel, R. J. Davis, C. B. Yackulic, and Z. J. Ruff. 2021a. Simulating the effort necessary to detect changes in northern spotted owl (*Strix occidentalis caurina*) populations using passive acoustic monitoring. Res. Pap. PNW-RP-618. Volume PNW-RP-618. USDA Forest Service, Pacific Northwest Research Station, Portland, OR.
- Lesmeister, D. B., R. J. Davis, P. H. Singleton, and J. D. Wiens. 2018. Northern spotted owl habitat and populations: status and threats. Pages 245-298 in T. A. Spies, P. A. Stine, R. Gravenmier, J. W. Long, and M. J. Reilly, editors. *Synthesis of Science to Inform Land Management within the Northwest Forest Plan Area*. PNW-GTR-966. USDA Forest Service, Pacific Northwest Research Station, Portland, OR.
- Lesmeister, D. B., M. S. Pruett, D. Kelso, and K. Williamson. 2019. Demographic Characteristics of Northern Spotted Owls (*Strix occidentalis caurina*) in the Olympic National Forest, Washington, 1987–2018. USDA Forest Service, Pacific Northwest Research Station.
- Lesmeister, D. B., S. G. Sovern, A. J. Mikkelsen, and M. Nickols. 2021b. Demography of Spotted Owls on the East Slope of the Cascade Range, Washington, 1989-2020. USDA Forest Service, Pacific Northwest Research Station.
- Lint, J., B. Noon, R. Anthony, E. Forsman, M. Raphael, M. Collopy, and E. Starkey. 1999. Northern Spotted Owl Effectiveness Monitoring Plan for the Northwest Forest Plan. USDA Forest Service, Pacific Northwest Research Station. Report PNW-GTR-440.
- Ruff, Z. J., D. B. Lesmeister, C. L. Appel, and C. M. Sullivan. 2021. Workflow and convolutional neural network for automated identification of animal sounds. *Ecological Indicators* 124:107419.
- Ruff, Z. J., D. B. Lesmeister, L. S. Duchac, B. K. Padmaraju, and C. M. Sullivan. 2020. Automated identification of avian vocalizations with deep convolutional neural networks. *Remote Sensing in Ecology and Conservation* 6:79-92.
- Schilling, J. W., K. M. Dugger, and R. G. Anthony. 2013. Survival and home-range size of northern spotted owls in southwestern Oregon. *Journal of Raptor Research* 47:1-14.

- Singleton, P. H., J. F. Lehmkuhl, W. L. Gaines, and S. A. Graham. 2010. Barred owl space use and habitat selection in the eastern Cascades, Washington. *Journal of Wildlife Management* 74:285-294.
- Sovern, S. G., D. B. Lesmeister, K. M. Dugger, M. S. Pruett, R. J. Davis, and J. M. Jenkins. 2019. Activity center selection by northern spotted owls. *Journal of Wildlife Management* 83:714-727.
- Tegeler, A. K., M. L. Morrison, and J. M. Szewczak. 2012. Using extended-duration audio recordings to survey avian species. *Wildlife Society Bulletin* 36:21-29.
- USFWS. 2021. Northern Spotted Owl Recovery Information Site: Survey Protocol <https://www.fws.gov/oregonfwo/Species/Data/NorthernSpottedOwl/SurveyProtocol.asp>. in US Fish and Wildlife Service, Oregon Fish and Wildlife Office, Pacific Region Ecological Services, Portland, OR.
- Wiens, J. D., R. G. Anthony, and E. D. Forsman. 2014. Competitive interactions and resource partitioning between northern spotted owls and barred owls in Western Oregon. *Wildlife Monographs* 185:1-50.
- Wiens, J. D., K. M. Dugger, J. M. Higley, D. B. Lesmeister, A. B. Franklin, K. A. Hamm, G. C. White, K. E. Dilione, D. C. Simon, R. R. Bown, P. C. Carlson, C. B. Yackulic, J. D. Nichols, J. E. Hines, R. J. Davis, D. W. Lamphear, C. McCafferty, T. L. McDonald, and S. G. Sovern. 2021. Invader removal triggers competitive release in a threatened avian predator. *Proceedings of the National Academy of Sciences* 118:e2102859118.
- Yackulic, C. B., L. L. Bailey, K. M. Dugger, R. J. Davis, A. B. Franklin, E. D. Forsman, S. H. Ackers, L. S. Andrews, L. V. Diller, S. A. Gremel, K. A. Hamm, D. R. Herter, M. Higley, R. B. Horn, C. McCafferty, J. A. Reid, J. R. Rockweit, and S. G. Sovern. 2019. The past and future roles of competition and habitat in the rangewide occupancy dynamics of Northern Spotted Owls. *Ecological Applications* 29:e01861.

## 10. Tables

Table 1. The number of autonomous recording unit stations deployed during 2021 in designated Wilderness Areas administered by US Forest Service or US National Park Service<sup>a</sup>.

Wilderness Area	Study area	Number of stations
Alpine Lakes	CLE	4
Buckhorn	OLY	9
Colonel Bob	OLY	8
Cummins Creek	COA	3
Devil's Staircase	COA	16
Drift Creek	COA	2
Menagerie	HJA	4
Mount Jefferson	HJA	1
Mount Rainier <sup>a</sup>	RAI	44
Mount Skokomish	OLY	4
Mount Washington	HJA	2
Mountain Lakes	CAS	5
Daniel J. Evans <sup>a</sup>	OLY	234
Phillip Burton <sup>a</sup>	MAR	7
Rock Creek	COA	1
Rogue-Umpqua Divide	CAS	10
Sky Lakes	CAS	63
The Brothers	OLY	4
Three Sisters	HJA	30
Trinity Alps	NWC	11

