

RESEARCH ARTICLE

Comparing manual and automated methods for identifying individual great gray owls via territorial calls

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Abstract

Unique identification is essential for understanding population demography and often relies on capturing, tagging, and re-sighting or tracking known individuals. Recent advances in acoustic analysis show that individual birds can be identified using spectral analysis of vocalizations. However, spectral analysis can be a time-consuming process, often requiring measurement of multiple sound attributes by hand. The use of mel-frequency cepstral coefficients (MFCC), which analyze the entire spectrum of a vocalization, is an alternative method to identify individuals within a species. Our goal was to compare the effectiveness of 2 techniques, 1) manual spectral analysis and 2) automated MFCC analysis, for identifying individuals across space and time, using vocalizations of the great gray owl (*Strix nebulosa*). We combined GPS tracking data of known individuals with audio data from autonomous recording units (ARUs) deployed in great gray owl territories during the breeding season to compare spectral analysis methods to automated MFCC methods for identifying individuals. Our analysis utilized territorial calls from 26 ARUs across 4 years (2019–2022) and 14 territories in the Greater Yellowstone Ecosystem in Wyoming, USA. We found that the average classification accuracy of the spectral analysis was 77.2%, whereas the accuracy of the MFCC method was 97.6% based on discriminant analysis. Call analysis using MFCCs was also successful in identifying the

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same unique individual owl across multiple ARU locations, both within and across years and territories. Our results demonstrated that automated MFCC methods are effective and efficient non-invasive tools to identify individual great gray owls using territorial calls. The automated MFCC audio analysis method can be applied to other species for which individual identification is possible based on vocalizations. The use of ARUs and MFCC analysis of vocalizations to distinguish individuals can allow for non-invasive monitoring of individuals and contribute to improved understanding of population dynamics, for example, by providing information on individual fitness and movement behavior.

KEYWORDS

autonomous recording unit, bioacoustics, great gray owl, Greater Yellowstone Ecosystem, mel-frequency cepstral coefficients, spectral analysis, *Strix nebulosa*, territorial call, vocal individuality

The identification of individual animals is critical for many aspects of ecological inquiry and management. Individual identification is integral to understanding the life history of species and for assessing individual behavior (e.g., movement), fitness, and population dynamics of wildlife. Ecologists can assess individual movements (Brown 1992) and behaviors in relation to habitat and climate (Brooks et al. 2019) and monitor trends and changes over time (Stirling et al. 1999). Furthermore, survival, fitness, and recruitment can all be determined when individuals of a species are identified (Seber 1972, Steenhof and Newton 2007, DeCesare et al. 2012). Individual movements, behavior, fitness, and population dynamics are all components of wildlife and population ecology that are essential for assessing long-term trends in populations and guiding decisions in conservation and management of species and populations (Allen and Singh 2016).

Bird species typically do not have unique markings or other physical identifiers that allow for identification of individuals. As such, almost all studies of birds that require individual identification rely on capture and tagging (Nichols et al. 2004). Vocalizations of birds are commonly used to identify species (Marler 1958); however, recent advances in bioacoustics allow for the identification of individuals by call differentiation (Terry et al. 2005, Knight et al. 2024). The adaptation of using territorial call differentiation to identify individual raptors is increasing, particularly for owl species (Holschuh and Otter 2005, Odum et al. 2013). Detailed spectral measurements of owl calls can be used to accurately identify individuals for several species, including great gray owls (Rognan et al. 2009), spotted owls (*Strix occidentalis*; Wood et al. 2021), barred owls (*S. varia*; Freeman 2000), great horned owls (*Bubo virginianus*; Odom et al. 2013), and eastern screech-owls (*Megascops asio*; Nagy and Rockwell 2012). Call attributes of a spectrogram typically are measured by researchers on computer audio software programs by hand to analyze calls for individual identification (Holschuh and Otter 2005, Rognan et al. 2009). The specific call attributes measured to distinguish individuals can vary by species because of differences in call structure (Galeotti and Pavan 1991, Freeman 2000). As such, notable challenges exist related to the subjectivity of manually measuring specific call attributes and the time-intensive process involved in manually analyzing spectrograms.

