

RESEARCH NOTE

Implementing real-time acoustic monitoring for conservation: A case study using edge computing and satellite transmission

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Abstract

Passive acoustic monitoring is widely used in conservation but often limited by delayed results due to manual retrieval and post-processing. To explore the feasibility of real-time monitoring in remote landscapes, we conducted field evaluations of a prototype automated surveying unit (ASU). The ASU integrated onboard convolutional neural network-based sound classification with satellite data transmission for near real-time species detection. We deployed ASUs alongside conventional autonomous recording units at eight sites to survey for northern spotted owls (*Strix occidentalis caurina*) and marbled murrelets (*Brachyramphus marmoratus*) in old-growth forests of the Pacific Northwest, USA. We compared detection rates, background noise levels, and operational performance. ASUs successfully transmitted detection summaries and system status, though the elevated background noise in ASU recordings reduced detection rates relative to conventional units. These preliminary findings suggest that real-time autonomous monitoring systems demonstrate potential to support time-sensitive conservation efforts, while highlighting current limitations and areas for improvement.

KEYWORDS

automated surveying unit, autonomous recording unit, conservation technology, ecological monitoring, marbled murrelet, northern spotted owl, passive acoustic monitoring

1 | INTRODUCTION

Rapid advances in passive acoustic monitoring (PAM) and machine learning have transformed ecological research and conservation. Increasingly, researchers use PAM to non-invasively monitor biodiversity, detect elusive or rare species, and assess ecosystem health across terrestrial, freshwater, and marine environments (Lahoz-

Monfort & Magrath, 2021; Sugai et al., 2019; Teixeira et al., 2024; Tosa et al., 2021). Convolutional neural networks (CNNs) have further accelerated this progress by enabling automated identification of vocalizing species within vast soundscape datasets (Ruff et al., 2020; Wang et al., 2022). As the scale of monitoring expands, these technologies have become central to detecting species presence, biodiversity monitoring, activity patterns,

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phenological shifts, and ecological disturbances (Gibb et al., 2019; Lesmeister & Jenkins, 2022; Ross et al., 2023).

Autonomous recording units (ARUs) play a pivotal role in PAM, providing long-term, non-invasive data collection in remote and inaccessible areas. ARUs have already revolutionized population monitoring for a wide range of vocal species (Appel et al., 2023; Duarte et al., 2024; Fleishman et al., 2023; Shonfield & Bayne, 2017). Yet despite their utility, ARUs are constrained by their need for manual data retrieval and external post-processing, which introduce delays between recording and data interpretation. These delays limit responsiveness in time-sensitive contexts such as early detection of invasive species, monitoring of disturbance events, or conservation interventions in dynamic landscapes. Furthermore, many priority monitoring areas lack reliable cellular networks or terrestrial communication infrastructure, complicating efforts to remotely access data in real time. Without immediate feedback, researchers and managers risk instances where devices malfunction or run out of power in the field without notice until retrieval.

To address these challenges, Instinct Environmental (Instinct, 2025) developed an automated surveying unit (ASU) that integrates real-time, onboard sound classification with satellite communication capabilities. Instinct Environmental is a conservation technology company focused on developing field-ready tools for automated biodiversity monitoring. The ASU is designed to process acoustic data directly in situ using edge computing and transmit detection summaries and system status updates from remote locations via satellite link. The real-time functionality has the potential to bridge the gap between data collection and ecological decision-making, enabling rapid detection of target species, monitoring of habitat use dynamics, and immediate operational insights from remote landscapes.

To evaluate the first generation ASU's performance in an applied context, we deployed ASUs that processed audio data using a CNN trained for species in the Pacific Northwest, USA (PNW-Cnet; Ruff et al., 2023), including conservation-priority species, the northern spotted owl (*Strix occidentalis caurina*) and marbled murrelet (*Brachyramphus marmoratus*). Both species are old forest obligates and listed under the US Endangered Species Act, and the northern spotted owl has steeply declining populations (Franklin et al., 2021). PAM is increasingly used to support monitoring, conservation planning, and status assessments of these threatened species (Duarte et al., 2024; Lesmeister & Jenkins, 2022). Our evaluation focused on assessing whether the ASU could provide timely and reliable detection information in remote areas

with dense forest canopies, which are conditions representative of many real-world monitoring needs in conservation practice.