<sup>a</sup> Administered by US National Park Service

Table 2. The number of hexagons and stations surveyed using passive acoustics monitoring in each study area during 2018–2021 within in the Northwest Forest Plan Area. Also reported are the number of hours of sound data collected and processed for automated species identification with a trained convolutional neural network. Unless noted, surveys were conducted with Song Meter SM4 autonomous recording units. COA = Oregon Coast Range, OLY = Olympic Peninsula, KLA = Klamath, CLE = Cle Elum, TYE = Tyee, HJA = H.J. Andrews Experimental, CAS = South Cascades, NWC = Northwest California, MAR = Marin County, RAI = Mt. Rainer NP

Study area	Number of hexagons				Number of stations				Hours processed			
	2018	2019	2020	2021	2018 <sup>a</sup>	2019	2020	2021	2018 <sup>a</sup>	2019	2020	2021
COA	120	106	120	120	577	412 <sup>b</sup>	473 <sup>c</sup>	473	200,036	154,936	190,312	215,495
OLY	88	120	119	119	435	472	464	472	148,015	163,227	219,026	214,841
KLA		63	73	73		244	290 <sup>d</sup>	274		89,748	130,122	133,461
CLE			69	75			267 <sup>e</sup>	298			104,651	153,590
TYE				40				158				77,013
HJA				70				294				131,239
CAS				98				387				177,723
NWC				30				114				47,971
MAR				7				27				11,001
RAI				11				44				11,204
TOTAL	208	289	381	643	1,012	1,128	1,494	2,538	348,051	407,911	644,111	1,162,538

<sup>a</sup> During 2018 survey design was five stations per hexagon.

<sup>b</sup> 49 SWIFT units used in addition to SM4s.

<sup>c</sup> 66 SWIFT units and 95 Song Meter Minis used in addition to SM4s.

<sup>d</sup> 43 Song Meter Minis used in addition to SM4s.

<sup>e</sup> 15 Song Meter Minis used in addition to SM4s.

Table 3. Precision and recall estimates for each sound class by version of the convolutional neural network (PNW-Cnet v2, v3, and v4) used to process bioacoustics data collected during 2018–2021. Unless noted for spotted owl location call, estimates are based on a prediction threshold of 0.95 and were generated with a test set of 120,269 spectrogram images. Some classes were not included in each the PNW-Cnet version (--).

Sound class	PNW-Cnet v2		PNW-Cnet v3		PNW-Cnet v4	
	Precision	Recall	Precision	Recall	Precision	Recall
Spotted owl location call (Threshold = 0.95)	0.4031	0.4034	0.6631	0.4832	0.7642	0.4534
Spotted owl location call (Threshold = 0.25)	0.1410	0.7590	0.0590	0.9920	0.2790	0.9330
<i>Strix</i> owl contact whistle <sup>a</sup>	--	--	0.9457	0.4652	0.9524	0.4545
Barred owl eight-note	0.7371	0.5920	0.8829	0.9411	0.9834	0.6085
Barred owl series	--	--	0.9917	0.3703	0.9921	0.5644
Barred owl inspection	0.8498	0.4839	0.9650	0.8035	0.9769	0.8025
Great horned owl	0.7233	0.5308	0.9359	0.9712	0.9930	0.8944
Flammulated owl	--	--	--	--	0.7792	0.9093
Western screech-owl	0.8628	0.4621	0.9717	0.9088	0.9945	0.8642
Northern pygmy-owl	0.9784	0.6551	0.9774	0.9604	0.9865	0.8624
Northern saw-whet owl	0.9743	0.5918	0.9747	0.9089	0.9789	0.9082
Marbled murrelet	--	--	0.8236	0.9727	0.9881	0.9323
Common raven	0.9226	0.5965	0.8754	0.8863	0.9293	0.7745
Steller's jay	0.5869	0.1534	0.8783	0.3773	0.9648	0.3187
Canada jay	--	--	0.6587	0.9009	0.9591	0.7629
Sooty grouse	--	--	0.9895	0.5793	0.9819	0.6066
Pileated woodpecker	0.3327	0.6378	0.6954	0.8752	0.9229	0.7482
Woodpecker drum	--	--	--	--	0.6364	0.0074
Northern flicker series	--	--	0.8870	0.9310	0.9356	0.8896
Sapsucker <i>spp</i> drum <sup>b</sup>	0.1600	0.0848	--	--	0.5000	0.0042
Wrentit	--	--	0.9853	0.7979	0.9853	0.7819
Common nighthawk call	--	--	--	--	1.0000	0.1429
Common nighthawk dive	--	--	--	--	0.8182	0.2647
Hermit thrush	--	--	0.9933	0.4874	0.9911	0.4483
Swainson's thrush	--	--	0.9921	0.6215	0.9790	0.6529
Varied thrush	--	--	0.9964	0.6771	0.9990	0.3013
Mountain quail	0.0815	0.2160	--	--	0.6273	0.1285
Band-tailed pigeon	0.8525	0.4676	0.9831	0.8254	0.9895	0.8507
Common poorwill	--	--	--	--	0.7418	0.7031
Spotted towhee	--	--	0.9615	0.6466	0.9508	0.5918
Chickadee <i>spp</i> <sup>c</sup>	--	--	--	--	0.7143	0.0459
Olive-sided flycatcher	--	--	--	--	0.9492	0.2887
Nuthatch <i>spp</i> <sup>d</sup>	--	--	0.9950	0.4578	0.9912	0.4466
American robin whinny	--	--	--	--	0.4375	0.0617
Canada goose	--	--	0.9658	0.8599	0.9908	0.7652
Mourning dove	--	--	0.5657	0.9897	0.7444	0.7319
Chipmunk <i>spp</i> chirp <sup>e</sup>	0.9771	0.4862	0.9442	0.9549	0.9609	0.8809
American pika	--	--	--	--	0.8750	0.4375



