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Notes

EXPANDING BIODIVERSITY MONITORING IN THE SOUTHWESTERN UNITED STATES WITH PASSIVE ACOUSTIC MONITORING

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ABSTRACT–Wildlife monitoring technologies like passive acoustic monitoring (PAM) show great promise in overcoming biodiversity monitoring challenges over broad spatial scales. We demonstrate that PAM can be an effective monitoring approach for wildlife species and communities in the southwestern United States. After collecting >51,000 hours of audio data in the Cibola, Gila, and Kaibab National Forests, we processed data with the BirdNET algorithm. We confirmed that BirdNET can currently identify at least fifty-two species, including six species of management interest: the Mexican spotted owl (*Strix occidentalis lucida*), pinyon jay (*Gymnorhinus cyanocephalus*), yellow-billed cuckoo (*Coccyzus americanus*), Grace's warbler (*Setophaga graciae*), western bluebird (*Sialia mexicana*), and Mexican gray wolf (*Canis lupus baileyi*). We detected many species during our pilot study to target future validation efforts and algorithm refinement (n=93). Results from this study are an integral part of designing a regional PAM program in the Southwest to evaluate trends in individual species and animal communities in response to multiple stressors.

RESUMEN–Las tecnologías de monitoreo de vida silvestre, como el monitoreo acústico pasivo (PAM, por sus siglas en inglés), muestran un gran potencial para superar los desafíos del monitoreo de la biodiversidad en grandes escalas espaciales. Demostramos que PAM puede ser un enfoque de monitoreo efectivo para las especies y comunidades de vida silvestre en el suroeste de los Estados Unidos. Después de recopilar >51,000 horas de datos de audio en los bosques nacionales de Cibola, Gila y Kaibab, procesamos los datos con el algoritmo BirdNET. Confirmamos que BirdNET actualmente puede identificar al menos cincuenta y dos especies, incluyendo seis especies de interés para el manejo: el búho moteado mexicano (*Strix occidentalis lucida*), el arrendajo piñonero (*Gymnorhinus cyanocephalus*), el cuclillo de pico amarillo (*Coccyzus americanus*), la reinita de Grace (*Setophaga graciae*), el azulejo occidental (*Sialia mexicana*) y el lobo gris mexicano (*Canis lupus baileyi*). Detectamos varias especies durante nuestro estudio piloto para futuras iniciativas de validación y afinamiento del algoritmo (n = 93). Los resultados de este estudio son una parte integral del diseño de un programa regional de PAM en el suroeste de los Estados Unidos para evaluar las tendencias en especies individuales y comunidades animales en respuesta a múltiples factores estresantes.

With a high diversity of birds and multiple stressors on these populations from disturbance like fire (Hurteau et al., 2025), there is a need for monitoring approaches in the southwestern US that provide cost-effective information on population status across broad scales. One of the biggest challenges in species monitoring is the ability to efficiently allocate sampling effort in space and time with limited budgets (Sanderlin et al., 2014).

Traditional sampling methods (i.e., point counts) tend to require substantial funding and skilled person effort to obtain adequate samples in space and time to monitor species, especially those that are rare. Moreover, most broad-scale monitoring programs do well at tracking common species, yet many other species have insufficient observations to detect trends with standard monitoring protocols (Legg & Nagy, 2006).

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[B] Retired

Wildlife monitoring technologies like passive acoustic monitoring (PAM) surveys show great promise in overcoming these challenges to monitoring multiple species at the same time at reduced costs across broad spatial and temporal scales (Darras et al., 2018; Navine et al., 2024; Wood, Gutiérrez, et al., 2019; Wood, Popescu, et al., 2019). The emergence of low-cost recording hardware and machine learning tools capable of identifying hundreds of vocally active species in an ecosystem, like the BirdNET algorithm (Kahl et al., 2021), opens many possibilities in biodiversity monitoring (Wood, Socolar, et al., 2024). Acoustic technologies can detect multiple species over continuous time, without the need for personnel to revisit the sites as frequently. With reduced budgets, PAM can still be accomplished over large areas while increasing overall safety. Field personnel do not have to mitigate hazards of rough terrain with limited visibility at night (e.g., while surveying for nocturnally-active species). The frequency of passive acoustic survey site visits is a function of battery life, influenced by recording schedule and sample rate (availability of multi-Terabyte SD cards translates to memory capacity not being a limiting factor). Another advantage of PAM is that field personnel do not need to have specialized training in species-detection techniques (i.e., point counts), which expands horizons in engaging different types of field personnel, including citizen (or community or participatory) science organizations (Dickinson et al., 2010).

