

Comparing field performance of ultrasonic microphones to facilitate analysis of long-term acoustic bat monitoring data

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Abstract

Passive acoustic monitoring is a standard technique for studying bat ecology and behavior. However, an issue that has received little attention is how to appropriately analyze data within a long-term acoustic monitoring dataset when the equipment has been replaced and updated. Equipment changes are often inevitable, especially for microphones, which need to be replaced regularly due to extended weather exposure and associated reductions in recording quality. We compared 2 ultrasonic microphone models (Wildlife Acoustics SMM-U1 and SMM-U2) by deploying them side-by-side with the same acoustic detector unit. We tested 9 or 10 microphones per model in field deployments lasting an average of 9 nights. We compared triggering frequency, species classification, detection rates, and echolocation call parameters (as indicators of signal quality) from both microphones. The vast majority (97%) of our 25,949 paired recordings were captured simultaneously by both microphones. Yet, the SMM-U2 outperformed the SMM-U1 in terms of proportion of files classifiable to the species level (70% versus 61%), rate of bat detections per night (1–6.5 more detections per night depending on species), and recording quality. Based on our results, we propose a correction factor to facilitate direct comparison of datasets collected with these 2 different microphones. Our study will assist bat

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researchers in selecting appropriate equipment and accounting for potential biases in long-term acoustic monitoring programs.

KEYWORDS

acoustic detector, bats, correction factor, echolocation, passive acoustic monitoring, ultrasonic microphone

Passive acoustic monitoring is a widely used method for studying bats and other cryptic wildlife. Passive monitoring is efficient in both time and cost, less invasive than capturing and handling animals, and effective for documenting species presence (Coleman et al. 2014, Appel et al. 2021). However, there are technical decisions researchers must make that can influence the results they will obtain from passive acoustic monitoring. Choice of detector (Adams et al. 2012), detector settings (Fraser et al. 2020), microphone (Darras et al. 2020), equipment placement (Britzke et al. 2010), and analysis software (Lemen et al. 2015) can all affect outcomes.

At least 10 models of acoustic bat detectors are currently available, differing widely in their technical specifications. Previous studies have compared different brands and models of detectors, identifying significant differences in the number of bat echolocation calls recorded, detection probabilities, and species richness (Adams et al. 2012, Kaiser and O'Keefe 2015, Perea and Tena 2020, Phinney 2020, Kunberger and Long 2023). Because each brand of detector is paired with its own proprietary microphone, one cannot determine whether differing outcomes are a result of the detector's capabilities, user-selected detector settings, microphone specifications, or a combination of all three.

Here, we focus on comparing microphones while holding detector-related factors constant. A microphone's signal-to-noise ratio, sensitivity, and directionality contribute to determining the size and shape of the effective detection space (Ratcliffe and Jakobsen 2018, Darras et al. 2020) and the quality and quantity of recordings (Darras et al. 2016). Understanding these technical differences is essential for 2 reasons. First, researchers will want to select equipment that best suits their specific research objectives. For example, if the target species is a bat that echolocates in the high-frequency range, it is important to consider that some microphones are more effective than others at picking up high-frequency sounds (Kaiser and O'Keefe 2015). Second, datasets collected using different equipment may not be directly comparable, necessitating calibration between equipment systems (Loeb et al. 2015). The lack of comparability among different equipment types is an issue of particular concern for long-term monitoring programs because microphones will eventually need to be replaced as they are lost or damaged. Microphones with more cumulative field deployment time have lower sensitivity, reducing the effective detection area and species detection probability (Turgeon et al. 2017). Replacing worn microphones is therefore critical for maintaining data quality, but with continually changing technology it is not always feasible to buy the same microphone model that was originally used, and switching microphones could lead to bias (Rempel et al. 2013).

There is little work focused specifically on ultrasonic microphone comparisons. Darras et al. (2020) tested 12 different microphones; however, they did not include 2 widely used, commercially available models: the SMM-U1 and SMM-U2 (Wildlife Acoustics Inc., Maynard, MA, USA). Phinney (2020) developed an equipment correction factor to compare older data from Anabat detectors (Titley Scientific) to newer data from Song Meters (Wildlife Acoustics Inc.). Phinney's (2020) study utilized both SMM-U1 and SMM-U2 microphones on Song Meters, and noted that their specifications were different, but did not directly compare their performance.