We co-located ASUs with conventional ARUs to assess reliability, background noise levels, and species detection rates between the devices, using identical post-processing methods for standardized evaluation. We report detection performance, recording quality, and system functionality under field conditions, and we describe technical limitations encountered during the deployment. We also recommend improvements to address key performance issues. While our evaluation was limited in scope, the findings provide preliminary evidence that real-time acoustic monitoring using autonomous, satellite-connected systems is technically feasible and may offer significant value to conservation efforts in remote or infrastructure-limited regions.

2 | METHODS

2.1 | Automated surveying unit design and components

The ASU was developed by Instinct Environmental and is a self-contained, field-deployable acoustic monitoring system designed for remote, off-grid operations (Instinct, 2025). ASUs integrate a weatherized enclosure housing the onboard processor, data recorder, and local storage, paired with dual external analog microphones, a rechargeable lithium iron phosphate (LiFePO₄) battery, and a removable satellite antenna (Figure S1, Table 1).

The onboard processor executed immediate post-recording sound classification using PNW-Cnet v5, a CNN trained on over 780,000 labeled spectrogram images, encompassing 135 sound classes across 80 species and key environmental sounds (Lesmeister et al., 2025; Ruff et al., 2023). Although ASUs were capable of higher sampling rates, we recorded audio at a native sampling rate of 32,244 Hz, in mono channel WAV format to optimize power efficiency and data storage (Table S1). Following each recording, the ASU processed audio in real time, generating human-readable summaries that listed PNW-Cnet v5 class detections and timestamps for each detection. For detections, we used confidence scores of $\geq 95\%$ to balance precision and recall for focal species (Lesmeister et al., 2025; Ruff et al., 2021). Processing times scaled with recording duration, averaging 25–30 min for the longest recording slots used in this study (i.e., 4 h). The summary messages were queued for satellite uplink, transmitting data to an online cloud dashboard that featured a map view of ASU location, ASU status indicators (e.g., battery life, recording activity),

TABLE 1 Specifications, limitations, and summary detection rates of generation 1 automated survey units (ASUs; Instinct Environmental) and autonomous recording units (ARUs; Wildlife Acoustics SM4).

Specification	ASU	ARU
Detection model	Onboard PNW-Cnet v5; supports additional CNNs	External processing required
Data transmission	Real-time via satellite uplink	None (data retrieved manually)
Microphones	Dual analog, moderate sensitivity	Stereo omnidirectional, high sensitivity
Sample rate options	16, 32, 48 kHz, mono	8, 12, 16, 24, 32, 44, 48, 96 kHz, stereo
Recording format	WAV, 16-bit	WAV, 16-bit
Signal-to-noise ratio	Lower: unknown (mean background noise pre-noise reduction 24.11 dB [5.6 dB post] higher than ARU)	Higher: 80.0 decibels at 1 kilohertz
Recording schedule	Max 8 slots/day, capped at 12 h per day; fixed clock	Unlimited slots; dynamic sunrise/sunset options
Maximum storage capacity	256 GB expandable to 1 TB	2 SD card slots 1 TB each
Battery life (avg)	47 days (with external LiFePO ₄ battery)	55 days (internal battery pack)
Weight (with battery)	~7.5 kg	~1.9 kg
Satellite communication	Yes (Iridium network)	No
Solar charging option	Available option, but not viable in dense forest canopies	Not available
Field configuration	Web dashboard or USB upload	Screen display
Spotted owl primary call type detection rate pre-noise reduction (avg)	0.07 detections/h	0.27 detections/h
Spotted owl primary call type detection rate post-noise reduction	0.15 detections/h	NA
Marbled murrelet primary call type detection rate pre-noise reduction (avg)	0.01 detections/h	0.14 detections/h
Marbled murrelet primary call type detection rate post-noise reduction	0.02 detections/h	NA
All species detection rate pre-noise reduction (avg)	23.87 detections/h	52.11 detections/h
All species detection rate post-noise reduction (avg)	31.14 detections/h	NA
Use case	Real-time detection in remote/no-network areas	High-quality archival monitoring

detection history, and alert notifications (Figure S2). Raw recordings were stored onboard, which we used for post-deployment noise analysis and data processing.