In general, rare species tend to be priority species for monitoring in conservation and management applications due to their relationships to desired vegetation conditions, low population numbers, and/or limited distributions driven by habitat relationships. Several priority species (i.e., Mexican spotted owl, *Strix occidentalis lucida* (Jones et al., 2023); yellow-billed cuckoo, *Coccyzus americanus* (M. J. Johnson et al., 2017); pinyon jay, *Gymnorhinus cyanocephalus* (K. Johnson & Sadoti, 2023)) are distributed across the Southwest, including in National Forests (NF). Efficient monitoring is of interest to managers across the Southwest, including the USDA Forest Service. For example, the USDA Forest Service's 2012 Planning Rule (USDA Forest Service, 2012) requires monitoring to assess land management plan ("forest plan") effectiveness. Each NF is mandated to select at least one focal species to track maintenance of or movement towards desired conditions through management actions. Another complementary component of the 2012 Planning Rule is to track ecological integrity (Miller-ter Kuile et al., 2025; Wurtzebach & Schultz, 2016). This requires knowledge of not just a subset of priority species, but entire wildlife and plant communities and the interrelated ecosystem processes they support. Therefore, monitoring technologies and/or modeling techniques that can adequately monitor trends in priority species and entire communities (biodiversity) in a cost-efficient manner are ideal.

Here, we evaluated the ability of PAM, that is passive acoustic surveys followed by semi-automated species' detection via machine learning tools and expert review, to detect priority and other bird species in a pilot study designed to guide decisions for a regional PAM program in the southwestern USA. We illustrate the utility of PAM using one year of pilot study data from 2022 in the Black Range Ranger District (RD) of the Gila NF in New Mexico, Williams RD of the Kaibab NF in Arizona, and the Sandia and Mountainair RDs of the Cibola NF & National Grasslands (NG) in New Mexico.

We deployed autonomous recording units (ARUs) in a network (Swift & SwiftOne Recorders, K. Lisa Yang Center for Conservation Bioacoustics) to passively record the vocalizations of wildlife communities and assess the efficacy of PAM (Fig. 1). We deployed 60 ARUs in the Black Range RD (BRRD), Gila NF, between May 9 and July 29 of 2022 in pinyon-juniper, pine/pine-oak, and mixed-conifer vegetation types using a sampling scheme consisting of 4-km^2 hexagons with four ARUS within each hexagon, like PAM approaches developed in California (Wood, Gutiérrez, et al., 2019) and the Pacific Northwest (Duchac et al., 2020). We used the Ecological Response Unit (ERU) dataset to delineate vegetation types to select sampling units. Hexagons were classified as belonging to a given vegetation sampling group (pinyon-juniper, pine/pine-oak, or mixed conifer) if its area consisted of 40% or greater of that vegetation type. We deployed 20 ARUs in the Williams RD, Kaibab NF between May 5 and July 5 of 2022 in a pre-treatment area for fuels reduction corresponding to point count locations selected with Integrated Monitoring of Bird Conservation Regions (Pavlacky et al., 2017) standardized point count surveys spaced 250m apart. We deployed 61 ARUS in the Cibola NF and NG between May 19 and December 27 of 2022 in pinyon-juniper, pinyon-juniper/pine, pine-oak, mixed conifer, mixed conifer/aspen vegetation types using the same sampling scheme as in the BRRD. We deployed ARUs in areas accessible by road or trail in the Sandia and Manzano Mountain ranges. We programmed ARUs to record daily 18:00 – 9:00 local time via one omnidirectional microphone at a sample rate of 32 kHz, gain +33 dB.