The first objective for our study was to conduct side-by-side comparisons of 2 commonly used ultrasonic microphone models, the SMM-U1 and SMM-U2, to determine if they provide equivalent results when sampling bat acoustic activity while connected to the same individual bat detector unit, thus avoiding all potential bias from detector effects. The SMM-U2 is described by the manufacturer as having a higher signal-to-noise ratio and greater sensitivity than the older SMM-U1 (Wildlife Acoustics 2022). Improved signal-to-noise ratio and sensitivity should allow the SMM-U2 to record bats that are farther away and to produce recordings that are less noisy and longer in

duration (Wildlife Acoustics 2022). Therefore, we hypothesized that the microphone model will affect recording results, and we predicted that the SMM-U2 would be triggered more frequently and would produce higher-quality recordings, allowing a greater proportion of files to be identified to the species level. Given our initial hypothesis, our second objective was to develop a method for adjusting data (using an additive correction factor) to allow direct comparison of datasets recorded with SMM-U1 and SMM-U2 microphone models.

METHODS

Equipment specifications and field sampling methods

The SMM-U1 and SMM-U2 microphone models differ in their technical specifications, including signal-to-noise ratio, sensitivity, intrinsic noise, and directional response pattern (Table 1). The range of ultrasonic frequencies we are interested in is 10 to 120 kHz, representing the echolocation frequencies of bats in the Great Lakes region of the United States. Over most of the frequency range, the SMM-U2 has a higher signal-to-noise ratio, improved sensitivity, and less intrinsic noise than the SMM-U1, based on plots on the manufacturer's website (Wildlife Acoustics 2023; Wildlife Acoustics declined to share the data underlying their plots). The SMM-U1 is an omnidirectional microphone (detecting sounds similarly from all directions) while the SMM-U2 is a cardioid microphone (detecting sounds better from the front and sides than from the back; Wildlife Acoustics 2022). Both microphones are constructed with integrated weatherproofing. We fitted SMM-U1 microphones with foam windscreens for additional protection, but because the SMM-U2 weatherproofing is more robust, we did not add a foam windscreen. The SMM-U1 microphones we tested had been used previously for several weeks during 1 to 6 ($\bar{x} = 4$) summer seasons; the SMM-U2 microphones were new. Prior to deployment, we calibrated each microphone by testing it against an ultrasonic calibration device that produces a steady 40 kHz tone and noting whether the observed decibels relative to voltage (dBV) fell within the acceptable range, according to the manufacturer's guidance (Wildlife Acoustics 2022).

To isolate the effects of microphone type and avoid potential bias related to detector type or variation between individual detector units, we connected both microphone models to the same individual detector unit. We deployed one Song Meter SM3BAT (Wildlife Acoustics Inc., Maynard, MA, USA) acoustic bat detector equipped with one SMM-U1 and one SMM-U2 microphone at each sample site. We tested a total of 10 SMM-U1 microphones and 9 SMM-U2 microphones. We deployed each microphone once, except one SMM-U2 which was used twice. The SM3BAT has 2 microphone ports that operate simultaneously, with each microphone recording on its own channel. Each time a sound triggers a microphone, no matter which microphone is triggered first, both microphones start

TABLE 1 Technical specifications of Wildlife Acoustics SMM-U1 and SMM-U2 microphones within the frequency range of 10–120 kHz. Numerical values were estimated based on plots from the manufacturer's publicly available website (Wildlife Acoustics 2023).

Microphone feature	Microphone model	
	SMM-U1	SMM-U2
Signal-to-noise ratio	79 to 102 dBFS/√Hz	88 to 113 dBFS/√Hz
Sensitivity at 0 dB gain	−5 to −34 dBFS	−7 to −35 dBFS
Intrinsic noise at 0 dB gain	−100 to −115 dBFS/√Hz	−108 to −126 dBFS/√Hz
Directional response pattern	Omnidirectional	Cardioid
Weatherproofing	Foam windscreen attached	No additional weatherproofing

recording simultaneously (Wildlife Acoustics 2018). Thus, for each trigger event, the result is a single stereo recording containing 2 channels of audio from the 2 microphones. We programmed the SM3BAT units to record in full spectrum format with a sample rate of 256 kHz and with files saved in .WAV format.

We sampled 10 sites located in Minnesota, Wisconsin, Indiana, and Michigan (Tables S1, S2, available in Supporting Information). Sites were located at national parks, a city park, and on private residential property. To control for the potential effects of microphone height, orientation, and environmental clutter (Weller and Zabel 2002, Freeze et al. 2021), we mounted the 2 microphones adjacent to each other at approximately the same height above the ground and oriented them in the same direction (Figure S1, available in Supporting Information). To prevent rain from directly entering the microphone element, we oriented microphones either horizontal (pointed parallel to the ground) or pointed slightly downward from horizontal. We aimed microphones toward open habitat types such as a meadow, lawn, forest clearing, or trail corridor. We sampled each site for at least 7 nights during July–August 2021, with detectors active from 18:00 to 08:00. For each deployment, we recorded immediate local habitat, surrounding habitat within 100 meters, microphone height, microphone orientation, and distance between the 2 microphones. We also estimated the distance from the microphones to the nearest clutter (vegetation, water, or building) and the percent clutter within a 2-meter radius of the microphone and within a 5-meter radius of the microphone.