Douglas' squirrel rattle	0.5082	0.7163	0.8578	0.9280	0.9833	0.8224
Douglas' squirrel chirp	0.7321	0.3981	0.8992	0.8897	0.9645	0.7716
Dog barking	--	--	0.6705	0.4157	0.9380	0.2893
Insect buzz	--	--	0.9521	0.2694	0.9881	0.1237
Frog chorus	--	--	0.9839	0.7066	0.9917	0.8354
Human speech	--	--	0.9227	0.8184	0.9435	0.7086
Yarder machine	--	--	0.8381	0.7632	0.9080	0.7662
Gunshot	--	--	--	--	0.1818	0.1000

<sup>a</sup> NSO and barred owl

<sup>b</sup> Red-breasted and Williamson's sapsuckers

<sup>c</sup> Black-capped, chestnut-backed, and mountain chickadees

<sup>d</sup> Red-breasted and white-breasted nuthatches

<sup>e</sup> Townsend's and yellow-pine chipmunks

Table 4. Estimated number of detections for 16 sound classes (14 wildlife species) from bioacoustics data collected during 2018 (COA, OLY) and 2019 (COA, OLY, KLA). Data were processed using PNW-Cnet v3. Estimates of detections were the number of automated sound class output (prediction threshold of 0.95 or 0.25) multiplied by precision estimate of PNW-Cnet v2 (Table 3). COA = Coast Range, OR; OLY = Olympic Peninsula, WA; KLA = Klamath, OR ( $n$  = number of stations surveyed).

Sound class	2018		2019		
	COA ( $n = 577$ )	OLY ( $n = 435$ )	COA ( $n = 412$ )	OLY ( $n = 472$ )	KLA ( $n = 244$ )
Spotted owl location (threshold = 0.95)	2,920	409	2,571	646	3,801
Spotted owl location (threshold = 0.25)	15,215	3,012	11,878	3,527	11,729
Barred owl eight-note	83,931	32,738	49,947	37,259	36,741
Barred owl inspection	23,994	4,708	15,447	5,158	6,276
Great horned owl	32,157	12,932	20,419	19,165	20,971
Western screech-owl	72,545	10,384	40,722	6,150	45,591
Northern pygmy-owl	246,587	61,001	84,913	64,898	41,835
Northern saw-whet owl	182,880	37,590	74,721	47,465	64,962
Common raven	132,226	35,157	93,689	41,063	81,484
Steller's jay	202,629	39,819	154,468	52,354	176,808
Pileated woodpecker	22,871	13,733	11,237	15,289	173,041
Sapsucker <i>spp</i> drum <sup>a</sup>	5,281	3,596	2,636	843	1,846
Mountain quail	13,926	676	10,176	1,022	10,588
Band-tailed pigeon	218,150	12,463	177,852	31,224	17,899
Douglas' squirrel rattle	105,005	78,596	58,162	70,623	172,153
Douglas' squirrel chirp	16,605	5,182	16,189	24,226	12,332
Chipmunk <i>spp</i> chirp <sup>b</sup>	65,770	3,385	92,193	15,223	36,501

<sup>a</sup> Red-breasted and Williamson's sapsuckers

<sup>b</sup> Townsend's and yellow-pine chipmunks

Table 5. Estimated number of detections for 33 sound classes (25 wildlife species) from bioacoustics data by study area in 2020 based on output from the third version of the PNW-Cnet (PNW-Cnet v3). Estimated detections for each sound class were calculated as the number of 12 s clips in the audio dataset to which PNW-Cnet v3 assigned a score exceeding 0.95 (or 0.25) for that class, multiplied by the precision estimate (Table 3). CLE = Cle Elum, WA; COA = Coast Range, OR; KLA = Klamath, OR; OLY = Olympic Peninsula, WA. ( $n$  = number of stations surveyed)

Sound class	CLE ( $n = 267$ )	COA ( $n = 473$ )	KLA ( $n = 290$ )	OLY ( $n = 464$ )
Spotted owl location call (Threshold = 0.95)	580	280	3,309	883
Spotted owl location call (Threshold = 0.25)	1,310	1,322	1,687	698
<i>Strix</i> owl contact whistle <sup>a</sup>	3	46	27	53
Barred owl eight-note call	14,093	55,519	18,516	44,319
Barred owl series	376	4,188	1,573	1,243
Barred owl inspection call	2,500	19,549	9,490	8,977
Great horned owl	36,765	11,578	38,186	9,211
Western screech-owl	2,529	66,086	198,204	8,390
Northern pygmy-owl	14,917	470,760	295,906	77,217
Northern saw-whet owl	49,164	284,500	120,320	27,155
Marbled murrelet	2,822	6,358	2,617	15,604
Common raven	82,050	145,627	163,708	55,027
Steller's jay	62,033	351,505	631,114	207,899
Canada jay	5,569	5,056	2,556	12,349
Sooty grouse	99,040	52,642	506,640	649,926
Pileated woodpecker	32,588	20,460	28,994	12,171
Northern flicker series	32,918	28,931	99,438	10,438
Wrentit	748	13,083	26,496	240
Hermit thrush	1,533,538	31,345	1,714,627	198,764
Swainson's thrush	104,114	1,921,600	87,087	344,707
Varied thrush	548,122	1,488,997	15,451	4,448,440
Band-tailed pigeon	5,968	175,400	30,818	83,080
Spotted towhee	0	78	78	0
Nuthatch <i>spp</i> <sup>b</sup>	681,530	199,849	1,154,123	411,715
Canada goose	907	9,405	9,619	933
Mourning dove	20,506	4,397	28,709	1,271
Douglas' squirrel rattle	35,322	14,955	24,065	52,519
Douglas' squirrel chirp	25,324	14,251	11,022	39,828
Chipmunk <i>spp</i> chirp <sup>c</sup>	61,377	20,003	35,781	44,238
Dog barking	17,991	7,035	66,819	6,624
Insect buzz	178,190	353,235	412,822	688,938
Frog chorus	130,130	113,464	201,765	115,178
Human speech	1,256	11,801	737	3,365
Yarder machine	1,077	72,997	94,447	8,946