We processed data using the algorithm BirdNET (Kahl et al., 2021), version 2.1 (current and previous versions of BirdNET are freely available here: https://github.com/birdnet-team/BirdNET-Analyzer). We used the command line interface version of BirdNET via the "analyze.py" script. We used the default BirdNET settings (sensitivity = 1.0, overlap = 0) and a custom species list comprised of many species known to occur in the study areas (n = 131 birds and 2 mammals). Future validation efforts should focus on an expanded species list of species known to occur in the southwestern region. After generating BirdNET predictions for all 51,498 hours of audio, we used the "segments.py" script to generate a set of 100 randomly selected BirdNET predictions for each species from confidence scores [0.1 – 1.0] and another set of 50 predictions for each species from confidence scores [0.85 – 1.0]. We focused our initial validation effort on a subset of species with BirdNET predictions that were detected at our study areas with at least one confidence score ⩾ 0.1 (n = 99 birds and 1 mammal) out of the larger species list. For each species, we manually reviewed the 50 predictions from confidence scores [0.85 – 1.0] with one reviewer; for the six species of management interest (Mexican spotted owl, pinyon jay, yellow-billed cuckoo, Grace's warbler [*Setophaga graciae*], western bluebird [*Sialia mexicana*], Mexican gray wolf [*Canis lupus baileyi*]) we also reviewed the 100 additional predictions from across the entire confidence score range. Additional reviewers to the re-