Acoustic file processing

We used 2 features of Kaleidoscope Pro software (Version 5.4.2, Wildlife Acoustics Inc., Maynard, MA, USA) to process our acoustic files. First, we split the original stereo files (containing audio from both channels) into 2 separate mono files (containing data from only one channel each). The result is one mono audio file per trigger event per microphone. At the time of recording, the SM3BAT automatically assigns a filename prefix specifying which microphone channel was triggered first, or if both were triggered at the same time (Wildlife Acoustics 2018). The prefix carries over to the filenames of the mono files. In addition, when splitting the stereo files into mono files, Kaleidoscope Pro automatically adds another filename prefix indicating which microphone channel made the recording.

Second, we classified the split files to species using Kaleidoscope's Bats of North America Classifier Version 5.4.0 with sensitivity set to 0 (Balanced/Neutral). We used Kaleidoscope's default signal detection parameters: 8–120 kHz frequency range, 2–500 ms pulse length, 500 ms maximum intersyllable gap, and minimum of 2 pulses required. For species classification, we allowed the software to consider only bat species whose documented ranges (Kurta 2017) include or are in close proximity to the sample site. Seven species found throughout the Great Lakes region were included for all sample sites: big brown bat (*Eptesicus fuscus*), eastern red bat (*Lasiurus borealis*), hoary bat (*L. cinereus*), silver-haired bat (*Lasionycteris noctivagans*), little brown bat (*Myotis lucifugus*), northern long-eared bat (*M. septentrionalis*), and tricolored bat (*Perimyotis subflavus*). We also included evening bat (*Nycticeius humeralis*; 3 sites) and Indiana bat (*M. sodalis*; 2 sites) for the more southerly sites.

Statistical analysis

We performed all statistical analyses in R (Version 4.1.2; R Core Team 2021). To evaluate recording quality and likelihood of audio files being identifiable, for each microphone type we calculated the proportion of files in 3 categories: classified as a particular species of bat, classified as an unknown bat (NoID), or classified as non-bat noise. We used the chi-square test of independence to assess whether these proportions differed significantly between microphone types ($\alpha = 0.05$). We applied post-hoc comparisons to identify which of the 3 categories had significant differences. Using the proportion of files in the category of interest versus the combined proportion in

the other 2 categories, we ran 3 additional chi-square tests of independence, one for each category. Due to multiple post-hoc comparisons, we applied the Bonferroni correction ($\alpha = 0.0167$). We used the `chisq.test` function in R (R Core Team 2021).

Next, to assess responsiveness to bats or bat-like sounds, we calculated the mean proportions of audio files that were triggered by both microphones at the same time, versus triggered by the SMM-U1 first, versus triggered by the SMM-U2 first. To evaluate detections at the species level, we calculated overall species richness for each microphone type, and for each bat species we assessed whether the 2 microphone models differed significantly in the count of classified files per detector-night. We calculated the difference in species-specific file counts for each night at each site by subtracting the SMM-U1 count from the SMM-U2 count. For each species, we ran a 1-sample Wilcoxon signed-rank test to evaluate whether the difference in file counts was significantly different from 0. The Wilcoxon test calculates a test statistic (V) and an estimate of the pseudomedian, which is a measure of centrality similar to a median. The pseudomedian is defined as the median of the midpoints of the paired observations in the sample (Love 2017). We selected the Wilcoxon signed-rank test because our data were not normally distributed. We used the `wilcox.test` function in R (R Core Team 2021) and applied the Bonferroni correction due to running simultaneous tests for the 9 bat species ($\alpha = 0.0056$).

To understand how audio recordings differed between the 2 microphone types, we assessed 4 echolocation call parameters that are important for species classification: the total number of echolocation pulses detected within the audio file, the average duration of a pulse (milliseconds), and the average minimum and maximum frequencies of a pulse (kHz). Kaleidoscope Pro calculates these parameters during audio file processing. A greater number of echolocation pulses in a file indicates that a more complete echolocation sequence was recorded, as opposed to a truncated sequence. Longer duration, higher maximum frequency, and lower minimum frequency indicate that echolocation pulses were captured more completely, and thus are presumably more easily identifiable compared to fragmented or poor-quality pulses. For each of the 4 parameters, we calculated the mean and standard deviation per species per microphone type. We then used Welch's t-test to assess whether the means of the parameters were significantly different between microphone types, testing each species separately. We chose the Welch's t-test due to the unequal sample sizes and unequal variances in our data. We used the `t.test` function in R (R Core Team 2021) and applied the Bonferroni correction to account for running multiple tests simultaneously ($\alpha = 0.0014$).