Improvements in bioacoustics have enabled automated analysis of spectrograms, including for larger-scale studies that identify individuals based on their vocalizations. Measuring call attributes automatically can reduce the potential for human measurement error (Zhou et al. 2020) and processing time. To overcome these limitations, Mielke and Zuberbuhler (2013) explored using mel-frequency cepstral coefficients (MFCC) to analyze the entire

spectrum of a call instead of focusing on specific spectral features within the call. Mel-frequency cepstral coefficients are an automated method of feature extraction that map the full spectrum of a call by dividing it into slices using time and frequency axis and calculating amplitude values in each slice using the mel acoustic scale (Mielke and Zuberbühler 2013). For wildlife, automated methods using MFCCs have been successful in frog and cricket call identification to the species level (Lee et al. 2006), bird song classification to the species level (Chou et al. 2008) and, more recently, bird song (Cheng et al. 2010) and primate call classification (Clink et al. 2018) to the individual.

We evaluated the extent to which automated bioacoustic analysis can distinguish individuals of a sensitive, difficult-to-study raptor species. Specifically, our goal was to determine the efficacy of using great gray owl territorial calls recorded with autonomous recording units (ARUs) to identify individuals. We have been relying on traditional capture and marking techniques to facilitate a long-term study of great gray owls (*Strix nebulosa*) in the southern Greater Yellowstone Ecosystem for the past decade to investigate population demographics, survival, territoriality, and other ecological aspects of this rare and at-risk species (Gura 2023). Great gray owls are highly territorial and exhibit high territory fidelity between years (Bull and Henjum 1990; Gura et al. 2025a, b). Nonetheless, it can be difficult to track tagged individuals over time and space due to the owls' secretive nature and large home ranges (Gura et al. 2025a), the difficulty of resighting bands on owls, and limitations in transmitter battery life. Given the history of identifying individual owls from call characteristics and advancements in automating the process, our goal was to develop an efficient and reliable method to identify individual great gray owls using territorial calls recorded on ARUs. We compared 2 methods of call identification: (1) spectral analysis computed by hand measuring individual features in a spectrogram of a call, and (2) MFCC feature extraction that computes the amplitude across multiple time and frequency axes in a call. Our goal was to determine the accuracy and ease of each method for identifying individual great gray owls using territorial calls. Because we also collected location data from GPS transmitters for concurrent study objectives, we could couple movement data from known owls, new automated methods of unambiguously collecting detailed measurements on individual calls, and discriminant analyses to explore the potential of using acoustic data as a reliable method to identify individual great gray owls across space and time.

STUDY AREA

We collected data in the Greater Yellowstone Ecosystem in northwest Wyoming, USA from 2019–2022, where the elevation ranges from 1,800 m to 2,200 m. The study area comprises portions of the Bridger-Teton National Forest as well as Grand Teton National Park, and the habitat was dominated by coniferous or mixed coniferous and deciduous forest with interspersed meadows. The average annual precipitation across the study area ranged from 43 cm to 58 cm, including an average annual snowfall of 195 cm to 368 cm.

METHODS

We collected audio data at 14 active great gray owl breeding territories between 2019 and 2022 (Figure 1). Active territories were defined as having a pair of owls present during the breeding season. We deployed 1–3 SoundScout ARUs (Teton Raptor Center, Wilson, WY, USA) within each known breeding territory during the courtship period between mid-March and early May (Bedrosian et al. 2015). We placed single ARUs adjacent to (<100 m from) known nests, whereas we deployed 3 ARUs in a triangular array (~600 m apart) within historic nesting areas if nest locations were unknown prior to the breeding season. We collected data from 26 ARU deployments across 4 years representing 14 individuals with an average of 16 territorial calls per ARU (min–max = 7–31; Table 1). Autonomous recording units collected 24-hr, continuous data at a sample rate of 48 kHz for 5–7 days at a time, per deployment, depending on fieldwork limitations. Recordings typically had high signal-to-noise ratios due to being recorded in the quiet nighttime hours, allowing for detection of calls ≥12 dB louder than the background noise.

