Trade-offs in Designing a Participatory Acoustic Study of Bats: Comparison of User Engagement and Data Quality between Two Ultrasonic Detectors

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Abstract - Technology for the acoustic detection of animals has advanced rapidly over the past few decades. Due to ease of use, consistency, and safety, acoustic methods are particularly useful for science applications that engage the public. In this study, we evaluated the technological and educational trade-offs between 2 acoustic bat detectors in a participatory science application along the Colorado River in the Grand Canyon, Arizona. Both devices were deployed simultaneously by commercial river guides in parallel with sampling insect prey for 1 h at dusk on 48 dates between April and October 2022. The detector with higher data quality capabilities recorded more bats overall (a mean of 231 more passes per hour) and more species (19 species, including 4 not detected by the lower quality detector). However, data from both detectors showed a decrease in total bat activity from spring to fall, despite the differences in recording capabilities. We conclude that detector quality matters, but user engagement is important when designing participatory research.

Introduction

Bats are a diverse group of mammals that serve important ecological roles on a global scale. However, their ecology is poorly understood, relative to other vertebrates, due to the inherent challenges of studying flying, nocturnal animals (Frick et al. 2020). Improvements in ultrasonic detector technology have broadened options for researchers designing acoustic studies of bats. The first acoustic bat detector was constructed in 1938 from a modified AM radio receiver that converted ultrasonic sounds to frequencies audible to humans (Zamora-Gutierrez et al. 2021). Since then, advancements in detector design and associated software have increased our capacity to detect, record, display, store, and identify echolocation calls. Modern detectors are portable, durable, and commercially available to the general public. They sometimes incorporate user-friendly live displays with audio-visual interpretation of bat activity.

These technological advancements have made bat research far more accessible for the participatory sciences (e.g., community science and citizen science; López-Bosch et al. 2023). Important considerations in designing participatory ecological research are safety, environmental ethics, data quality, repeatability, and participant engagement (Lundberg et al. 2021, Metcalfe et al. 2022). Acoustic data collection by the public has been used to document the occurrence of poorly known bat species (Lundberg et al. 2021), describe roosting habitats (Schorr et al. 2022), monitor population-level impacts of white-nose syndrome (Perea et al. 2022), and aid in urban planning that promotes bat conservation (Border et al. 2022).

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Ultrasonic detection of bats varies with hardware (Adams et al. 2012, Starbuck et al. 2024, Zamora-Gutierrez et al. 2021). In this study, we collected data using 2 acoustic devices that differ in their technological capabilities, as well as in their potential for public outreach. One device, the Song Meter (model SM4BAT FS; Wildlife Acoustics, Maynard, MA) is optimized for research-quality recording of bat echolocation and employs a high-quality microphone but no visual display. The other, an Echo Meter Touch (1st edition, Wildlife Acoustics), uses a lower quality microphone and is designed for user engagement (i.e., the instrument provides a visual display of sonograms and suggests species identifications contemporaneously).

To evaluate differences in data quality, we used paired acoustic field data over a 7-month period to compare total calls recorded and total species richness, as recorded by each device. Logically, our hypothesis was that data quality (e.g., number of calls per hour, species richness per hour) would be better when using a high-quality microphone. However, we also expected that the lower-quality microphone would be able to track the same broad patterns in bat activity and species richness over time and space, though with lower rates of call detection. We provide here a case-study evaluating both detectors and the trade-offs of using high-quality microphones that do not prioritize user engagement, as opposed to lower-quality microphones that are more user-friendly for participatory sciences.

Field-site Description

In 2022, we collaborated with commercial river guides through a broader participatory science project (Metcalfe et al. 2023) to record bat activity and sample aquatic insects along the Colorado River in Grand Canyon National Park in northern Arizona. The Grand Canyon region is an arid environment with little precipitation (<25 cm/year), though summers are characterized by intense and brief conductive storms (i.e., monsoons). Our sampling spanned a 327-km segment of river between North Canyon, 33 km downstream of Lees Ferry, near the town of Page, and Diamond Creek, on land of the Hualapai Nation, near the town of Peach Springs. In this region, the Colorado River runs roughly east to west and has step-pool morphology. The average river surface slope throughout the study area is 0.0015 but is punctuated by large rapids, where the gradient exceeds 0.01 (Magirl et al. 2008). This section of river runs through the center of Grand Canyon National Park, where the river cuts as deep as 1.8 km below the canyon rims. The distance separating the north and south rims of the Grand Canyon ranges from 183 m in Marble Canyon, which is at the eastern end of our study area, to 29 km at the Bright Angel fault, which runs perpendicular to the river, about 142 km downstream of Lees Ferry. The river itself ranges in width from 20 to 407 m along our study area and has no canopy cover (Magirl et al. 2008).