<sup>a</sup> NSO and barred owl

<sup>b</sup> Red-breasted and white-breasted nuthatches

<sup>c</sup> Townsend's and yellow-pine chipmunks

Table 6. Estimated number of detections for 45 sound classes (36 wildlife species) from bioacoustics data by study area in 2021 based on output from the fourth version of PNW-Cnet (PNW-Cnet v4). Estimated detections for each sound class were calculated as the number of 12 s clips in the audio dataset to which the PNW-Cnet v4 assigned a score exceeding 0.95 (or 0.25) for that class, multiplied by the precision estimate (Table 3). CAS = Southwest Cascades, OR; CLE = Cle Elum, WA; COA = Coast Range, OR; HJA = H.J. Andrews Experimental Forest, OR; KLA = Klamath Range, OR; NWC = Northwest California, CA; OLY = Olympic Peninsula, WA; RAI = Mount Rainier, WA; TYE = Tyee, OR. (*n* = number of stations surveyed)

Sound class	CAS ( <i>n</i> = 387)	CLE ( <i>n</i> = 298)	COA ( <i>n</i> = 473)	HJA ( <i>n</i> = 294)	KLA ( <i>n</i> = 274)	NWC ( <i>n</i> = 114)	OLY ( <i>n</i> = 472)	RAI ( <i>n</i> = 44)	TYE ( <i>n</i> = 158)	MAR ( <i>n</i> = 27)
Spotted owl location call (Threshold = 0.95)	1,897	935	324	1,628	3,422	848	378	6	473	2,454
Spotted owl location call (Threshold = 0.25)	3,466	1,606	2,745	2,082	4,731	1,059	1,053	20	2,066	2,868
<i>Strix</i> owl contact whistle <sup>a</sup>	146	30	454	203	854	67	258	0	267	530
Barred owl eight-note	14,689	4,657	56,133	16,589	21,842	1,278	29,655	1,226	21,349	396
Barred owl series	3,076	542	24,115	4,598	7,685	673	6,346	104	9,741	338
Barred owl inspection	11,510	6,704	41,796	11,607	19,334	1,698	12,464	1,144	18,016	259
Great horned owl	47,720	90,309	13,319	5,772	30,217	3,807	5,853	46	14,398	19,236
Flammulated owl	12,648	299,498	282	111	652	64,285	144	0	1,349	100
Western screech-owl	9,749	252	80,767	11,368	169,526	35,237	7,934	8	147,781	395
Northern pygmy-owl	60,500	21,511	646,904	90,027	166,968	71,437	67,460	2,276	231,294	221
Northern saw-whet owl	215,146	27,910	480,613	65,559	134,257	61,564	121,048	247	180,449	35,714
Marbled murrelet	366	409	17,411	870	114	132	21,753	187	117	107
Common raven	131,351	126,055	253,094	61,110	172,793	50,400	91,738	1,172	106,853	40,696
Steller's jay	232,008	35,593	411,720	183,769	591,163	222,233	109,532	3,230	188,987	42,015
Canada jay	4,246	5,933	17,567	6,876	2,548	427	19,226	1,548	4,346	1,166
Sooty grouse	262,170	180,165	65,995	306,998	497,780	13,659	1,500,849	658	431,729	0
Pileated woodpecker	30,763	7,635	42,455	13,585	37,605	7,648	17,779	78	27,447	3,811
Woodpecker drum	4,541	3,429	5,995	1,076	5,460	1,172	3,543	46	2,049	323
Northern flicker series	174,276	70,913	57,207	54,659	203,479	42,709	37,536	713	99,543	4,543
Sapsucker <i>spp</i> drum <sup>b</sup>	11	16	193	13	6	18	19	0	42	0
Wrentit	2,549	340	205,802	134	150,157	4,567	348	18	22,448	68,813
Common nighthawk call	120,691	21,464	2,429	14,273	17,029	1,631	29,993	79	15,847	4

Common nighthawk dive	118,650	6,961	3,763	12,856	17,383	1,150	9,200	0	23,118	25
Hermit thrush	1,583,105	1,312,636	29,964	521,355	1,229,607	125,734	176,447	80,603	482,356	1,993
Swainson's thrush	84,657	219,742	4,540,350	868,766	90,502	16,741	351,701	21,445	531,515	3,433
Varied thrush	30,933	311,216	904,329	412,573	1,319	83	1,978,572	124,820	93,506	3,124
Mountain quail	23,804	613	23,232	10,810	166,948	31,659	368	16	27,073	156
Band-tailed pigeon	5,484	982	438,958	18,652	58,413	7,774	110,354	815	67,664	18,284
Common poorwill	86,052	164,842	65	232	18,632	20,482	39	0	98	9
Spotted towhee	1,345	9	2,766	375	3,607	1,703	58	0	1,516	764
Chickadee <i>spp</i> <sup>c</sup>	7,483	16,100	52	99	235	365	120	2	26	6
Olive-sided flycatcher	100,943	85,682	4,526	53,790	32,692	16,579	26,699	44	3,784	541
Nuthatch <i>spp</i> <sup>d</sup>	2,910,517	855,631	624,340	1,005,022	1,624,549	561,092	599,205	53,070	885,586	43,701
American robin whinny	10,211	7,400	17,724	6,945	10,111	3,366	26,005	66	5,678	1,086
Canada goose	37,057	3,075	12,291	2,571	14,442	446	1,843	1	4,618	459
Mourning dove	2,103	493	9,320	864	21,335	541	1,599	0	1,595	4,949
Chipmunk <i>spp</i> chirp <sup>e</sup>	88,283	95,496	80,246	107,159	83,863	31,262	47,366	2,047	76,112	1,095
American pika	815	6,076	69	1,773	55	36	53	1	33	3
Douglas' squirrel rattle	73,735	55,665	57,443	22,073	33,752	38,898	53,377	902	41,755	116
Douglas' squirrel chirp	102,488	45,324	37,857	19,532	30,421	40,191	35,785	497	35,692	39
Dog barking	4,583	3,514	7,906	539	48,265	6,570	2,245	0	19,331	6,577
Insect buzz	329,819	285,272	331,508	121,994	229,122	90,553	197,933	18,729	134,060	3,827
Frog chorus	738,878	562,214	356,623	203,852	543,217	221,866	507,150	79	312,530	143,943
Human speech	631	2,367	1,513	1,526	522	234	1,603	108	258	129
Yarder machine	1,095	250	83,787	17,923	34,411	46	5,141	0	23,754	63
Gunshot	460	448	593	174	223	63	542	43	181	73