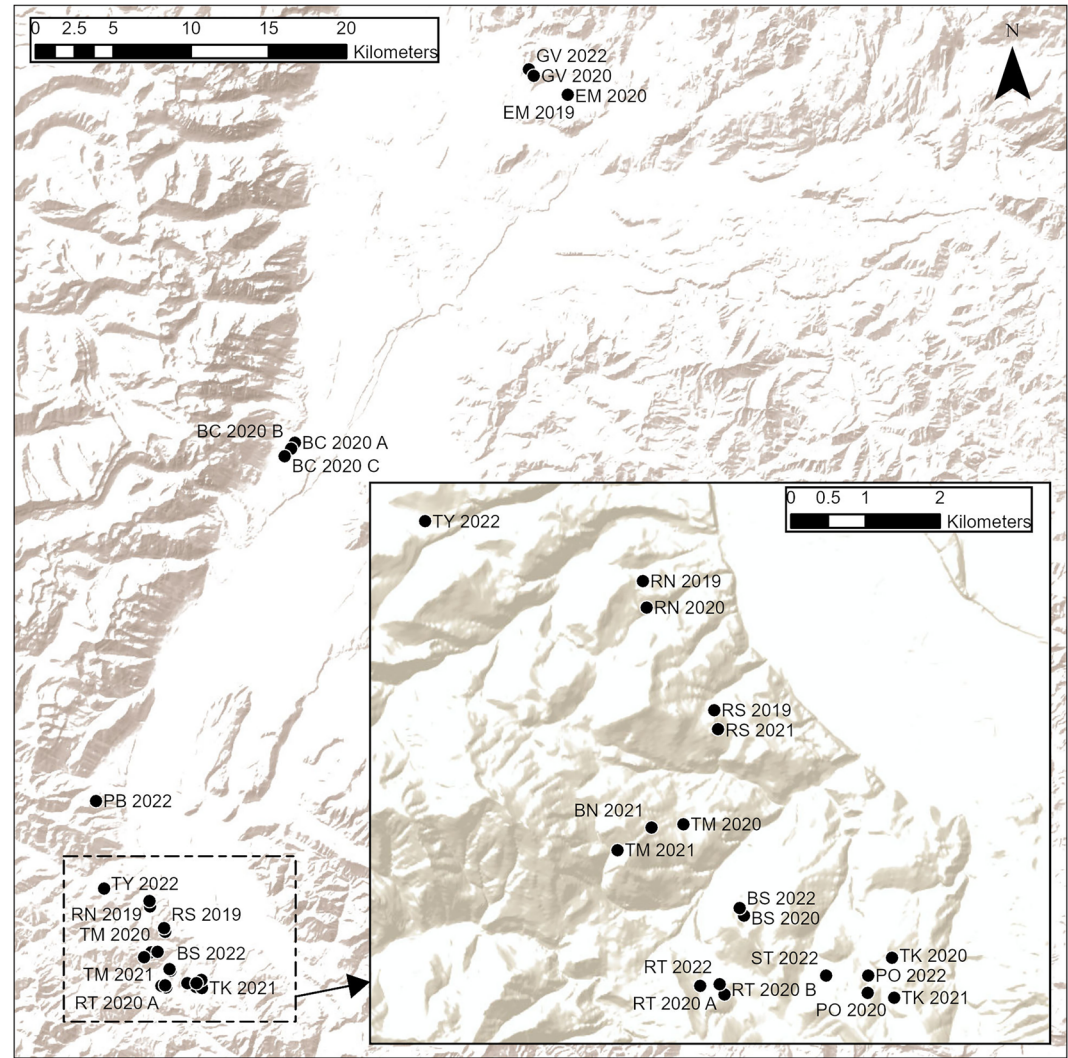


FIGURE 1 Deployment identification (ID) locations of autonomous recording units (ARUs) relative to one another for the 26 ARUs used in individual call analysis for great gray owls in the Greater Yellowstone Ecosystem, USA during 2019–2022. Each deployment ID represents the territory ID (first 2 letters), year of deployment, and unique ARU deployment (last letter if provided) for that territory.

As part of a parallel study, we captured, banded, and deployed GPS remote-download transmitters (Lotek SwiftFix models PinPoint VHF 240, 1200, and 1800, Lotek Wireless Inc., Newmarket, ON, Canada) on adult great gray owls within breeding territories during 2017–2023 using either a backpack-style or a tail-mount attachment (Gura et al. 2025a, b). Remote-download transmitters collected hourly movement data, enabling us to track the movements of known individuals throughout the study period (Gura 2023; Gura et al. 2025a, b). We outfitted all captured individuals with size 8 aluminum leg bands (Nakash et al. 2023) that included an alphanumeric color flag made from polyurethane with UV stabilizer (Varland et al. 2007), allowing for opportunistic resighting of known individuals throughout the study period and area and for instances when transmitters stopped working. Mortality events of known GPS-tagged individuals provided insight into instances when a new individual was expected to occur on the territory. Resight, movement, and mortality data resulted in key information on which

TABLE 1 Summary of audio data from automated recording unit (ARU) deployments in the Greater Yellowstone Ecosystem, USA during 2019–2022, including ARU deployment identification (ID) location and year, number of calls, and unique individual owl for great gray owl territorial calls used in individual call analysis and classification. Each ARU deployment ID represents the territory ID (first two letters), year of deployment, and unique ARU deployment (last letter if provided) for that territory.