Methods

We simultaneously used both models of detector to record bats. The Song Meter was paired with an ultrasonic microphone (SMM-U2, Wildlife Acoustics), and the Echo Meter Touch was paired with a handheld tablet (iPad mini-4, software version 13.3.1, Apple, Cupertino, CA; hereafter "Echo Meter Touch"). We trained 4 commercial river guides to use both detectors through in-person meetings before their river trips launched. Trip lengths ranged from 4 to 18 nights and included both motorized and non-motorized travel. We issued each of the guides a set of equipment that they used throughout the project.

On each night of their trip, participants initiated recording within 1 h of sunset; they were instructed to record for 1 h, although actual sampling duration ranged from 34 to 122 min. The microphone of the Song Meter was supported 40 cm off the ground by a small tripod and pointed directly upwards. Participants were allowed to move the Echo Meter Touch and tablet around camp for outreach purposes, though most deployments were ultimately stationary, with the microphone angled toward the river and within 9 m of its edge. Song Meters used the following settings: gain, 12 dB; sampling rate, 256 kHz; minimum duration, 1.5 msec; maximum duration, none; minimum triggering frequency, 16 kHz; trigger level, 12 dB; trigger window, 3 sec; and maximum length, 15 sec. Echo Meter Touch used the following settings: audio division rate, 1/20; trigger window, 3 sec; trigger sensitivity, medium; and sensitivity level, "balance".

We divided all recordings into 6-sec duration files in waveform audio format (i.e., wav files) and classified them to species using Kaleidoscope Pro automated identification software (version 5.5.0; Wildlife Acoustics 2023). To test the accuracy of the automated species identifications, we further reviewed a subset of recordings from each sampling night. This subset was chosen to include representative verification recordings of each species reported in Kaleidoscope. Verification recordings were processed using the Sonobatch module of the automated identification software Sonobat 30 (Sonobat 2024) with the northern Arizona classifier. We then sorted the files according to species identity and confidence level expressed by Sonobat on each night. We reviewed files in order of confidence until we identified a recording as being produced by a particular species. We also reviewed species identifications suggested by Kaleidoscope. Multiple recordings were verified for rare species, to ensure actual detection (Table 1).

In addition to recording bats, river guides sampled insects using light traps via an extant monitoring program (Kennedy et al. 2016; Metcalfe et al. 2022, 2023; pictured in background of Fig. 1a). Light-trapping data were incorporated into statistical models of total bat activity to compare the 2 detectors. At each camp, river guides set out light traps within 3 m of the river's edge concurrently with bat detectors. After 1 h, collectors turned off the light trap and transferred the contents to a labeled 250-ml plastic bottle. Samples were processed and archived at the U.S. Geological Survey (USGS) Grand Canyon Monitoring and Research Center in Flagstaff, Arizona. In the laboratory, insects were identified and enumerated by trained USGS technicians using microscopes. Aquatic taxa were identified to family, and terrestrial taxa were identified to order, though some taxa were identified to species (Metcalfe et al. 2025). Insect abundance was calculated as total number of individuals captured per hour, and samples were only included in analyses if duration of light trapping was between 45 and 90 min.

We calculated bat species richness as total number of species per sampling event using the R package Vegan (version 2.6-4; Oksanen et al. 2022), and we calculated activity as the total number of calls per hour. We used paired t-tests to compare mean species richness and total activity between the 2 acoustic sampling methods. We used a generalized linear mixed modeling approach with a negative binomial distribution to analyze patterns of total bat activity for each acoustic sampling method. Our response variable was the total count of bat recordings during each sampling event, offset by the log of sampling duration to account for variation in sampling effort. We used collector identity (name of river guide) as a random effect. Based on models of Echo Meter Touch data described in Metcalfe et al. (2023), we considered month, sampling site (number of km downstream from Glen Canyon Dam), and 3 categories of prey (all aquatic insects, all terrestrial insects, and aquatic flies [order Diptera]) as fixed effects. We scaled and centered all continuous covariates, by subtracting the mean and dividing by the standard deviation. We fit models to data using the R package brms (Bürkner 2017), which fits Bayesian models via Hamiltonian Monte Carlo and No-U-Turn sampler (Hoffman and Gelman 2014) and implemented in Stan (Carpenter et al. 2017). Models for both sampling

Table 1. Bat species identified from acoustic files recorded with Song Meter and Echo Meter Touch and identified using auto-identification software in Kaleidoscope (KS). All species were verified to occur with Sonobat, except Underwood's Bonneted Bat and the Western Yellow Bat. Number of nights detected (ND) are reported overall and for each detector. Species are listed in order of decreasing number of total nights detected.