Finally, to assess the importance of microphone model in comparison to environmental factors and microphone installation height, we evaluated a set of generalized linear mixed effects models. For our response variable, we used the count of classified files on each night at each site. We tested fixed effects of microphone model, microphone height, distance to nearest clutter, percent clutter, and habitat type. To avoid categorical variable groups containing only a single sample site, we reclassified distance to clutter into 3 distance ranges (0 to 2 meters, 2 to 5 meters, and 10 meters or more) and reclassified habitat into 3 general types (open, forested, and edge). Clutter percentage within a 2-meter radius and within a 5-meter radius were correlated, therefore we retained only the latter as a variable in our models. We used sample site and recording night as random effects with varying intercepts to account for site-specific or night-specific sources of variation that we did not directly measure (e.g., weather conditions). We also used species classification as a random effect with varying intercepts and varying slopes to account for expected differences among species.

We fit a null model, global model, and 15 additional models with different combinations of fixed effects (Table S3, available in Supporting Information). We fit models with the `glmmTMB` package in R (Brooks et al. 2017), using a negative binomial distribution with a log link function. We used the `model.sel` function in the `MuMIn` package (Barton 2020) to compare the fitted models, ranking them by Akaike's Information Criterion corrected for small sample sizes (AIC_c). We considered the best-fitting model to be the most parsimonious model from among those having substantial support, defined here as $\Delta AIC_c < 2$ (Burnham and Anderson 2004). We checked model diagnostics for the best-fitting model using the `DHARMA` package (Hartig 2022). We calculated 95% confidence intervals around the parameter estimates and considered intervals that included 0 to be nonsignificant.

RESULTS

All 19 microphones showed acceptable sensitivities in the pre-deployment calibration. Mean sensitivity of SMM-U1s was -27.1 dBV (SD = 3.0) and mean sensitivity of SMM-U2s was -30.1 dBV (SD = 5.0). We collected acoustic data between July 15 and August 16, 2021, recording a total of 27,880 stereo files. We excluded files from incomplete recording nights and improper microphone connections, leaving 25,949 pairs of mono files to use in our analyses. The average deployment length was 9 nights per site (min-max = 7–26 nights). The microphones were installed an average of 2.6 meters off the ground (min-max = 1–4.6 meters) and the spacing between each pair of microphones averaged 11 cm (min-max = 5–20 cm).

The 2 microphone types did not differ in species richness; both detected 9 species based on automated Kaleidoscope Pro classifications. However, the 2 microphones had significantly different proportions of audio files classified as bat species, unknown bats, and non-bat noise ($\chi^2_{(2)} = 797.8$, $P \leq 0.001$; Figure 1). The proportion of files classified as a bat species was smaller for the SMM-U1 than for the SMM-U2 (60.9% vs. 70.3%, $\chi^2_{(1)} = 513.7$, $P \leq 0.001$). Likewise, the proportion of files classified as an unknown bat was smaller for the SMM-U1 than for the SMM-U2 (8.7% vs. 10.0%, $\chi^2_{(1)} = 25.9$, $P \leq 0.001$). The proportion of files classified as noise was larger for the SMM-U1 than for the SMM-U2 (30.5% vs. 19.7%, $\chi^2_{(1)} = 797.7$, $P \leq 0.001$).

For audio files classified as bats, we found the mean percentage of files initially triggered by both microphones at the same time was 96.8% (SD = 2.49). Only a small percentage of files were initially triggered by the SMM-U1 alone ($\bar{x} = 0.07\%$, SD = 0.12) or by the SMM-U2 alone ($\bar{x} = 3.10\%$, SD = 2.45).