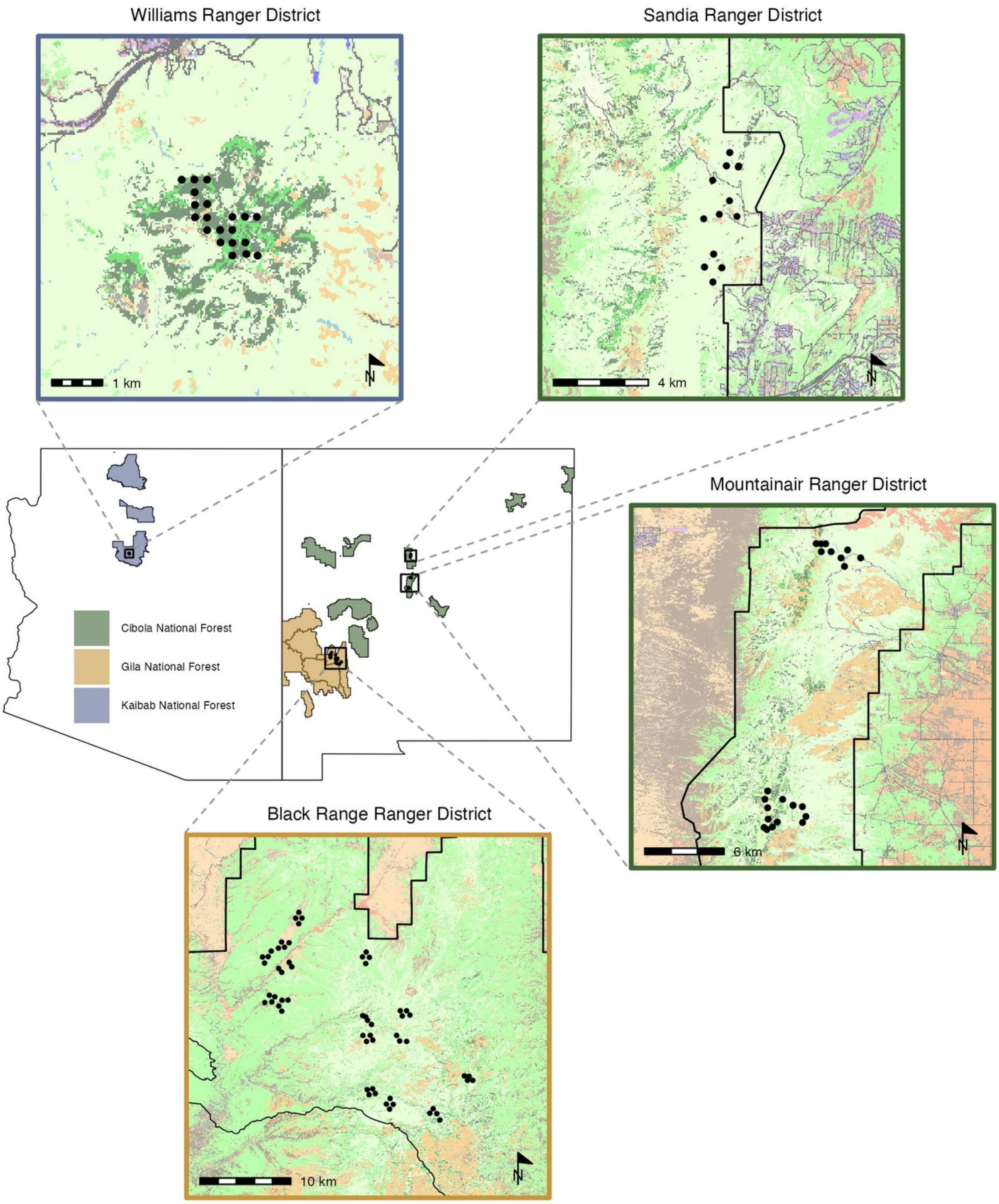

FIG. 1. Network of autonomous recorder units (black dots) deployed during 2022 across the Cibola, Gila, and Kaibab National Forests, Arizona and New Mexico, USA to demonstrate the efficacy of passive acoustic monitoring in the Southwest. Colors on the inset maps indicate landcover types, where green and dark gray colors indicate forest and woodland types, browns indicate shrub and shrub-steppe, oranges indicate grassland and prairie, and pinks indicate developed area. Black borders on the inset maps indicate National Forest boundaries.

viewer with the 50 predictions assessed the 150 additional predictions with Mexican Spotted Owl (n = 2), 100 additional predictions with pinyon jay (n = 1), and 150 predictions with Mexican gray wolf (n = 1). For the six focal species, we combined results from all reviewers in the next steps. Predictions for all three study sites were combined, thus randomly sampled across sites for inclusion in the validation data sets. Following the procedure described by Wood & Kahl (2024), we used logistic regression to relate the binary prediction outcome (correct/incorrect) to the continuous BirdNET confidence score, enabling us to estimate the probability a BirdNET prediction is correct at any given score for the six focal species.

Using the full set of predictions from confidence scores, we were successfully able to attain high probabilities (⩾85%) of correct BirdNET predictions for the six focal species