		Echo Meter Touch			Song Meter 4		
Species	ND Total	KS	Verified		KS	Verified	
		n	*n*	ND	*n*	*n*	ND
Unidentified bat	48	2186		48	3627	0	48
Parastrellus hesperus (H. Allen) (Canyon Bat)	48	2097	163	47	7876	127	46
Myotis californicus (Audubon and Bachman) (California Myotis)	45	265	78	41	2058	60	41
Tadarida brasiliensis (I. Geoffroy) (Mexican Free-tailed Bat)	39	116	77	34	468	68	35
Myotis yumanensis (H. Allen) (Yuma Myotis)	32	448	27	17	1078	40	30
Nyctinomops macrotis (Gray) (Big Free-tailed Bat)	18	0	70	13	177	69	14
Nyctinomops femorosaccus (Merriam) (Pocketed Free-tailed Bat)	14	0	22	8	46	73	13
Eumops perotis (Schinz) (Greater Bonneted Bat)	12	96	56	8	50	39	6
Lasionycteris noctivagans (Le Conte) (Silver-haired Bat)	10	104	6	3	107	10	7
Myotis lucifugus (Le Conte) (Little Brown Bat)	9	1	3	3	0	10	7
Eptescius fuscus (Palisot de Beauvois) (Big Brown Bat)	7	30	10	4	277	4	4
Antrozous pallidus (Le Conte) (Pallid Bat)	6	7	3	3	40	7	4
Corynorhinus townsendii (Cooper) (Townsend's Big-eared Bat)	4	1	3	2	3	4	3
Lasiurus cinereus (Palisot de Beauvois) (Hoary Bat)	4	62	5	3	44	5	3
Myotis ciliolabrum (Merriam) (Western Small-footed Myotis)	4	8	3	3	78	2	2
Euderma maculatum (J.A. Allen) (Spotted Bat)	2	7	1	1	15	2	1
Idionycteris phyllotis (G.M. Allen) (Allen's Big-eared Bat)	1	0	0	0	0	1	1
Lasiurus frantzii (Peters) (Western Red Bat)	1	197	0	0	556	1	1
Myotis thysanodes (Miller) (Fringed Myotis)	1	1	0	0	4	5	1
Myotis volans (H. Allen) (Long-legged Myotis)	1	0	0	0	1	1	1
Eumops underwoodi Goodwin (Underwood's Bonneted Bat)	0	0	0	0	40	0	2
Lasiurus xanthinus (Thomas) (Western Yellow Bat)	0	0	0	0	8	0	1

methods used Bayesian priors that we extracted from the model of total bat activity for 1428 sampling events with Echo Meter Touch (Metcalfe et al. 2023; Students *t* distribution, with df = 3, $\mu = 4.98$, $\Sigma = 2.5$). For model selection, we incorporated a forward stepwise approach and used the "leave-one-out cross-validation information criterion" (looic) for model comparison, using loo (Vehtari et al. 2017). To visualize bat activity in relation to date and river kilometer, we generated locally estimated scatterplot smoothing (LOESS) curves with the geom smooth () function within ggplot2 (Wickham 2011). We included date and river kilometer as fixed effects in the smoothing model, using the standard smoothing parameter (span = 0.75).