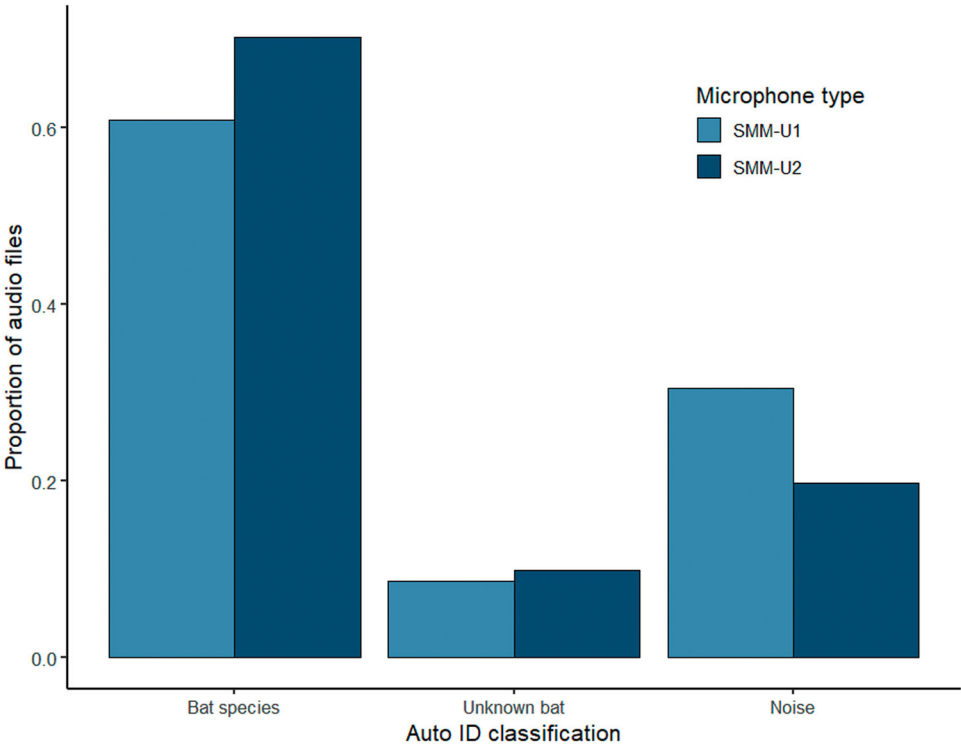


FIGURE 1 Proportion of audio files classified by Kaleidoscope Pro as a specific bat species, as an unknown bat, or as non-bat noise for each ultrasonic microphone model (Wildlife Acoustics SMM-U1 or SMM-U2). Bat acoustic data (sample size of 25,949 paired recordings) were collected from 10 sites in July–August 2021 in Minnesota, Wisconsin, Indiana, and Michigan, USA.

The SMM-U2 had higher file counts per detector-night than the SMM-U1 (Figure 2). The estimated pseudomedian difference in file counts per detector-night was significantly different from 0 for 5 species: big brown, eastern red, hoary, silver-haired, and little brown bats ($V = 1803\text{--}3036$, $P \leq 0.001$). For 8 of 9 species, the estimated pseudomedian difference was a positive value, indicating that file counts were higher for the SMM-U2 microphone (Figure 2; Table 2). However, for Indiana bat the pseudomedian difference was approximately 0 and the confidence interval was very wide. Sample sizes of detector-nights and/or number of classified call files were much smaller for evening bat, northern long-eared bat, tricolored bat, and Indiana bat than for the other 5 species (Table 2). We propose an additive correction factor (ranging from 2 to 6.5 files per detector-night) based on the difference between the SMM-U1 and SMM-U2 counts of classified files per detector-night.

We calculated the means of 4 echolocation call parameters (total pulses, pulse duration, maximum pulse frequency, and minimum pulse frequency) for each microphone type and species (Table S4, available in Supporting Information). The SMM-U2 recorded more total pulses on average than the SMM-U1 for all 9 species; differences were significant for 4 species (eastern red bat, hoary bat, silver-haired bat, and little brown bat). The SMM-U2 also recorded longer pulse durations than the SMM-U1 for 7 species; differences were significant for 2 species (silver-haired bat and little brown bat). The SMM-U2 captured higher mean maximum frequencies for 7 species, of which 3 were significant (big brown bat, silver-haired bat, and little brown bat), and lower mean minimum frequencies for 4 species, of which one was significant (little brown bat).