ARU deployment ID	Number of calls used	Unique individual owl
BC 2020 A	9	1 - BC 2020 A, B & C
BC 2020 B	18	1 - BC 2020 A, B & C
BC 2020 C	11	1 - BC 2020 A, B & C
BN 2021	10	2 - BS 2020 & BN 2021
BS 2020	31	2 - BS 2020 & BN 2021
BS 2022	20	3 - BS 2022
EM 2019	20	4 - EM 2019, 2020 & GV 2020, 2022
EM 2020	7	4 - EM 2019, 2020 & GV 2020, 2022
GV 2020	10	4 - EM 2019, 2020 & GV 2020, 2022
GV 2022	13	4 - EM 2019, 2020 & GV 2020, 2022
PB 2022	15	5 - PB 2022
PO 2020	23	6 - PO 2020
PO 2022	15	7 - PO 2022
RT 2022	13	8 - RT 2020 A, B & RT 2022
RT 2020 A	20	8 - RT 2020 A, B & RT 2022
RT 2020 B	12	8 - RT 2020 A, B & RT 2022
RS 2019	10	9 - RS 2019
RS 2021	27	10 - RS 2021 & RN 2019, 2020
RN 2019	23	10 - RS 2021 & RN 2019, 2020
RN 2020	20	10 - RS 2021 & RN 2019, 2020
ST 2022	11	11 - ST 2022
TL 2022	15	12 - TL 2022
TM 2020	16	13 - TM 2020, 2021
TM 2021	13	13 - TM 2020, 2021
TK 2020	15	14 - TK 2020, 2021
TK 2021	19	14 - TK 2020, 2021

individuals were (or were not) present at a breeding territory during ARU deployment periods and provided a unique opportunity to validate techniques for distinguishing individual owls based on vocalizations.

We identified great gray owl territorial calls using cluster analysis in the program Kaleidoscope Pro (Wildlife Acoustics, Maynard, MA, USA), which 11 professionally trained biologists and volunteers then verified manually. We used R (version 4.4.2, R Core Team 2024) and the package tuneR (version 1.4.7, Ligges et al. 2018) to clip high-quality territorial calls from recordings. Male territorial calls were separated from female territorial calls based on

males having an average lower maximum call frequency (287 Hz) than females (340 Hz), as determined from duets (2 individuals calling simultaneously at different frequencies) of great gray owls in our study area and previous audio analysis research (Rognan 2007). Because it can be difficult to accurately measure note characteristics from distant calls, we only used territorial calls that were considered high-quality for analysis, which were calls with a clear call signal and little to no background noise. High-quality calls were determined by visual verification of call spectrograms based on clear visibility of every feature being measured for manual methods (e.g. high frequency, start and end frequencies, and duration of each note) against the background noise (Figure 2).

To examine territory fidelity and to better evaluate our results of individuality, when possible, we selected audio data from territories where known, tagged individuals were present during the time of ARU deployments. We also included data from territories with multiple ARUs deployed simultaneously (via an array) to evaluate if the analysis methods identified the same individual across multiple ARUs. Use of high-quality calls from territories with resighted or tracked birds and territories with multiple ARUs deployed during the same time frame allowed for verification that a given analytical method identified the same individual across space and time. Our study design enables spatiotemporal testing of individual call identification through the utilization of known, tagged individuals and simultaneous ARU deployments.

For spectral analysis of great gray owl territorial calls, we measured 12 different variables from visual spectrograms of each territorial call, based on methods used in Rognan et al. (2009). We conducted spectral measurements in the program Kaleidoscope with the following Faus-Fourier transform (FFT) settings: FFT size of 2048,