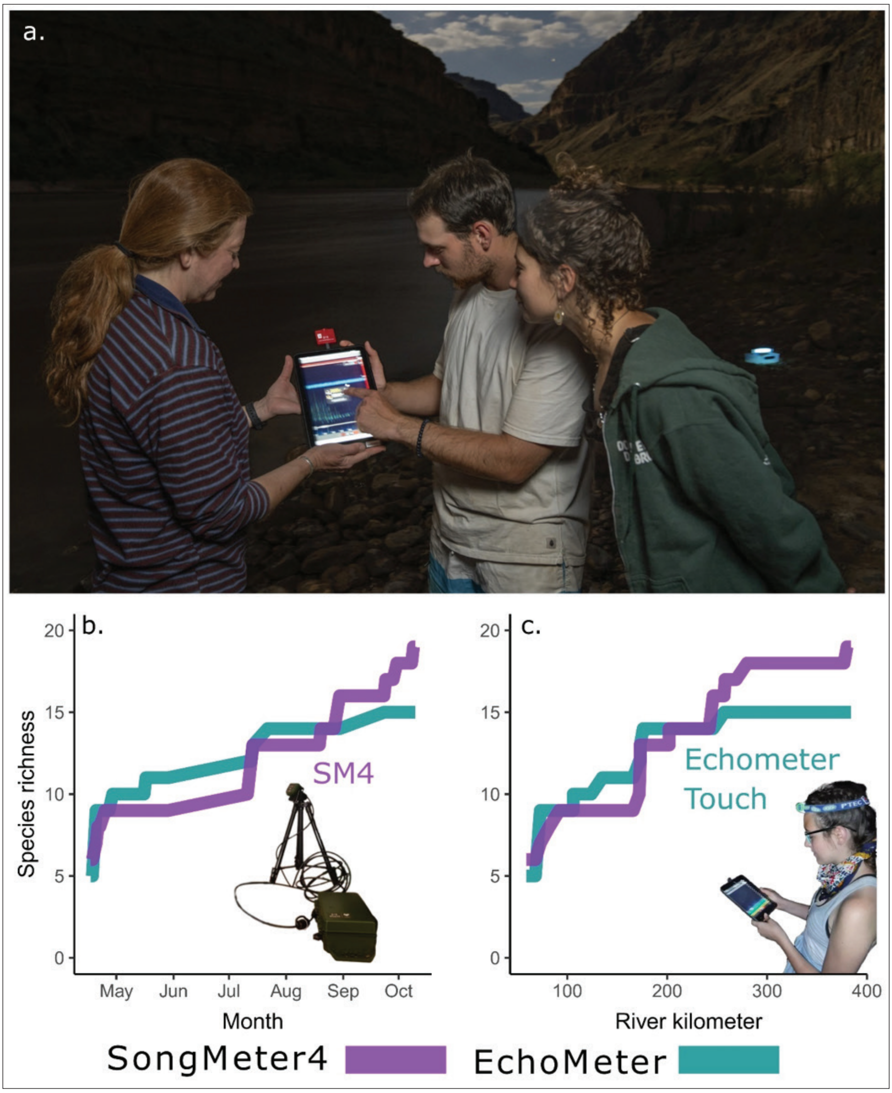

Figure 1. Echo Meter Touch microphones, paired with a tablet, engage river guides in actively observing live bat acoustics (a) but do not cumulatively record as many species of bats as Song Meter microphones over time (b) or space (c). River kilometer = distance downstream from Glen Canyon Dam). During 48 paired sampling events between April and October 2022, we recorded 4 species with the Song Meter that were not detected with the Echo Meter Touch. Photo © David Herasimtschuk/ Freshwaters Illustrated.

Results

River guides recorded bats using both acoustic detectors in parallel with insect sampling for about 1 h at dusk on 48 nights between 17 April and 10 October 2022. Fifteen species were recorded using Echo Meter Touch, with 13 detected by auto-identification and 2 added via visual review. Nineteen species were recorded using the Song Meter, with 17 detected by auto-identification and 2 added during the verification process (Table 1). While more species were documented using the Song Meter than the Echo Meter Touch, the 8 most common species were initially detected by both detectors equally over time and space (Table 1; Fig. 1). Late summer and early fall recording with the Song Meter led to higher detection rates of less common species, compared to early season sampling (Fig. 1b), especially in the western canyon (Fig. 1c).

We recorded significantly more bat activity (passes/h) using the Song Meter than the Echo Meter Touch (mean paired difference of 231.3 more recordings per hour; $t = 8.27$, $P < 0.001$; Fig. 2). Mean overall bat activity per hour was 301.6 ± 181.9 (*SD*) with the Song Meter and 113.1 ± 66.7 with the Echo Meter Touch. Data quality was higher with the Song Meter than with the Echo Meter Touch, as evidenced by the ability of Kaleidoscope to auto-identify a species (as opposed to a "no identification") on 78% of calls with the Song Meter, compared to 61% of those recorded with Echo Meter Touch.

Four species were detected using the Song Meter that were not recorded with the Echo Meter Touch: Allen's Big-eared Bat, Western Red Bat, Fringed Myotis, and Long-legged Myotis (Table 1). However, the total number of species recorded per hour did not vary significantly between detectors ($t = 2.4$, $P = 0.02$). Mean species richness per hour was 4.6 ± 2.2 with the Song Meter and 3.9 ± 1.5 with the Echo Meter Touch. Species richness per hour increased in the fall when measured with the Song Meter, but not significantly with the Echo Meter Touch (Fig. 2c).

Using light traps, community scientists caught an average of 1421 insects per hour ($n = 70{,}501$). Most insects caught in light traps were emergent aquatic insects (winged adult insects that have aquatic juvenile life stages), with 2.2 times more aquatic insects than terrestrial insects. The most common aquatic insects captured were micro-caddisflies (Trichoptera, Hydroptilidae, $n = 31{,}447$), non-biting midges (Diptera, Chironomidae, n = 16,356), and fungus gnats (Diptera, Sciaroidea, $n = 12{,}537$). Moths were the most abundant terrestrial insect captured in light traps (Lepidoptera, $n = 5329$) and were predominantly Cisthene angelus (Dyar) (Angel Lichen Moths) ($n = 3905$). Other common terrestrial insects were rove beetles (Coleoptera, Staphylinidae, $n = 1344$) and muscoid flies (Diptera, Muscomorpha, $n = 1284$). The dominant taxa collected in this study are consistent with larger published datasets resulting from light trapping in the Grand Canyon (Kennedy et al. 2016, Metcalfe et al. 2023) and are further detailed in (Metcalfe et al. 2025).