2.2 | Field deployment and device pairing

We deployed eight ASUs at seven active northern spotted owl territories and one marbled murrelet nesting area across Oregon and Washington, USA, during the 2024

breeding season (April–August). Each ASU was co-located with a conventional ARU (e.g., Song Meter SM4; Wildlife Acoustics, Maynard, MA), mounted within 5 meters of the ASU to ensure comparable acoustic conditions. Conventional ARUs recorded stereo audio at 32,000 Hz, storing audio data in WAV format locally on SD cards for later retrieval and post hoc processing (Table 1). We programmed ARUs to follow a fixed schedule of continuous recordings from 1 h before sunset to 3 h after sunset, 2 h before sunrise to 2 h after sunrise, and 10-min recordings at the top of every hour over the 24-h cycle.

We configured ASUs using Instinct's web-based dashboard (Instinct, 2025) to follow a similar recording schedule as the ARUs. The ASUs also had four-hour recording slots that overlapped sunrise and sunset, and eight nocturnal 10 min recording slots per day. These recording schedules prioritized dawn and dusk windows aligned with peak vocal activity of target species. Configurations were transmitted via satellite or installed manually via USB drive. Because animal vocal activity is often highly correlated with sunrise and sunset times, an identified limitation of the ASU scheduling system was its reliance on static clock times rather than adaptive scheduling tied to local sunrise and sunset shifts over the deployment period.

2.3 | Post-deployment data processing and validation

We conducted a noise reduction and data quality enhancement procedure for ASU recordings. Initial analyses revealed that native ASU recordings exhibited higher background noise levels than ARUs. To address this, we applied standardized noise reduction workflows using Audacity (v3.6). We extracted representative ambient noise profiles to reduce noise (17 dB reduction, sensitivity 6.00, frequency smoothing 6 bands) and batch processed via macros for site-level efficiency. For all data collected, we conducted sound pressure level (SPL) analysis using Kaleidoscope Pro (Wildlife Acoustics, Maynard, MA).

To compare detection performance between devices, we calculated the number of target species detections per recording hour for each ASU and ARU. All recordings were processed using PNW-Cnet v5 on external hardware to ensure consistency across platforms. After data retrieval, we analyzed ASU recordings both before and after a standardized noise reduction workflow. Detection rates were summarized by site and visualized as hourly detection rates for each unit type. Detections included vocalizations of northern spotted owl, marbled murrelet, and other regionally relevant focal species identified by the model with $\geq 95\%$ confidence (Lesmeister et al., 2025). We calculated mean detection rates across the full deployment duration for each site.

3 | RESULTS

3.1 | Deployment and recording performance

The ASUs functioned reliably across all field sites, demonstrating suitability for remote, off-grid monitoring. Battery life ranged from 34 to 56 recording days

(mean = 47 days), supporting an average of 8.3 h of daily recording. In comparison, conventional ARUs achieved slightly longer operational durations, ranging from 51 to 63 days (mean = 55 days), and recorded an average of 10.7 h per day (Table 1). Across eight field sites, total recording time for ASUs reached 3309 h, while ARUs accumulated 4599 h. Variations in deployment length primarily reflected differences in battery capacity and wildfire-induced early retrieval at two locations, which were excluded from battery life calculations.

3.2 | Recording quality and noise analysis

Native ASU recordings exhibited elevated background noise levels relative to ARU recordings (Table 1). Sound pressure level (SPL) analysis indicated that ASU recordings were consistently noisier, with mean SPLs ranging from 2.7 to 8.3 dB higher than ARUs at the same sites (mean difference = +5.57 dB; Figure 1). This elevated noise floor was linked to hardware factors, including microphone quality and internal electronic noise.

Application of noise reduction protocols significantly improved ASU recording quality, reducing SPL differentials relative to ARU recordings. After noise reduction, ASU recordings showed improved signal-to-noise ratios, resulting in increased detection rates of target species vocalizations. Despite these improvements, noise-reduced ASU recordings remained noisier than those from ARUs (Figure 1), indicating that further hardware refinement is necessary to achieve parity.