<sup>a</sup> NSO and barred owl

<sup>b</sup> Red-breasted and Williamson's sapsuckers

<sup>c</sup> Black-capped, chestnut-backed, and mountain chickadees

<sup>d</sup> Red-breasted and white-breasted nuthatches

<sup>e</sup> Townsend's and yellow-pine chipmunks

Table 7. Proportion of autonomous recording unit stations with validated detections of target species for years that surveys were conducted in four study areas during 2018–2020 within the Northwest Forest Plan Area. Data collected in 2021 are not yet fully validated (Appendix C).

Species	COA			OLY			KLA		CLE
	2018	2019	2020	2018	2019	2020	2019	2020	2020
Spotted owl	0.07	0.06	0.04	0.06	0.08	0.13	0.27	0.34	0.06
Barred owl	0.94	0.93	0.93	0.68	0.73	0.81	0.75	0.82	0.43
Great horned owl	0.19	0.17	0.18	0.06	0.10	0.11	0.55	0.69	0.60
Northern saw-whet owl	0.45	0.33	0.67	0.33	0.30	0.28	0.26	0.53	0.41
Western screech-owl	0.42	0.43	0.40	0.10	0.13	0.17	0.77	0.84	0.07
Northern pygmy-owl	0.82	0.74	0.83	0.47	0.53	0.63	0.73	0.89	0.36
Common raven	0.94	0.97	0.89	0.67	0.75	0.55	0.99	0.80	0.94
Steller's jay	0.99	0.99	0.93	0.83	0.90	0.77	1.00	0.94	0.84
Pileated woodpecker	0.90	0.92	0.82	0.55	0.63	0.48	0.97	0.68	0.62
Sapsucker <i>spp</i> drumming <sup>a</sup>	0.23	0.27	0.24	0.07	0.05	0.01	0.31	0.25	0.13
Band-tailed pigeon	0.94	0.98	0.91	0.58	0.80	0.61	0.83	0.64	0.15
Mountain quail	0.26	0.05	0.16	0.03	0.00	0.00	0.32	0.55	0.00
Chipmunk <i>spp</i> <sup>b</sup>	0.65	0.90	0.71	0.13	0.47	0.49	0.71	0.75	0.66
Douglas' squirrel	0.76	0.92	0.78	0.50	0.94	0.89	0.73	0.77	0.82
Marbled murrelet			0.60			0.63		0.00	0.00
Varied thrush			0.97			0.97		0.50	0.83
Nuthatch <i>spp</i> <sup>c</sup>			0.75			0.73		0.89	0.96
Canada jay			0.81			0.77		0.51	0.61
Northern flicker			0.56			0.51		0.71	0.78
Sooty grouse			0.07			0.59		0.44	0.36
Hermit thrush			0.13			0.39		0.80	0.97
American robin			0.48			0.46		0.45	0.58
Swainson's thrush			0.61			0.34		0.30	0.43
Canada goose			0.39			0.17		0.51	0.25
Spotted towhee			0.13			0.02		0.17	0.03
Mourning dove			0.06			0.02		0.39	0.13
Wrentit			0.49			0.01		0.42	0.00
Dog			0.39			0.29		0.65	0.40
Yarder			0.32			0.09		0.41	0.08
Insects			0.93			0.72		0.80	0.87
Frogs			0.15			0.16		0.34	0.23

<sup>a</sup> Red-breasted and Williamson's sapsuckers

<sup>b</sup> Townsend's and yellow-pine chipmunks

<sup>c</sup> Red-breasted and white-breasted nuthatches

Table 8. Proportion of hexagons with validated detections of target species for years that surveys were conducted in four study areas during 2018–2020 within the Northwest Forest Plan Area. Data collected in 2021 are not yet fully validated (Appendix C).

Species	COA			OLY			KLA		CLE
	2018	2019	2020	2018	2019	2020	2019	2020	2020
Spotted owl	0.18	0.13	0.10	0.16	0.18	0.25	0.43	0.53	0.18
Barred owl	1.00	0.99	1.00	0.92	0.93	0.94	0.90	0.95	0.70
Great horned owl	0.43	0.35	0.33	0.14	0.18	0.24	0.83	0.90	0.80
Northern saw-whet owl	0.73	0.56	0.93	0.61	0.52	0.63	0.48	0.84	0.59
Western screech-owl	0.76	0.73	0.69	0.30	0.28	0.38	0.97	0.97	0.20
Northern pygmy-owl	0.98	0.95	0.94	0.76	0.78	0.87	0.90	0.97	0.62
Common raven	1.00	1.00	1.00	0.90	0.91	0.95	1.00	1.00	0.99
Steller's jay	1.00	1.00	1.00	0.95	1.00	0.99	1.00	1.00	0.97
Pileated woodpecker	0.99	1.00	1.00	0.78	0.81	0.81	1.00	0.99	0.80
Sapsucker <i>spp</i> drumming <sup>a</sup>	0.52	0.57	0.51	0.23	0.14	0.03	0.60	0.53	0.22
Band-tailed pigeon	1.00	1.00	1.00	0.86	0.93	0.97	0.95	0.99	0.39
Mountain quail	0.46	0.14	0.36	0.09	0.00	0.00	0.57	0.77	0.00
Chipmunk <i>spp</i> <sup>b</sup>	0.88	1.00	0.95	0.30	0.74	0.81	0.98	0.96	0.90
Douglas' squirrel	0.98	1.00	0.98	0.86	1.00	0.99	0.97	0.96	0.99
Marbled murrelet			0.79			0.84		0.00	0.00
Varied thrush			1.00			1.00		0.78	0.96
Nuthatch <i>spp</i> <sup>c</sup>			0.91			0.98		0.99	1.00
Canada jay			0.99			0.98		0.78	0.91
Northern flicker			0.88			0.93		1.00	1.00
Sooty grouse			0.13			0.87		0.62	0.65
Hermit thrush			0.29			0.69		0.93	1.00
American robin			0.78			0.67		0.73	0.83
Swainson's thrush			0.74			0.65		0.66	0.78
Canada goose			0.65			0.39		0.78	0.42
Spotted towhee			0.40			0.07		0.40	0.09
Mourning dove			0.12			0.05		0.63	0.28
Wrentit			0.82			0.02		0.79	0.00
Dog			0.67			0.55		0.92	0.72
Yarder			0.44			0.18		0.63	0.16
Insects			1.00			1.00		1.00	0.99
Frogs			0.35			0.36		0.64	0.52