For both acoustic detection methods, the best Bayesian model for predicting bat activity was a null base model with collector as a random effect (see Supplemental File Table S1, available online at https://www.eaglehill.us/NABRonline/suppl-files/nabr-010m-Metcalfe-s1.pdf). Adding fixed effects to the model did not significantly improve model performance. Adding aquatic flies (Diptera) as a fixed effect to the models for Song Meter decreased the overall looic, but as an uninformative parameter (Arnold 2010). As a post hoc analysis, we also fit simpler linear models to compare the relationship between catch rates of aquatic flies and total bat activity recorded with each detector. Previous modeling efforts have found aquatic flies to be the best predictors of total bat activity along the Colorado River in the Grand Canyon (Metcalfe et al. 2023). Simple linear models indicate a significant positive relationship between catch rates of aquatic flies and bat activity using a Song Meter (P =

0.03) but not with an Echo Meter Touch ($P = 0.93$; see Supplemental File Fig. S1, available online at https://www.eaglehill.us/NABRonline/suppl-files/nabr-010m-Metcalfe-s2.pdf).

Discussion

We found that Song Meters recorded nearly 3 times more bat passes per hour and detected more species overall than the Echo Meter Touch. However, in comparing models of total bat activity, we found that data collected with either detector supported the same final

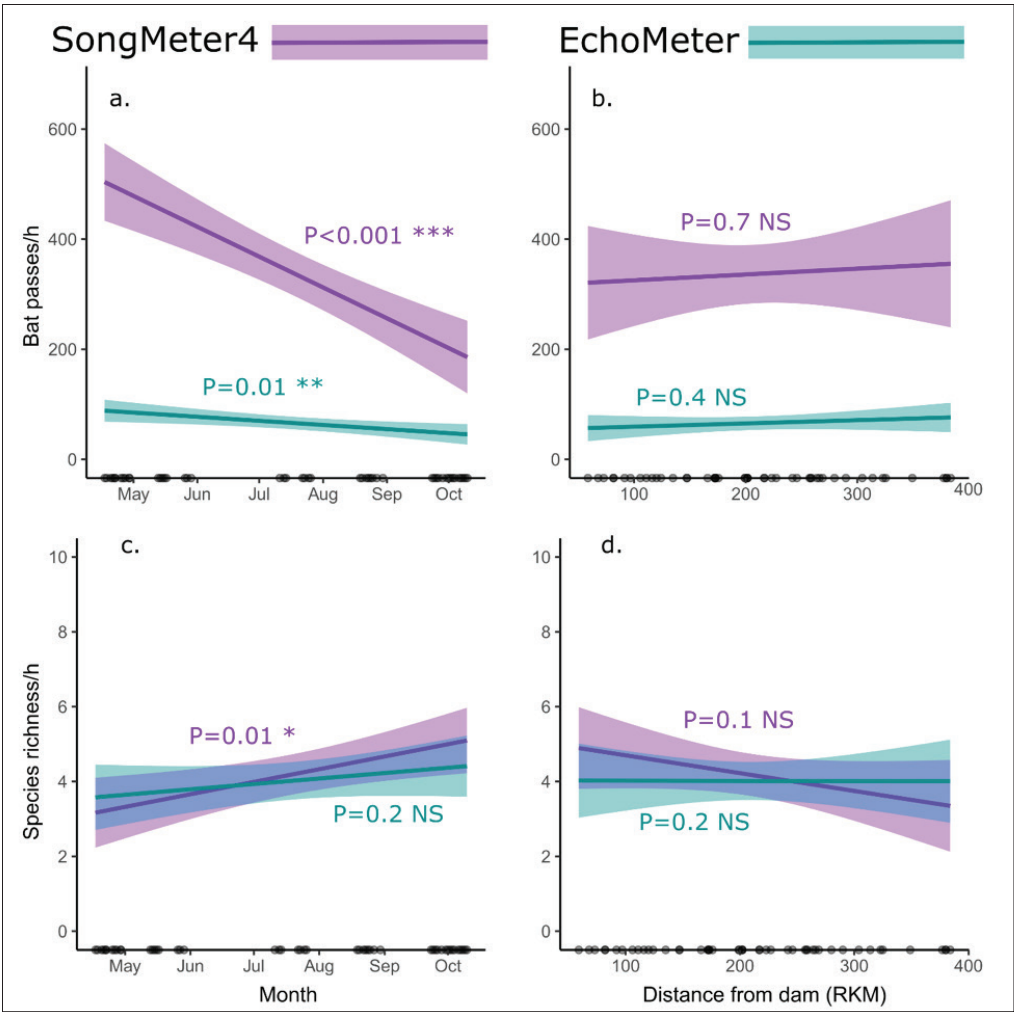

Figure 2. Using a paired sampling protocol on 48 nights, we recorded higher bat activity over time (a) and space (b) using Song Meter detectors than using Echo Meters. On average, the Song Meter detected 320 more passes per hour than the Echo Meter Touch. Data from both detectors showed a decrease in bat activity from spring to fall but no significant variation along the Colorado River. The Song Meter, but not the Echo Meter Touch, detected an increase in species richness in the fall (c). Neither detector found significant spatial variation in species richness per hour (d), and overall rates of species richness per hour did not vary significantly between the 2 detectors ($P = 0.5$). Points along x axes show distribution of sampling events, which occurred for approximately 1 h at dusk. Shaded bands represent 95% confidence intervals.

null model. In linear models of the 2 methods fit to LOESS curves, both devices detected a decrease in bat passes per hour from May to August, but only the data from the Song Meter resulted in significant relationships between species richness recorded over time and between bat activity and prey availability. Data from neither detector indicated a significant relationship between bat activity or species richness and distance along the river.