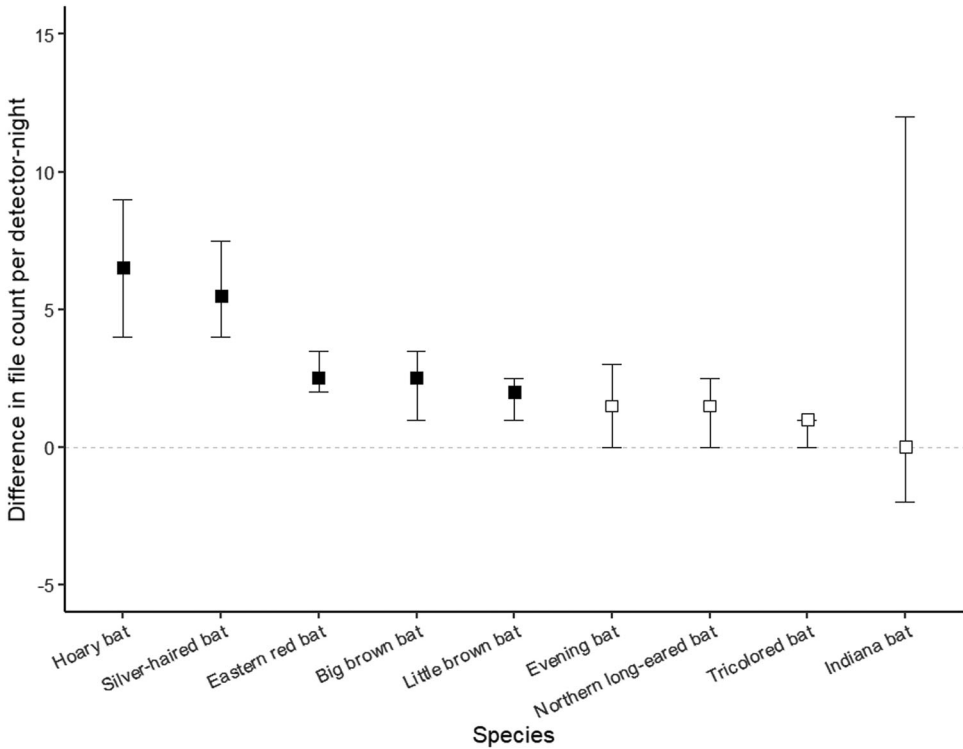


FIGURE 2 Difference between 2 ultrasonic microphone models (SMM-U2 minus SMM-U1) in the count of files classified to each bat species per detector-night. Points represent the pseudomedian of the difference based on the Wilcoxon signed-rank test. Filled points are significantly different from 0; open points are not significantly different from 0. Bars represent 90% confidence intervals. Bat acoustic data (sample size of 25,949 paired recordings) were collected from 10 sites in July–August 2021 in Minnesota, Wisconsin, Indiana, and Michigan, USA.

TABLE 2 Pseudomedian of the difference in classified call files per detector-night between 2 ultrasonic microphones (SMM-U2 minus SMM-U1) based on the Wilcoxon signed-rank test, sample sizes of detector-nights and classified call files and proposed additive correction factor for each species. A user would add the correction factor to the SMM-U1 call files per detector-night to approximate the SMM-U2 call files per detector-night. Sample size of call files is shown as number of files from SMM-U2/number of files from SMM-U1. Bat acoustic data were collected from 10 sites in July–August 2021 in Minnesota, Wisconsin, Indiana, and Michigan, USA.

Species	Pseudomedian	Sample size of detector-nights	Sample size of classified call files	Correction factor
Hoary bat	6.50	94	2,894/2,210	+6.50
Silver-haired bat	5.50	94	4,353/3,427	+5.50
Eastern red bat	2.50	94	1,160/830	+2.50
Big brown bat	2.50	94	3,138/2,875	+2.50
Little brown bat	2.00	94	6,387/6,235	+2.00
Evening bat	1.50	28	149/111	+2.50 ^a
Northern long-eared bat	1.50	94	39/22	+2.00 ^b
Tricolored bat	1.00	94	92/58	+2.50 ^a
Indiana bat	0.00	16	34/25	+2.00 ^b

^aCorrection factor based on eastern red bat, the most acoustically similar species with large sample size.

^bCorrection factor based on little brown bat, the most acoustically similar species with large sample size.

In sum, the newer microphone showed significant improvement in at least one call parameter for 5 species, and in all 4 call parameters for the little brown bat.

For our generalized linear mixed effects model analysis, we compared 17 candidate models, 2 of which did not converge (Table S3). The best-fitting model included only microphone type as a fixed effect (Table 3), and did not indicate any issues with dispersion or zero inflation. Our best-fitting model predicts that the SMM-U2 microphone will yield a significantly higher number of classified files than the SMM-U1 microphone, based on a positive parameter estimate and a 95% confidence interval that does not overlap 0 (Table 4). None of the other fixed effects we tested (microphone height, clutter percent, clutter distance, habitat type) were significant predictors of file count, as determined by their 95% confidence intervals all overlapping 0.

DISCUSSION

The primary objective of our study was to assess differences in the quality and quantity of recordings made by 2 popular microphone models, the Wildlife Acoustics SMM-U1 and SMM-U2. Importantly, the experimental setup kept detector effects constant, such that any observed differences should be solely due to the microphones. Our first conclusion, after assessing proportional and count data from paired recordings, is that the SMM-U2 created better quality, more readily identifiable recordings. While 5 of the 9 studied species exhibited higher species-classifiable file counts for the SMM-U2, it is telling that none of the remaining 4 species had higher counts on the SMM-U1. Instead, differences between the microphones were nonsignificant for those 4 species. Modeling results further agree with this conclusion, finding that the primary variable associated with the count of files classified to a species per detector-night was microphone type. Other factors, such as general habitat type and distance to clutter, were not part of the best-supported model. Our results are in alignment with statements from