<sup>a</sup> Red-breasted and Williamson's sapsuckers

<sup>b</sup> Townsend's and yellow-pine chipmunks

<sup>c</sup> Red-breasted and white-breasted nuthatches

## 11. Figures

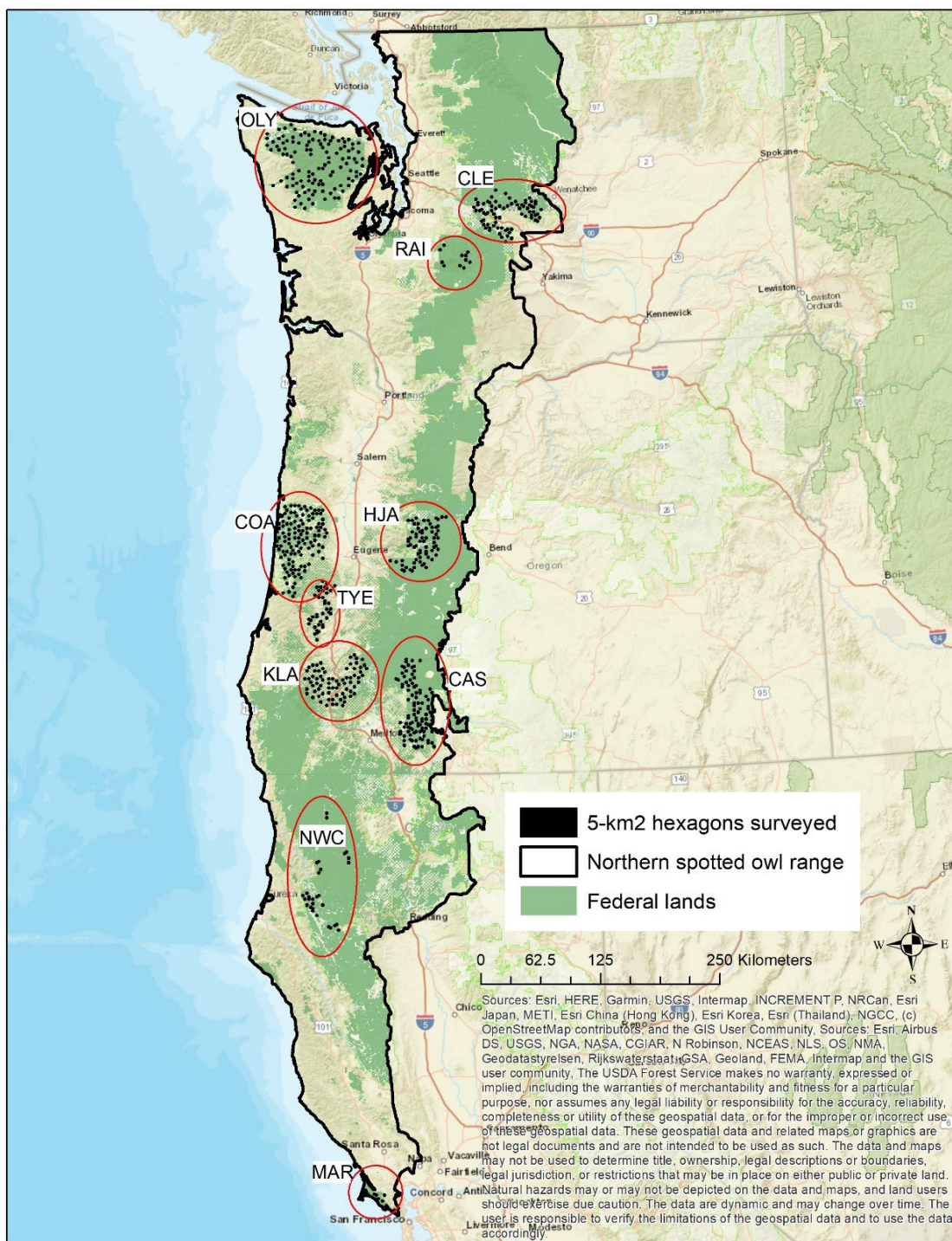


Figure 1. Locations of 5 km<sup>2</sup> hexagons ( $n = 643$ ) surveyed in 10 study areas using passive acoustic monitoring. All study areas overlapped with historical northern spotted owl demographic study areas. Study areas: OLY = Olympic Peninsula, CLE = Cle Elum, RAI = Mt. Rainier National Park, COA = Oregon Coast Range, HJA = HJ Andrews, TYE = Tye, KLA = Klamath, CAS = South Cascades, NWC = Northwest California, and MAR = Marin County.