We found that species richness per hour increased even as bat activity decreased over the course of the season. This likely results from high activity levels by common species early in the season and detections of species engaged in seasonal movements later in the season (Weller and Lee 2007). Notably, these trends all relate only to our dusk sampling period. While dusk is an active time for many bat species, patterns in richness and activity differ throughout an entire night. Indeed, *Myotis spp.* and Canyon Bats along the Colorado River even differ in their activity within the hour after sunset. Myotis activity increases later in the evening whereas canyon bat activity peaks early in the evening (Metcalfe et al. 2023).

Hardware was not the only difference in our 2 sampling methods. Microphone orientation and deployment height influence the total number of calls detected by as much as 70% (Weller et al. 2002). Our close-to-the-ground deployment of the Song Meter on a tripod was intended to provide ease of use for participants, consistency in deployments, and to prevent wind from knocking over equipment. However, our deployment of the Song Meter would have been improved by increased microphone height (Weller et al. 2002). Additionally, stable deployment conditions likely improved the detection rate of the Song Meter devices relative to Echo Meter Touch detectors. River guides and their clients were encouraged to hold and interact with the Echo Meter Touch during evening sampling, which meant inconsistent positioning and microphone orientation. Providing our participants with a stand that oriented the microphone upwards when the tablet was not being handled would likely have resulted in greater consistency and higher quality recordings from the Echo Meter Touch.

While the Echo Meter Touch yields lower quality and quantity data than a Song Meter, data recorded with an Echo Meter Touch is able to track spatial and temporal trends and can be incorporated in meaningful models of bat activity. Mixed-effects models, such as the ones employed in our comparison, are more reliable with large samples (Johnson et al. 2015). In our small subset of 48 paired nights, none of the fixed effects were important predictors of total bat activity. However, in a larger sampling effort involving only Echo Meter Touch, Metcalfe et al., (2023) reported that aquatic flies were important predictors of bat activity in the Grand Canyon. In a post hoc analysis using simplified linear models, we also found a significant positive relationship between aquatic flies and bat activity using Song Meter but not with Echo Meter Touch (Fig. S1). Because higher quality microphones are able to detect more bats than lower quality microphones within the same space and time, data collected from higher quality microphones can provide greater effective sample size and, therefore, statistical power in modeling efforts (Johnson et al. 2015). Studies using lower quality detectors require more sampling events to achieve equivalent statistical power, compared to studies using higher quality detectors.

Technology in the form of bat detectors, microphones, and identification programs is improving rapidly. Advances in software such as the implementation of artificial neural network architecture (i.e., "deep learning"; Khalighifar et al. 2022) may increasingly compensate for lower quality hardware, especially with large datasets. However, any auto-identification software will have a higher rate of success when fed high-quality recordings rather than those produced by a lesser quality microphone or collected in noisy or otherwise non-ideal conditions. Bat detectors that incorporate user-friendly interfaces, such as the Echo Meter Touch, are particularly accommodating for the development of new approaches to research and monitoring that involve participatory science.

Detector choice is critical when designing an acoustic study. Starbuck et al., (2024) compared a low-cost detector (AudioMoth) to a high-cost unit (Anabat Swift) and found the low-cost detector recorded lower-quality calls overall, but with key nuances. The less expensive instrument excelled at capturing low-frequency calls, while the high-cost detector recorded a higher proportion of Myotis calls. Both detectors performed equally well for mid-frequency calls. The results of Starbuck et al., (2024) highlight the importance of considering target taxa and frequency ranges when selecting detectors. Similarly, in a comparison of 5 common detectors, Adams et al., (2012) discovered significant variation among detectors, but also reported that distance from source (i.e., the bat) and frequency characteristics were the most important determinants of call quality, regardless of detector choice. Overall, research that is investigating inter-specific questions or targeting high-frequency taxa would benefit from investing in higher quality detectors (Starbuck et al. 2024). Researchers interested in broad-scale ecological questions such as total bat activity, regardless of species (e.g., Metcalfe et al. 2023), may benefit by prioritizing the quantity, rather than quality, of detectors deployed in a study area. Choosing detectors with user-friendly interfaces may further increase sampling effort and therefore data quantity through incorporation with participatory science methods.