TABLE 3 Results of generalized linear mixed effects model ranking (for models that converged). The response variable is the number of files receiving a particular Kaleidoscope Pro classification on each night at each site. Fixed effects include microphone type (microphone), microphone height off the ground (height), percent clutter within a 5-meter radius of the microphone (clutter percent), distance to nearest clutter (clutter distance), and habitat type (habitat). All models include random effects for sample site, recording night, and Kaleidoscope Pro species classification. Values shown include number of model parameters (K), Akaike information criterion for small sample size (AIC_c), difference in AIC_c from the top model (ΔAIC_c), and model weight. Bat acoustic data were collected from 10 sites in July–August 2021 in Minnesota, Wisconsin, Indiana, and Michigan, USA.

Fixed effects formula	K	AIC_c	ΔAIC_c	Weight
Microphone	8	11649.85	0	0.31
Microphone + Height	9	11650.65	0.81	0.20
Microphone + Clutter Percent	9	11651.66	1.81	0.12
Microphone + Clutter Distance	10	11652.24	2.40	0.09
Microphone + Habitat	10	11652.41	2.56	0.09
Null	7	11653.28	3.43	0.05
Height	8	11654.09	4.24	0.04
Clutter Percent	8	11655.08	5.23	0.02
Clutter Distance	9	11655.67	5.83	0.02
Habitat	9	11655.83	5.99	0.02
Height + Clutter Percent	9	11656.08	6.24	0.01
Height + Clutter Distance	10	11657.31	7.46	0.01
Height + Habitat	10	11657.66	7.81	0.01
Clutter Percent + Clutter Distance	10	11657.70	7.85	0.01
Clutter Percent + Habitat	10	11657.80	7.95	0.01

the microphone manufacturer about the increased quality of SMM-U2 recordings. Our results also agree with those of Darras et al. (2020), who found that microphones with a higher signal-to-noise ratio (as the SMM-U2 is advertised to have compared to the SMM-U1) result in higher quality acoustic recordings.

Contrary to our expectations, the 2 microphone types were equivalent in regard to triggering sensitivity, suggesting that the quantity of total recordings made by the 2 microphones is likely to be similar. Further, both microphones detected the same number of species. Yet, given the results described above, and that a larger proportion of all recordings made by the SMM-U1 were classified as noise, our second conclusion is that obtaining a similar number of recordings across the 2 microphones does not translate into comparable quality of those recordings. The results of our echolocation parameter analysis support our conclusion that recording quality differs between microphone models. Specifically, calls captured by the SMM-U2 were longer in duration and had broader spectral ranges compared to recordings from the SMM-U1, suggesting that the newer microphone model is more accurately capturing the fine-scale details of individual calls. Such detail is critical for call identification to the species level. Hence it is not surprising that more recordings from the SMM-U2 were classifiable to a species.

Our second objective was to propose a correction factor to facilitate comparison of datasets derived from SMM-U1 with datasets derived from SMM-U2. For the 5 species with large sample sizes of both detector-nights and classified files, our proposed additive correction factor values are species-specific and are derived directly from

TABLE 4 Parameter estimates for the 3 top-ranked, generalized linear mixed effects models (those with $\Delta AIC_c < 2$). Standard errors (SE) and 95% confidence intervals (Lower CI, Upper CI) are shown for fixed effects. Variances, standard deviations (SD), and correlations (Corr.) are shown for random effects. Fixed effects include microphone type (microphone), microphone height off the ground (height), and percent clutter within a 5-meter radius of the microphone (clutter percent). All models include random effects for sample site, recording night, and Kaleidoscope Pro species classification. The reference level for the microphone type variable is SMM-U1. Bat acoustic data were collected from 10 sites in July–August 2021 in Minnesota, Wisconsin, Indiana, and Michigan, USA.

Model formula	Fixed effects				
Microphone	Model parameter	Estimate	SE	Lower CI	Upper CI
	Intercept	1.666	0.739	0.218	3.113
	Microphone type SMM-U2	0.241	0.102	0.041	0.440
	Random effects				
	Model parameter	Variance		SD	Corr.
	Sample site (Intercept)	1.615		1.271	
	Recording night (Intercept)	0.116		0.341	
	Classification (Intercept)	4.136		2.034	
	Microphone type SMM-U2 (Slope)	0.051		0.227	−0.85
	Microphone + Height	Fixed effects			
Model parameter		Estimate	SE	Lower CI	Upper CI
Intercept		0.567	1.21	−1.801	2.935
Microphone type SMM-U2		0.241	0.102	0.041	0.441
Height		0.417	0.367	−0.302	1.135
Random effects					
Model parameter		Variance		SD	Corr.
Sample site (Intercept)		1.421		1.192	
Recording night (Intercept)		0.117		0.342	
Classification (Intercept)		4.132		2.033	
Microphone type SMM-U2 (Slope)	0.052		0.227	−0.85	
Microphone + Clutter Percent	Fixed effects				
	Model parameter	Estimate	SE	Lower CI	Upper CI
	Intercept	1.849	0.836	0.210	3.488
	Microphone type SMM-U2	0.241	0.102	0.041	0.440
	Clutter Percent	−0.008	0.017	−0.041	0.025
	Random effects				
	Model parameter	Variance		SD	Corr.
	Sample site (Intercept)	1.579		1.257	
	Recording night (Intercept)	0.116		0.341	
	Classification (Intercept)	4.136		2.034	
Microphone type SMM-U2 (Slope)	0.051		0.227	−0.85	