3.3 | Detection performance following noise reduction

Following noise reduction, the ASU system identified an average of 31.1 target species detections per recording hour, compared to 52.1 detections/h for conventional ARUs with no noise reduction procedure (Table 1). Unprocessed ASU recordings yielded 23.9 detections/h, demonstrating clear gains from the applied noise reduction workflow. Detection rates varied substantially across the eight field sites, closely tracking differences in ambient noise levels and recording conditions (Figure S3). At the quietest site, noise-reduced ASUs achieved 69% of the ARU detection rate; at the noisiest site, ASUs achieved just 26%. Across all deployments, the mean ASU detection rate represented approximately 58% of that recorded by the ARUs.

Both ASUs and ARUs successfully detected northern spotted owl vocalizations at the same six of eight sites,

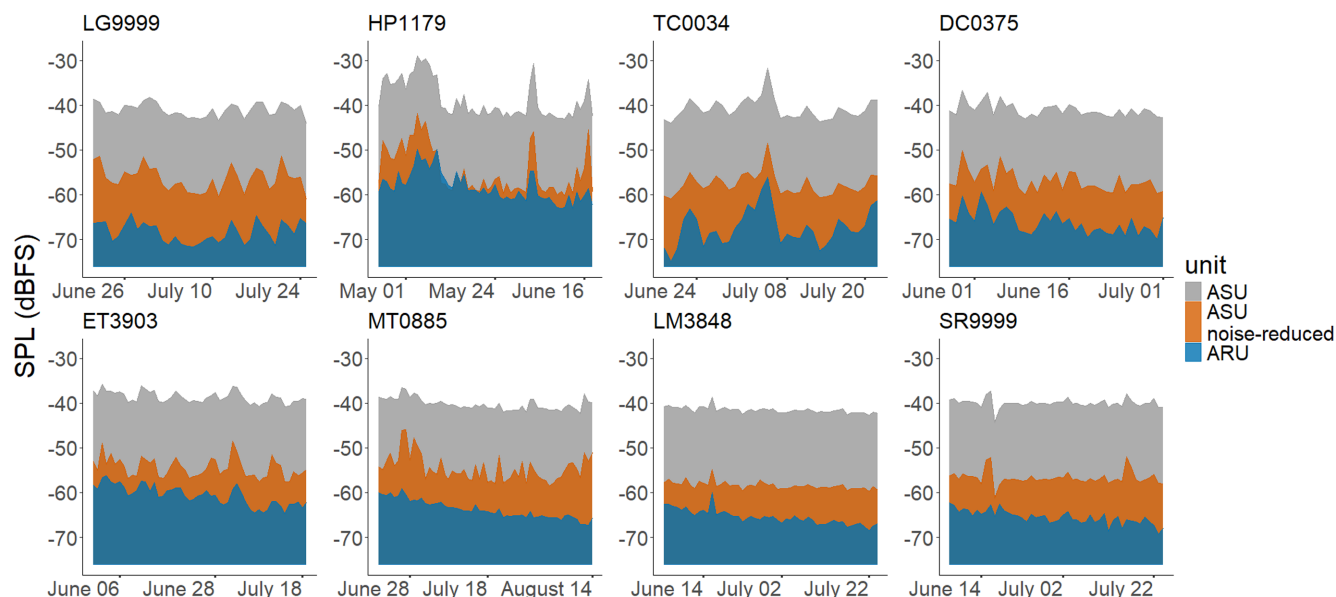


FIGURE 1 Comparison of background noise levels across sites for automated surveying unit (ASU) and conventional autonomous recording unit (ARU) recordings. The mean sound pressure level (SPL, dB) values are shown for ASU native recordings (gray), ASU noise-reduced recordings (orange), and ARU recordings (blue). Noise reduction significantly improved the signal-to-noise ratio of ASU recordings, reducing the mean SPL difference relative to ARUs (initial mean difference = +5.57 dB). Despite improvements, ASU recordings remained noisier than ARUs, highlighting a target area for future hardware refinement.

consistently capturing the species' distinctive four-note territorial call. Marbled murrelet vocalizations were detected by both devices at two coastal sites, with peak ASU detections occurring between 10 and 22 July. These detections coincided with periods of high recording effort prior to battery depletion, highlighting both the system's potential and the importance of power management in long-term deployments.

3.4 | Onboard processing validation

Onboard ASU processing using PNW-Cnet v5 performed consistently, producing outputs nearly identical to those generated via post-deployment external processing (pre-noise reduction) of retrieved audio files. We observed minor discrepancies at one site, involving a small number of additional detections during external reprocessing. The source of this variation remains unclear but did not materially affect overall performance assessment.