Regardless of detector type, human review is a critical component of acoustic data analyses (Zamora-Gutierrez et al. 2021). In this study, we rejected the auto-identification of 2 species (Western Red Bat and Fringed Myotis) and added 2 species (Pocketed Free-tailed Bat and Big Free-tailed Bat) that were absent from the auto-identifications produced from Echo Meter Touch recordings. Similarly, verification of Song Meter data negated records of 2 species (Underwood's Bonneted Bat and Western Yellow Bat) and added 2 otherwise undetected species (Allen's Big-eared Bat and Little Brown Bat). Both detectors, when paired with auto-identification software, resulted in hundreds of records of Western Red Bats, but we found only 1 recording from the Song Meter that we confirmed as that species; the remainder were misidentified Canyon Bats. Failing to conduct expert verification of automatic acoustic identifications is highly likely to result in misidentified and overlooked species records.

Finally, incorporating participatory sciences into bat research has expanded the geographic scope of bat species detection and is an effective tool for increasing public awareness of bat biology and conservation (Lundberg et al. 2021, Lewanzik et al. 2022, López-Bosch et al. 2023). Informally, our participants reported this project increased their interest in bats. Collector SB said, "I always thought bats were interesting but had never taken the time to learn much about them." When asked if this project got them or their passengers interested in bats, river guides reported, "Very much so" (AS) and "Yes! Youth and adults alike!" (SB). Both river guides whom we talked with in support of this article said that they would continue participating in the project, regardless of which bat monitor we used, but that the interactive components of the Echo Meter Touch engaged considerably more of their rafting passengers. Both river guides emphasized that seeing photographs of bats associated with the live-feed of auto-identifications boosted user engagement, "The passengers really enjoy seeing the pictures of the bat species that are flying overhead pop up" (AS).

Conclusion

Is it necessary for the scientific community to design research and monitoring that generates the highest quality data? Ostensibly, the answer is yes. However, our comparison here demonstrates the answer to this question is context dependent and, in the case of participatory science projects, there are significant trade-offs among data quality, equipment costs, and user interface that must be balanced at the design stage of a project. Ultimately, as with any scientific pursuit, the methods are dependent on the study goals and research questions. A typical participatory science project that employs echolocation monitoring will require 2 components—first, an engaging user experience that provides near real-time species identification, and second, ability to archive high-quality recordings for use in research. Ideally, a single, versatile acoustic tool could address diverse research and outreach needs. Increased adoption of participatory methods in bat research may drive demand for technology that does not require the trade-off that we describe. Prioritizing user engagement, especially when done in combination with large data collection efforts and transparent reporting, has the potential to improve public engagement in biodiversity monitoring.

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Literature Cited

Adams, A.M., M.K. Jantzen, R.M. Hamilton, and M.B. Fenton. 2012. Do you hear what I hear? Implications of detector selection for acoustic monitoring of bats. Methods in Ecology and Evolution 3:992–998.

Arnold, T.W. 2010. Uninformative parameters and model selection using Akaike's Information Criterion. Journal of Wildlife Management 74:1175–1178.

Border, J.A., S. Gillings, T. Reynolds, G. Neeve, and S.E. Newson. 2022. Can citizen science provide a solution for bat friendly planning? Landscape and Urban Planning 223:104402.

Bürkner, P.C. 2017. brms: An R package for Bayesian multilevel models using Stan. Journal of Statistical Software 80:1–28.

Carpenter, B., A. Gelman, M.D. Hoffman, D. Lee, B. Goodrich, M. Betancourt, M.A. Brubaker, G. Guo, P. Li, and A. Riddell. 2017. Stan: A probabilistic programming language. Journal of Statistical Software 76:1–32.

Frick, W.F., T. Kingston, and J. Flanders. 2020. A review of the major threats and challenges to global bat conservation. Annals of the New York Academy of Sciences 1469:5–25.

Hoffman, M.D., and A. Gelman. 2014. The No-U-Turn Sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. Journal of Machine Learning Research 15:1593–1623.

Johnson, P.C.D., S.J.E. Barry, H.M. Ferguson, and P. Müller. 2015. Power analysis for generalized linear mixed models in ecology and evolution. Methods in Ecology and Evolution 6:133–142.

Kennedy, T.A., J.D. Muehlbauer, C.B. Yackulic, D.A. Lytle, S.W. Miller, K.L. Dibble, E.W. Kortenhoeven, A.N. Metcalfe, and C.V. Baxter. 2016. Flow management for hydropower extirpates aquatic insects, undermining river food webs. BioScience 66:561–575.

Khalighifar, A., B.S. Gotthold, E. Adams, J. Barnett, L.O. Beard, E.R. Britzke, P.A. Burger, K. Chase, Z. Cordes, P.M. Cryan, E. Ferrall, C.T. Fill, S.E. Gibson, G.S. Haulton, K.M. Irvine, L.S. Katz, W.L. Kendall, C.A. Long, O. Mac Aodha, T. McBurney, S. McCarthy, M.W. McKown, J. O'Keefe, L.D. Patterson, K.A. Pitcher, M. Rustand, J.L. Segers, K. Seppanen, J.L. Siemers, C. Stratton, B.R. Straw, T.J. Weller, and B.E. Reichert. 2022. NABat ML: Utilizing deep learning to enable crowdsourced development of automated, scalable solutions for documenting North American bat populations. Journal of Applied Ecology 59:2849–2862.