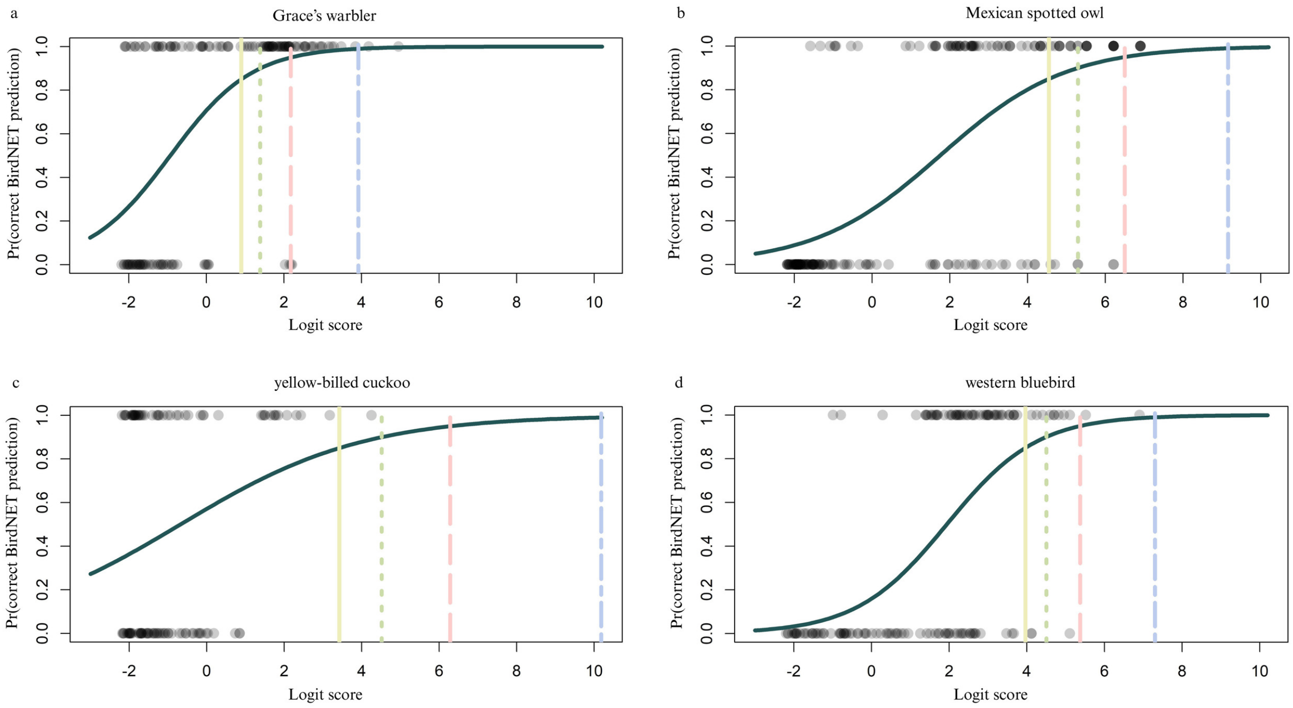

FIG. 2. Example BirdNET validation plots from passive acoustic monitoring (PAM) during 2022 across the Cibola, Gila, and Kaibab National Forests, Arizona and New Mexico, USA for Grace's warbler (a), Mexican spotted owl (b), yellow-billed cuckoo (c), and western bluebird (d) illustrating the potential of generating thresholds for the probability of a correct BirdNET prediction (99% - blue line with long dashes and short dashes, 95% - red line with long dashes, 90% - green line with short dashes, 85% - solid yellow line) for reliable species' detections. These are just a few species of management interest across the Southwest. The logit score (x-axis) is the output of a linear classifier of a 'confidence score' (Wood & Kahl, 2024), which is not based on a probabilistic model. The ratio of correct and incorrect BirdNET predictions (y-axis) is used to generate the probability of a correct BirdNET prediction (solid blue line showing a logistic curve). Higher thresholds (i.e., 99% probability of a correct BirdNET prediction) will be more conservative, resulting in fewer PAM-based detections of a species. Higher thresholds may be used in cases where misclassification errors would be problematic (e.g., many occupancy modeling approaches) and when staff time available to review high-scoring predictions is limited.

(Table 1, Fig. 2), including priority species on the Gila NF (Mexican spotted owl, pinyon jay, yellow-billed cuckoo), focal species on the Kaibab NF (Grace's warbler, western bluebird), and a focal species on the Cibola NF (Grace's warbler). PAM also shows promise in detecting focal species of management interest across the Southwest within all ten NFs (Table 1), with species classified as focal species by NFs (one forest is undergoing forest plan revision) and species of interest by the Four Forests Restoration Initiative (4FRI) Multi-party Monitoring Board within the 4FRI footprint, a Collaborative Forest Landscape Restoration (USDA Forest Service, 2025a) and in a high-risk fireshed (USDA Forest Service, 2025b).

With the rest of the species evaluated at only high confidence scores [0.85 – 1.0], more validation work is needed to generate probabilities of correct BirdNET predictions using the full sample of confidence scores [0.1-1.0]. With this small sample, we did, however, see some variation with the number of correct BirdNET predictions from our pilot study (Table 1). Species with 100% of the high confidence scores predicted correctly (n = 14) and at least 50% correct BirdNET predictions (n = 46) are excellent candidates for PAM. Additionally, we identified 17 species with some correct (>0% and <50%) predictions that require more validation samples to produce probabilities of correct BirdNET predictions – these species are also potential candidates for PAM with more validation samples. Finally, we identified 30 species that did not have any correct BirdNET predictions within the small sample – this could mean these species were detected less frequently during the pilot study (low sample size for validation) and/or might be less suitable for PAM. For these species in particular, season and or time of day could be incorporated into logistic regression equations with the full sample of confidence scores [0.1-1.0] to account for differences in deployment periods for sites in the pilot study. Additionally, Wood et al. (2024) has shown that BirdNET can reliably identify many species that occur in the Southwest, including the highly under-studied Mexican Whip-poor-will (*Antrostomus arizonae*) (Gustafson & Wood, 2025).