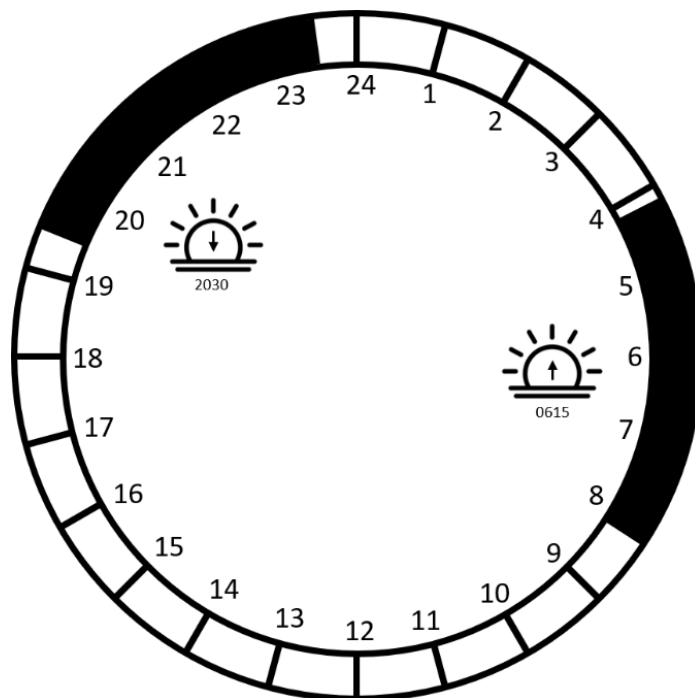


Figure 2. Example 24 h diel cycle (sunrise at 0615, sunset at 2030) recording schedule used on autonomous recording units to conduct passive acoustic monitoring within the Northwest Forest Plan area. Recording times shown with black bars occurring during 4 h blocks during crepuscular period and 10 minutes each hour. The first daily crepuscular block recording starts 2 h before (0415) and ends 2 h after (0815) sunrise, and the second block recording starts 1 h before (1930) and ends 3 h after (2330) sunset.

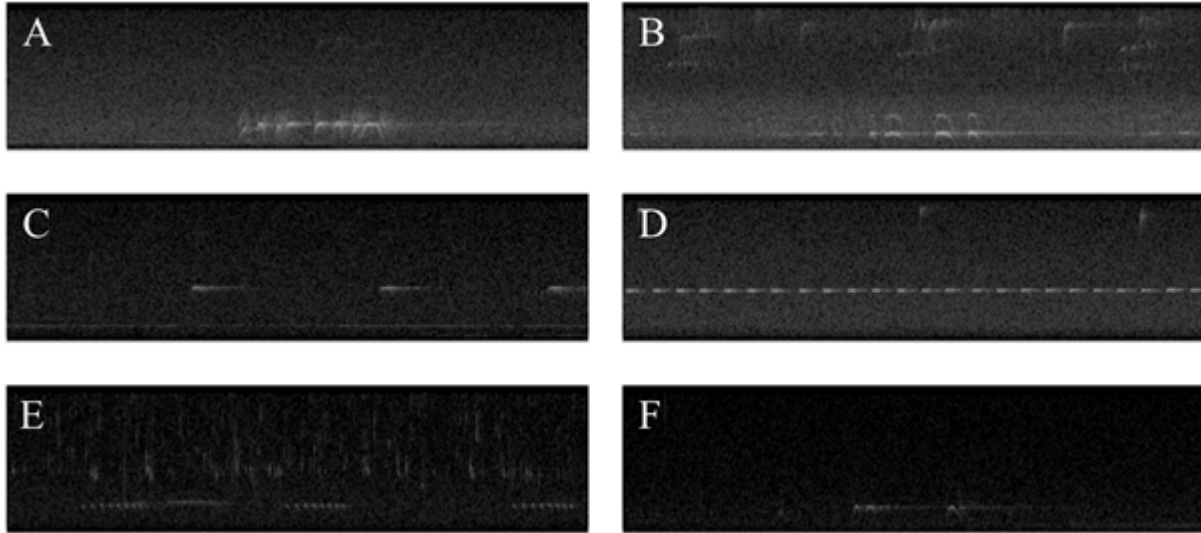
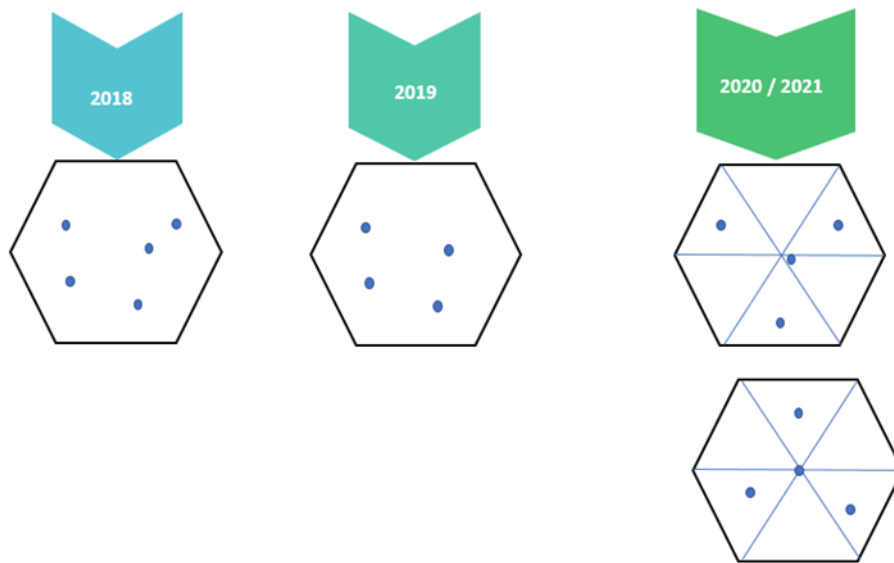