the results of the Wilcoxon signed rank test. For the 4 species with small sample sizes, we suggest using the correction factor for the species that has the most similar echolocation call characteristics, as the microphones should record similar calls in a similar fashion. Thus, we suggest using the little brown bat value for the northern long-eared and Indiana bats and using the eastern red bat value for evening and tricolored bats. To apply our additive correction factor, one would calculate the sum of classified call files per detector-night from the SMM-U1 dataset plus the correction factor to yield the equivalent of an SMM-U2 dataset. For example, a surveyor using an SMM-U1 microphone records 4 big brown bat call files per detector-night and applies the correction factor by adding 2.5 call files per detector-night, yielding an estimated equivalent of 6.5 call files per detector-night if the surveyor had used an SMM-U2 microphone.

One situation in which our correction factor could be applied is long-term monitoring programs, where microphones are likely to need replacing after a certain period of time due to loss, vandalism, general wear and tear, or discontinuation of older models by the manufacturers. Our correction factor could also be utilized when comparing recordings collected by different entities, each of whom had access to different equipment, such as in the continent-wide North American Bat Monitoring Program (Loeb et al. 2015). We acknowledge that for some study designs, it may be possible to account for microphone characteristics simply by explicitly including microphone type as a covariate in regression models, but in other cases having a quantitative correction factor will be valuable. We identified several recently published works (Gaulke et al. 2023, McKay et al. 2024) which describe using both SMM-U1s and SMM-U2s in their studies without accounting for or even mentioning the potential biases related to the different microphone models. Given these examples, we believe that many bat researchers have not adequately addressed the issue of between-microphone differences. Aside from our work, we are not aware of any other published additive correction factors for ultrasonic microphones used for bat monitoring. Phinney (2020) calculated a multiplicative correction factor to compare data from 2 different brands of bat detectors and Krings et al. (2022) standardized across different detectors by measuring the effective sampling radius per detector and calculating detections per sampling area to obtain bat activity density.

Due to small sample sizes for species that are less widespread or less common in our region, we were not able to directly determine additive correction factors for all species in our dataset. We recommend using the correction factor of the species with the most similar echolocation call characteristics, but we acknowledge this is a rough approximation. We therefore encourage other researchers to conduct similar studies to improve on our correction factors for the undersampled species (Indiana bat, northern long-eared bat, evening bat, and tricolored bat). Development of additional correction factors for species, habitats, and microphone types not included in our study is also needed.

We identified 2 potential confounding effects that could have influenced our results. First, the SMM-U1 microphones were deployed in previous years, while the SMM-U2 microphones were brand new. Microphone sensitivity and recording quality diminish with prolonged use (Turgeon et al. 2017); however, all of our microphones passed the pre-deployment calibration test satisfactorily and the SMM-U1 usually triggered as quickly as the SMM-U2, so we do not believe the previous use had a strong impact on our results. Second, the SMM-U1 microphones were deployed with foam windscreens, which could reduce sound transmission, particularly if wet after a rainstorm. There was 0 precipitation on 75% of our detector-nights, and significant rainfall (10 mm or more in an 18 hour period) occurred on only 6% of detector-nights in our study, therefore the impact of wet windscreens on our findings is likely minimal.

Overall, we recommend upgrading to microphones with greater sensitivity and signal-to-noise ratio when feasible, since they will likely produce clearer recordings that are more readily identifiable to the species level. However, it is imperative to evaluate microphone differences and develop correction factors before switching over to a new recording system. We also note that upgrading may not be necessary in some cases. We found older microphones triggered equally as often and recorded the same number of species as newer microphones, so they are certainly not obsolete and may still be appropriate for certain research objectives.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

Our study followed relevant regulations and guidelines regarding the ethics of animal welfare. Our study did not require capturing or handling of any live animals.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the authors. The data are not publicly available due to sensitive species restrictions.

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SUPPORTING INFORMATION

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