For the Mexican spotted owl, a species of high management interest and federally listed as a Threatened species (Jones et al., 2023), prediction score thresholds yielding ⩽1% and 5% chance that a prediction would be incorrect were attainable. At the ⩽1% threshold, six of the correct predictions (n = 90) were retained and none of the incorrect ones were included (n = 109). At the 5% threshold, fourteen of the correct predictions (n = 90) were retained and only

TABLE 1. Species identified by BirdNET and confirmed by experts during 2022 across the Cibola, Gila, and Kaibab National Forests (NF), Arizona and New Mexico, USA. Focal species from NFs and Four Forests Restoration Initiative (4FRI) Multi-party Monitoring Board across the Southwest are identified with subscripts (note that the Lincoln NF is undergoing plan revision so is not included). Importantly, these results reflect BirdNET performance in the context of our sampling and are not a comprehensive assessment of BirdNET performance (i.e., in studies in other USA regions, we found BirdNET classification accuracy to be high for some species that registered no correct predictions in our study). All species were evaluated from a set of 50 randomly selected BirdNET predictions for each species from confidence scores [0.85 –1.0], and a subset of priority species were further evaluated on an additional set of 100 predictions from across the confidence score range [0.1 – 1.0]. More validation work is needed to generate probabilities of correct BirdNET predictions with species only evaluated with high confidence scores. For the species that only received validation at the high confidence range, we present general categories of species for which BirdNET performed well with either a high (⩾50%), moderate (<50%), or no correct classifications.

150 samples from full range of confidence scores [0.1-1.0]	50 samples from a subset of confidence scores [0.85-1.0]		
Species with high percentages of correct BirdNET predictions and prediction score thresholds	Species with ⩾50% correct BirdNET classifications	Species with >0% and <50% correct BirdNET classifications	Species with no correct BirdNET classifications
Grace's warbler[2,3,4,7,11] (*Setophaga graciae*)	acorn woodpecker[5,8] (*Melanerpes formicivorus*)	American kestrel (*Falco sparverius*)	Abert's towhee (*Melozone aberti*)
Mexican gray wolf[12] (*Canis lupus baileyi*)	American robin (*Turdus migratorius*)	black-tailed gnatcatcher (*Polioptila melanura*)	American avocet (*Recurvirostra americana*)
Mexican spotted owl[1,4,5,6,10,12,13] (*Strix occidentalis lucida*)	ash-throated flycatcher[3] (*Myiarchus cinerascens*)	black-throated sparrow (*Amphispiza bilineata*)	American coot (*Fulica americana*)
pinyon jay (*Gymnorhinus cyanocephalus*)	Bewick's wren (*Thryomanes bewickii*)	Brewer's blackbird (*Euphagus cyanocephalus*)	American crow (*Corvus brachyrhynchos*)
western bluebird[7,11] (*Sialia mexicana*)	black-headed grosbeak (*Pheucticus melanocephalus*)	cactus wren (*Campylorhynchus brunneicapillus*)	Bell's vireo (*Vireo bellii*)
yellow-billed cuckoo[12] (*Coccyzus americanus*)	black-throated gray warbler[4,11] (*Setophaga nigrescens*)	canyon towhee (*Melozone fusca*)	black phoebe (*Sayornis nigricans*)
	blue-gray gnatcatcher (*Polioptila caerulea*)	common yellowthroat (*Geothlypis trichas*)	black-chinned hummingbird (*Archilochus alexandri*)
	broad-tailed hummingbird[11] (*Selasphorus platycercus*)	eastern meadowlark[8] (*Sturnella magna*)	black-crowned night-heron (*Nycticorax nycticorax*)
	brown-crested flycatcher (*Myiarchus tyrannulus*)	Gambel's quail (*Callipepla gambelii*)	black-necked stilt (*Himantopus mexicanus*)
	brown-headed cowbird[11] (*Molothrus ater*)	house finch (*Haemorhous mexicanus*)	Canada goose (*Branta canadensis*)
	Bullock's oriole (*Icterus bullockii*)	mallard (*Anas platyrhynchos*)	Cassin's finch (*Haemorhous cassinii*)
	bushtit (*Psaltriparus minimus*)	mountain chickadee[11] (*Poecile gambeli*)	cliff swallow (*Petrochelidon pyrrhonota*)
	canyon wren (*Catherpes mexicanus*)	pine siskin (*Spinus pinus*)	European starling (*Sturnus vulgaris*)
	Cassin's kingbird	rock wren	gadwall