Across the full dataset, onboard ASU processing produced 86,936 detection clips, representing approximately 40% of the 216,706 clips generated from ARU recordings processed after retrieval. When standardized by recording effort, ASU detection rates remained lower than ARUs but effectively demonstrated the capability for near real-time target detection and communication, even in remote and noisy environments.

4 | DISCUSSION

4.1 | Advances and remaining challenges

The development of the ASU represents a substantial advance in remote passive acoustic monitoring, especially for projects that benefit from real-time species detection. By integrating onboard species classification with satellite-based communication, the ASU enables near real-time monitoring of target species in environments where traditional ARUs require manual data retrieval and delayed post-processing (Shonfield & Bayne, 2017). Other terrestrial real-time acoustic detectors, such as the ecoPi system (<https://www.oekofor.de/de/>), perform onboard analysis and transmit data via cellular networks (Wood et al., 2024). In contrast, the ASU tested in our study uses satellite communication, allowing deployment in areas without cellular coverage. This innovation bridges the critical gap between data collection and timely ecological decision-making, especially in remote and dynamic ecosystems.

Our field trials demonstrated that ASUs functioned reliably under challenging conditions, providing near real-time detections and system health updates. Onboard processing matched external post-hoc analysis (pre-noise reduction) closely, confirming robust classification performance and ability to transmit accurate summary

results. However, co-located ARUs outperformed ASUs in detection rates, largely due to elevated background noise in ASU recordings. Noise reduction workflows improved ASU performance substantially, though detection rates remained lower than ARUs overall. These findings point to specific areas for hardware refinement, including improved microphone sensitivity, internal noise insulation, and signal pre-processing (Darras et al., 2020; Hill et al., 2018).

Battery life and recording durations were also somewhat shorter for ASUs than ARUs, reflecting the higher energy demands of onboard processing and satellite transmission. A critical constraint is the current size and weight of ASUs when deployed with the external battery pack (Table 1), which is necessary for prolonged operation in forested environments like the Pacific Northwest. Dense canopies severely limit solar charging potential to low-power devices in these ecosystems (Gunasagaran et al., 2016). Therefore, edge computing devices like ASUs require large, heavy batteries that increase logistical challenges for deployment. In contrast, ecosystems with more open canopies or higher solar irradiances, such as savannas, grasslands, or alpine environments, present opportunities for integrating solar power to extend deployments and reduce field labor.

4.2 | Enabling real-time ecological monitoring

Real-time acoustic monitoring opens transformative opportunities for ecological research and conservation management. Rapid notification of species detections can inform time-sensitive decisions, including targeted surveys, rapid retrieval of recording device once focal species presence is confirmed, habitat protection measures, and the adjustment of management activities to avoid disturbing sensitive species (Sethi et al., 2020; Whytock et al., 2023). For imperiled species like the northern spotted owl and marbled murrelet, real-time detection can support adaptive management in dynamic landscapes, where population persistence depends on timely knowledge of habitat use, presence, or shifts in distribution (Lesmeister et al., 2018; Raphael et al., 2018). These capabilities are especially valuable during narrow seasonal windows, such as breeding or migration, when rapid detection may determine whether conservation actions can be implemented effectively.

Real-time monitoring also has potential for rapidly detecting environmental change and disturbance. In fire-prone landscapes, for example, ASUs could detect changes in the acoustic community structure following wildfires, enabling land managers to initiate post-

disturbance recovery actions without delay (Southwell et al., 2021). Acoustic signatures could also be used to monitor ecosystem recovery trajectories or identify areas of ecological refuge. For invasive species, early detection of vocalizations (e.g., barred owls, *Strix varia*, encroaching into northern spotted owl territories) can trigger rapid intervention before substantial displacement or predation occurs (Wiens et al., 2021; Wood et al., 2024). In wetlands, rapid detection of bullfrogs (*Lithobates catesbeianus*) or invasive birds could support targeted removal campaigns before populations become established (Bota et al., 2024).