Lewanzik, D., T.M. Straka, J. Lorenz, L. Marggraf, S. Voigt-Heucke, A. Schumann, M. Brandt, and C.C. Voigt. 2022. Evaluating the potential of urban areas for bat conservation with citizen science data. Environmental Pollution 297:118785.

López-Bosch, D., E. Blanch, F. Páramo, C. Flaquer-Sánchez, and A. López-Baucells. 2023. What you hear may not be what you see: Potential of citizen science methods to use bats as riverine forest quality indicators. River Research and Applications 40:92–106.

Lundberg, P., M.B. Meierhofer, V. Vasko, M. Suutari, A. Ojala, A. Vainio, and T.M. Lilley. 2021. Next-generation ultrasonic recorders facilitate effective bat activity and distribution monitoring by citizen scientists. Ecosphere 12:e03866.

Magirl, C.S., M.J. Breedlove, R.H. Webb, and P.G. Griffiths. 2008. Modeling water-surface elevations and virtual shorelines for the Colorado River in Grand Canyon, Arizona. US Geological Survey, Scientific Investigations Report 2008-5075:1–32.

Metcalfe, A.N., C.A. Fritzinger, T.J. Weller, M.J. Dodrill, J.D. Muehlbauer, C.B. Yackulic, P.B. Holton, C.M. Szydlo, L.E. Durning, J.B. Sankey, and T.A. Kennedy. 2023. Insectivorous bat foraging tracks the availability of aquatic flies (Diptera). Journal of Wildlife Management 87:e22414.

Metcalfe, A.N., T.A. Kennedy, G.A. Mendez, and J.D. Muehlbauer. 2022. Applied citizen science in freshwater research. Wiley Interdisciplinary Reviews 9:e1578.

Metcalfe, A.N., T.J. Weller, and T.A. Kennedy. 2025. Bat echolocation data recorded using Song Meter SM4 and Echo Meter Touch paired with insect prey availability, Grand Canyon National Park, Arizona, 2022. US Geological Survey data release February 2025. Available online at https://doi.org/10.5066/P1MCPC4T. Accessed 22 January 2025.

Oksanen, J., Blanchet, F. G., Friendly, M., Kindt, R., Legendre, P., McGlinn, D., Minchin, P. R., O'Hara, R. B., Simpson, G. L., Solymos, P., Stevens, M. H. H., Szoecs, E., and H. Wagner. 2022. vegan: Community Ecology Package. Release 2.6-4, October 2022. Available online at http://CRAN.R-project.org/package=vegan. Accessed 22 January 2025.

Perea, S., J.A. Yearout, E.A. Ferrall, K.M. Morris, J.T. Pynne, and S.B. Castleberry. 2022. Seven-year impact of white-nose syndrome on Tri-colored Bat (Perimyotis subflavus) populations in Georgia, USA. Endangered Species Research 48:99–106.

Schorr, R.A., M.D. Matthews, and B.A. Hoover. 2022. Finding bat roosts along cliffs: Using rock climbing surveys to identify roosting habitat of bats. Acta Chiropterologica 24:167–176.

Sonobat. 2024. Sonobat 30. Available online at https://sonobat.com. Accessed 23 January 2025.

Starbuck, C.A., L.M. DeSchepper, M.L. Hoggatt, and J.M. O'Keefe. 2024. Tradeoffs in sound quality and cost for passive acoustic devices. Bioacoustics 33:58–73.

Vehtari, A., A. Gelman, and J. Gabry. 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and Computing 27:1413–1432.

Weller, T., and C.J. Zabel. 2002. Variation in bat detections due to detector orientation in forest. Wildlife Society Bulletin 30:922–930.

Weller, T.J., and D.C. Lee. 2007. Mist net effort required to inventory a forest bat species assemblage. Journal of Wildlife Management 71:251–257.

Wickham, H. 2011. ggplot2. Wiley Interdisciplinary Reviews: Computational Statistics 3:180–185.

Zamora-Gutierrez, V., M.C. MacSwiney G., S. Martínez Balvanera, and E. Robredo Esquivelzeta. 2021. The evolution of acoustic methods for the study of bats. Pp. 43–59, In B.K. Lim, M.B.

Fenton, R.M. Brigham, S. Mistry, A. Kurta, E.H. Gillam, A. Russell, and J. Ortega (Eds.). 50 Years of Bat Research: Foundations and New Frontiers. Springer International, Cham Switzerland. 374 pp.

Wildlife Acoustics. 2023. Kaleidoscope Pro. Release 5.5.0, March 2023. Available online at http://www.wildlifeacoustics.com/release-notes/kaleidoscope-pro. Accessed 22 January 2025.