150 samples from full range of confidence scores [0.1-1.0]		50 samples from a subset of confidence scores [0.85-1.0]	
Species with high percentages of correct BirdNET predictions and prediction score thresholds	Species with ⩾50% correct BirdNET classifications	Species with >0% and <50% correct BirdNET classifications	Species with no correct BirdNET classifications
	(*Tyrannus vociferans*)	(*Salpinctes obsoletus*)	(*Mareca strepera*)
	chipping sparrow[11] (*Spizella passerina*)	scaled quail (*Callipepla squamata*)	Gila woodpecker (*Melanerpes uropygialis*)
	common nighthawk (*Chordeiles minor*)	song sparrow[8] (*Melospiza melodia*)	great blue heron (*Ardea herodias*)
	Coopers hawk (*Accipiter cooperii*)	yellow-rumped warbler (*Setophaga coronata*)	great horned owl (*Bubo virginianus*)
	cordilleran flycatcher[9,11] (*Empidonax occidentalis*)		great-tailed grackle (*Quiscalus mexicanus*)
	dark-eyed junco[11] (*Junco hyemalis*)		green heron (*Butorides virescens*)
	greater roadrunner (*Geococcyx californianus*)		horned lark (*Eremophila alpestris*)
	green-tailed towhee (*Pipilo chlorurus*)		house sparrow (*Passer domesticus*)
	hairy woodpecker[11] (*Dryobates villosus*)		ladder-backed woodpecker (*Dryobates scalaris*)
	hermit thrush[2,11] (*Catharus guttatus*)		northern harrier (*Circus hudsonius*)
	house wren[11] (*Troglodytes aedon*)		pied-billed grebe (*Podilymbus podiceps*)
	killdeer (*Charadrius vociferus*)		red-winged blackbird (*Agelaius phoeniceus*)
	lesser goldfinch (*Spinus psaltria*)		rock pigeon (*Columba livia*)
	MacGillivray's warbler (*Geothlypis tolmiei*)		rufous hummingbird (*Selasphorus rufus*)
	mourning dove (*Zenaida macroura*)		spotted sandpiper (*Actitis macularius*)
	northern flicker[11] (*Colaptes auratus*)		western grebe (*Aechmophorus occidentalis*)
	northern mockingbird (*Mimus polyglottos*)		yellow-headed blackbird (*Xanthocephalus xanthocephalus*)
	pygmy nuthatch[8,11] (*Sitta pygmaea*)		

150 samples from full range of confidence scores [0.1-1.0]		50 samples from a subset of confidence scores [0.85-1.0]	
Species with high percentages of correct BirdNET predictions and prediction score thresholds	Species with ⩾50% correct BirdNET classifications	Species with >0% and <50% correct BirdNET classifications	Species with no correct BirdNET classifications
	Says phoebe (*Sayornis saya*)		
	spotted towhee (*Pipilo maculatus*)		
	Stellar's jay (*Cyanocitta stelleri*)		
	Swainson's hawk (*Buteo swainsoni*)		
	Vermilion flycatcher (*Pyrocephalus rubinus*)		
	violet-green swallow (*Tachycineta thalassina*)		
	Virginia's warbler (*Leiothlypis virginiae*)		
	warbling vireo (*Vireo gilvus*)		
	western meadowlark[8] (*Sturnella neglecta*)		
	western tanager[11] (*Piranga ludoviciana*)		
	western wood-pewee[11] (*Contopus sordidulus*)		
	white-breasted nuthatch[8,11] (*Sitta carolinensis*)		
	white-throated swift (*Aeronautes saxatalis*)		
	white-winged dove (*Zenaida asiatica*)		
	Woodhouse's scrub-jay[8] (*Aphelocoma woodhouseii*)		

[1] Apache-Sitgreaves NF
[2] Carson NF
[3] Cibola NF
[4] Coconino NF
[5] Coronado NF
[6] Gila NF
[7] Kaibab NF

[8] Prescott NF
[9] Santa Fe NF
[10] Tonto NF
[11] 4FRI Multi-party Monitoring Board focal species
[12] Federally listed Threatened & Endangered species
[13] This species had 199 samples from the range of confidence scores [0.1-1.0]

two of the incorrect ones were included (n = 109). For a regional monitoring program in the Southwest, these high thresholds would still yield detections for downstream analyses with longer deployments of ARUs. Broad-scale spotted owl surveys using this approach have achieved seasonal detection probabilities >0.9 for spotted owls across the Sierra Nevada (Kelly et al., 2023). Importantly, even massive-scale efforts such as that (which generates >550,000 hours of nocturnal audio annually) employ manual verification of spotted owl predictions to ensure data quality; achieving high precision with BirdNET is therefore primarily a matter of efficiency of review rather than owl data quality.