Real-time PAM systems may also play an important role in remote protected areas where routine access is limited or cost prohibitive. Satellite-linked acoustic units could be deployed to monitor rare species, allowing for real-time conservation oversight even in politically unstable or physically inaccessible regions. In such settings, automated systems could alert managers to the presence of focal species, or to human-associated noise events such as chainsaws, gunshots, or motor vehicles, supporting anti-poaching and protected area enforcement efforts. More broadly, real-time monitoring could help researchers respond opportunistically to rare or stochastic ecological events, including irruptions, early arrivals of migratory species, or shifting vocal activity associated with phenological change. These applications remain largely unexplored but represent a frontier for expanding the ecological utility of acoustic sensing technologies.

Beyond species detections, the ASU's we evaluated provided real-time system health updates, including data storage capacity status, satellite transmission status, and recording activity. These features improve operational reliability, effectively eliminating the risk of unnoticed equipment failure common in passive monitoring networks, and enhance long-term monitoring programs by ensuring data continuity and reducing costly field revisits.

Future improvements and broader applications

While the ASU demonstrated substantial utility, our results underscore several priorities for future development. Hardware improvements, particularly in acoustic components and electronic shielding, could reduce noise levels and improve detection performance, bringing onboard performance closer to parity with conventional ARUs. User interface refinements, including dynamic recording schedules that adjust with sunrise and sunset timing, will enhance usability for extended deployments. There is also potential to retrain CNN models using ASU-

generated audio, either by incorporating real-world noise conditions into model development or by leveraging long-term ASU deployments to build site-specific models that account for persistent background conditions. Such approaches could help mitigate the impacts of ambient noise and further improve classification accuracy over time.

Reducing device weight and power consumption is essential for increasing portability and deployment flexibility. Integration of alternative or hybrid power sources, such as intermittent solar charging in more open-canopy systems, could significantly extend deployment durations while reducing reliance on heavy batteries. The ASU platform's modular design supports broad applicability beyond the Pacific Northwest, so incorporating a variety of different CNNs would enable adaptation to different taxonomic groups and ecosystems, from monitoring gibbons in tropical rainforests (Clink et al., 2020) to tracking seasonal occurrence of marine mammals in arctic regions (Marcoux et al., 2017). Integration with other environmental sensors (e.g., barometric pressure, humidity, air quality) could further expand its role in ecosystem monitoring networks.

Finally, by reducing the need for frequent site visits for projects requiring rapid survey results and enabling automated data delivery, ASUs support accessible, scalable biodiversity monitoring that could inform conservation decisions. Importantly, the flexibility of satellite-based communication allows ASUs to function independently of terrestrial network infrastructure, making them especially valuable for projects requiring rapid survey results from under-resourced or geographically isolated areas. The ASUs evaluated in this study were approximately 50% more expensive than the conventional ARUs used, which could present a budgeting challenge for many projects. However, under scenarios with near real-time survey result needs, conventional monitoring can be difficult or prohibitive due to higher personnel costs associated with multiple site visits. A recent search of device status revealed that several hardware and firmware improvements in the next generation of ASUs have occurred (Instinct, 2025). These include a 50% reduction in device size, a 20% reduction in battery size and weight, and signal chain improvements that substantially reduce background noise through optimized gain settings and dynamic range compression. There are fewer constraints on recording schedule flexibility and the platform supports several CNNs, such as BirdNet (Kahl et al., 2021), to significantly broaden the ecological applications of the system. These advancements highlight the rapid pace of technology development to meet global biodiversity monitoring needs. As environmental change accelerates globally, the ability to deploy real-time, autonomous

monitoring networks at scale will be increasingly vital for early detection of ecological shifts, rapid response to emerging threats, and long-term stewardship of biodiversity across diverse and vulnerable landscapes.

AUTHOR CONTRIBUTIONS

Damon B. Lesmeister acquired funding, wrote the manuscript, and designed field testing. Christopher McCafferty, Natalie M. Rugg, and Kirsten Wert conducted field testing, data processing, validation, and analysis. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data are available at Lesmeister et al. (2025). Processed data for field evaluation of real-time acoustic monitoring. Data set. Zenodo. <https://doi.org/10.5281/zenodo.15334799>.

ETHICS STATEMENT

Passive acoustic monitoring involved no direct interaction with wildlife and did not require animal handling or disturbance, so did not trigger the need for Scientific Collection permits or Institutional Animal Care and Use Committee review.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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