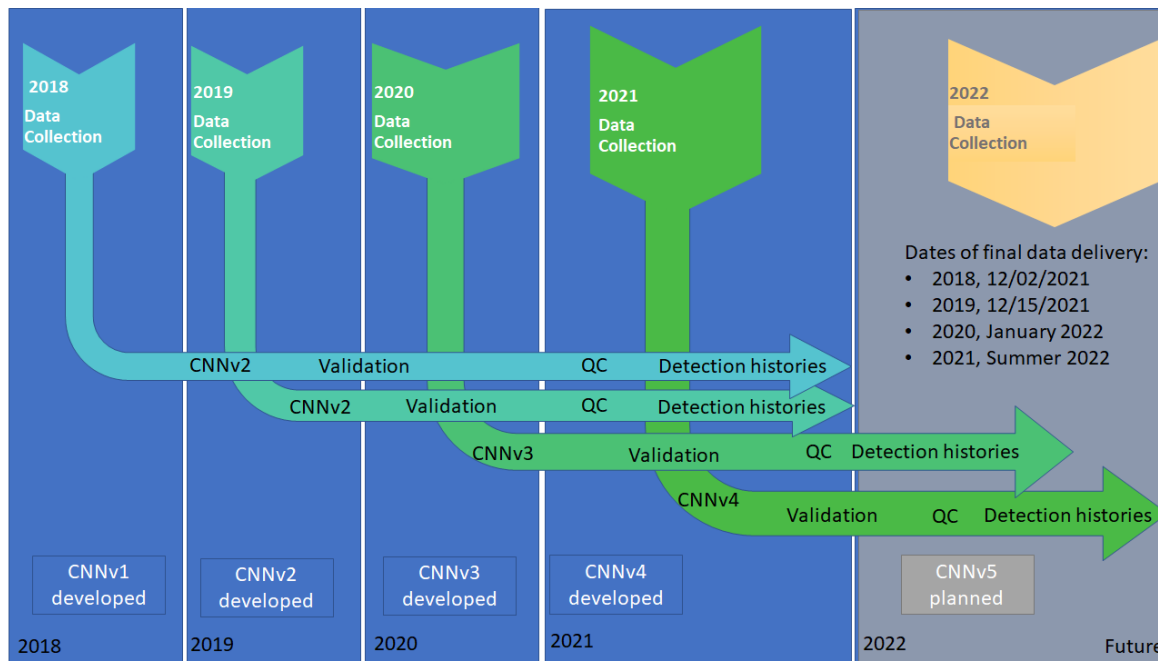
Figure 3. Example spectrogram images of target species calls used by Ruff et al. (2020) to train a convolutional neural network (PNW-Cnet ) to detect owl calls in field recordings. A = barred owl, B = great horned owl, C = northern pygmy owl, D = northern saw-whet owl, E = western screech owl, F = northern spotted owl. Each spectrogram is 500 x 129 resolution and represents 12 s of audio in the frequency range 0-3000 Hz. Spectrograms like those shown were used in PNW-Cnet v1 and v2. From PNW-Cnet v3 and v4, spectrograms were 1000 x 257 resolution and included the frequency range 0-4000 Hz. Lighter areas represent greater sound intensity.

Appendix A. Workflow for the passive acoustic monitoring program within the Northwest Forest Plan area. The process includes data collection, training the convolutional neural network (PNW-Cnet ) for automated species identification, processing data, analyzing data, and reporting findings. Highlighted are steps 3–5 which are steps focused primarily on data processing.

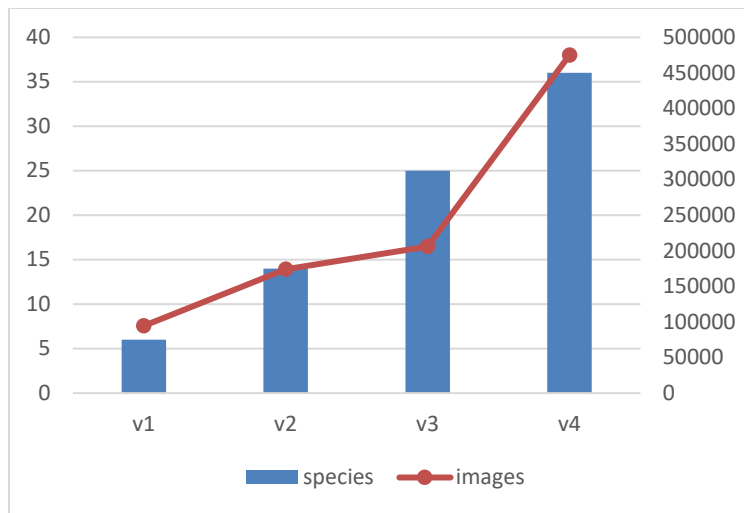




Appendix B. Example sampling station layouts by year. In 2018, five sampling stations were randomly placed within hexagons (no further than 1.5 km from a road or trail) following this rule set: on federal land; mid-to-upper slope positions;  $\geq 50$  m from roads, trails, and streams; spaced  $\geq 500$  m apart; and located  $\geq 200$  m from edge of hexagon. Starting in 2019, established hexagons on COA and OLY had one sampling station randomly removed based on sampling design change, leaving four sampling stations. Newly established hexagons in KLA during 2019 had four random sampling stations selected following within-hexagon placement rule set established in 2018. Newly established hexagons in 2020 and 2021 followed a more standard sampling station layout with one station centrally located and three stations in non-adjacent triangles within the hexagons. Other within-hexagon placement ruleset established in 2018 was also applied, thus some stations needed to be adjusted to meet rule set requirements.



Appendix C. Timeline of data collection, versions of convolutional neural network (CNNv2 = PNW-Cnet v2, CNNv3 = PNW-Cnet v3, CNNv4 = PNW-Cnet v4) used, status of validation, and plans for 2022.



Appendix D. Convolutional Neural Network version (v1 = PNW-Cnet v1, v2 = PNW-Cnet v2, v3 = PNW-Cnet v3, v4 = PNW-Cnet v4), number of species (primary y-axis) and sample size of images in model training set (secondary y-axis).