Our results indicate that our combination of passive acoustic surveys and audio analysis is also effective at detecting pinyon jays, another species of high management interest across the species' range, if present. The majority (93%) of BirdNET predictions in the sample (n = 147) were classified as correct with confidence scores ranging from 0.102 to 1.000. As a colonial species, pinyon jays occur in clusters and have wide home ranges creating monitoring challenges. Additional advantages with PAM could be provided over traditional monitoring methods. For example, it might be possible to use acoustic activity (e.g., number of detections per day) as an index of group size if visual observations of flock size were available to calibrate such a metric (Wood, Klinck, et al., 2021).

Prediction score thresholds and high percentages of correct BirdNET predictions are also achievable for other species of interest like the yellow-billed cuckoo, Graces' warbler (Fig. 2), and western bluebird (Table 1). In the Southwest, PAM is already being used with the yellow-billed cuckoo (Beauregard et al., 2024). The Grace's warbler and western bluebird are examples of focal species selected to indicate different desired conditions in NFs; therefore, understanding drivers of trends, not just determining whether a population metric is changing, is essential for proposing management recommendations. Sanderlin et al. (2019) generated population metrics of apparent survival, population size, and gains from reproduction using integrated population models (Schaub & Abadi, 2011) with the western bluebird in the Southwest by combining broad-scale monitoring methods for occupancy modeling (i.e., point counts, PAM) with fine-scale, more intensive monitoring approaches (i.e., banding). This modeling structure, combined with increased monitoring scales, was important for determining the drivers of western bluebird trends. Relative information gain (i.e., Sanderlin et al., 2019) over different PAM sampling design choices (Wood, Kahl, et al., 2021) will be important to evaluate when considering PAM as an additional or sole data source using optimal monitoring design approaches (i.e., Sanderlin et al., 2014).

We verified multiple Mexican gray wolves at multiple ARUs and, critically, many high-scoring predictions were true positives. However, the logistic regression approach to understanding BirdNET scores is not appropriate because wolf predictions are non-independent. Wolf predictions are more likely generated in clusters because wolf howls tend to be longer than BirdNET's 3sec analysis window. Moreover, wolf howls are an intrinsically challenging signal to identify because they are generally long, low-frequency, and have minimal frequency modulation (i.e., they are slow, low, and monotonous), making misclassification errors potentially pervasive (Sossover et al., 2024). Our classification accuracy was more promising than that reported in the Sierra Nevada using a nearly identical PAM design (Sossover et al., 2024), suggesting that regional differences in soundscapes could perhaps make PAM a more readily usable tool to the management of this high-profile endangered species in the Southwest. For example, real-time acoustic monitoring (Wood, Günther, et al., 2024) could be employed to rapidly locate individuals that have gone beyond the boundaries of designated recovery areas. Acoustics could also complement camera trap arrays as a means of assessing group size (Papin et al., 2019) and increasing overall detection probability (Garland et al., 2020).

Monitoring priority species and the broader animal community responses to prescribed fire, forest thinning, and wildfire at ecosystem scales with PAM is possible (e.g., Brunk et al., 2023; Kelly et al., 2023). Also, PAM could facilitate evaluating broad-scale patterns in pyrodiversity (Jones & Tingley, 2022; Steel et al., 2024). Our pilot study shows that PAM has similar potential to monitor animal community responses to disturbance in the Southwest, with reliable detections of multiple species, including several priority species which can be used to generate detection histories for downstream analyses (Dorazio et al., 2006; MacKenzie et al., 2002, 2006; D. A. Miller et al., 2011; Royle & Link, 2006; Wood, Socolar, et al., 2024). In addition, PAM can provide another data source for leveraging detections of species that are rarer on the landscape using data integration approaches (i.e., D. A. W. Miller et al., 2019). For all these reasons, PAM can provide for robust monitoring of species across broad spatial and temporal scales and leverage cost-effective automated habitat monitoring for adaptive management (Shirk et al., 2023).

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