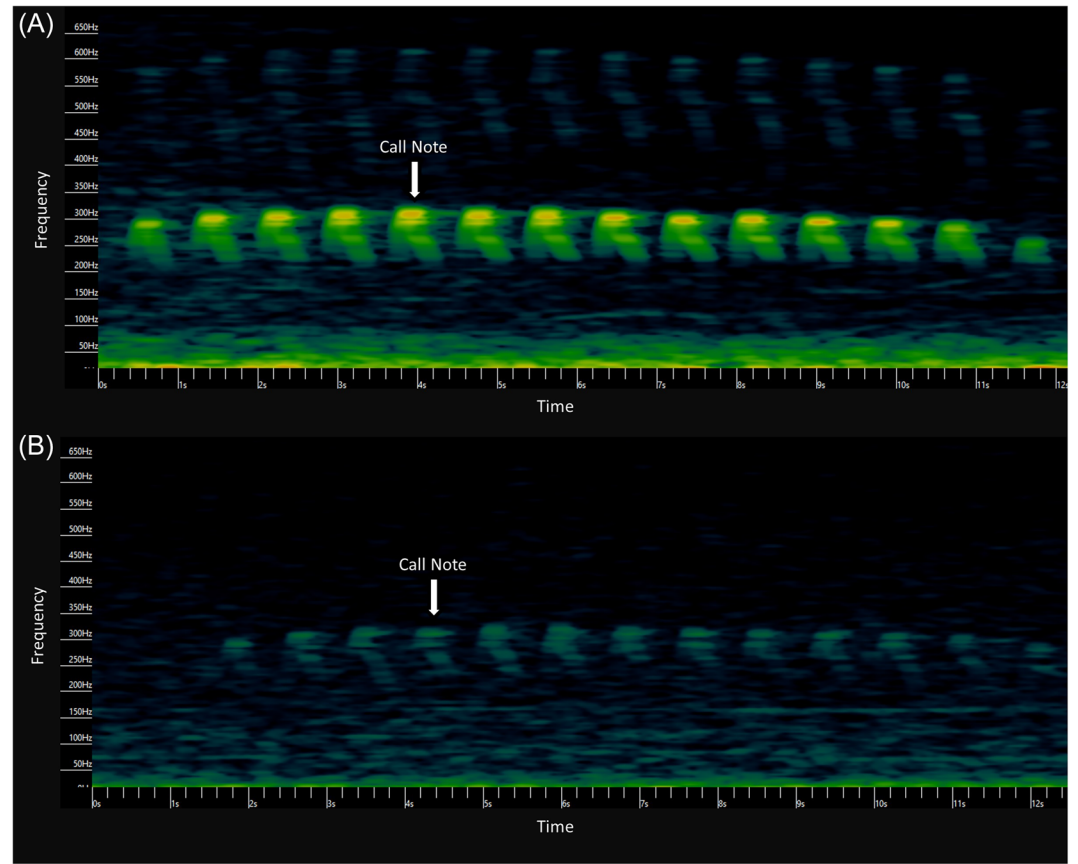


FIGURE 2 Spectrograms of a (A) high-quality great gray owl territorial call, and (B) low quality territorial call.

window size of 128, and max cache size of 256 MB, within a frequency range of 0–650 Hz to best visually represent great gray owl territorial calls. We manually measured total call duration, total number of notes, calling rate, and for notes 2–4: the start frequency, end frequency, dominant frequency, high frequency, frequency range, note duration, inter-note duration, time to amplitude, and tail duration (Rognan et al. 2009). We determined collinearity using Pearson's correlation in the stats package (version 4.4.2) and removed variables that were collinear ($r = 0.6$) for use in discriminant analysis. We then used linear discriminant analysis in R (R Core Team 2024) to determine the predicted probability that each individual was identified correctly based on spectral analysis of call characteristics. We ran discriminant analysis at the ARU level for the spectral analysis method to determine the probability that an individual could be classified correctly based on territorial calls collected on a single ARU. We assessed how much the difference in individuals could be described by combinations of predictor variables, called linear discriminant functions, in the discriminant analysis. We used k -fold cross validation by first withholding 30% and then 40% of the data to evaluate the model and determine if training data sample size influenced the accuracy of model classification.

The second method we used to determine vocal individuality of great gray owls used MFCCs (Clink et al. 2018). Mel-frequency cepstral coefficients measure the amplitude of a signal across time and frequency axes and assign those values to the cells using the mel acoustic scale (Mielke and Zuberbühler 2013). For the MFCC process, we limited the high-quality territorial call clips to a frequency range of 150–425 Hz based on the lower and upper limits of territorial calls. We extracted MFCC features from each call by calculating MFCCs for 12 band pass filters in 0.25 second overlapping frame within the territorial call. We then calculated average and standard deviations across each of the 12 0.25-second periods of the territorial call using R code from Clink et al. (2018) and R packages tuneR, seewave, and sound (Sueur et al. 2008, Heymann 2017, Ligges et al. 2018). We standardized MFCC values and then used the same discriminant analysis and verification methods as were used for spectral analysis above to classify individuals at the ARU level based on the mean and standard deviation of calculated MFCC values. To determine the classification accuracy of individuals based on data from multiple ARUs across space and time, we combined data from multiple ARU locations that represented the same unique individual owl into groups (Table 1), used MFCC features from territorial calls to classify them with discriminant analysis, and verified results with k -fold cross validation. We determined ARU groupings that occurred within the same territory location and represented a unique individual owl *a priori* based on location data from individuals with transmitters to determine cases where the same individual should be recorded on multiple ARUs. We compared the timing of calls detected on ARUs with hourly GPS locations of owls to determine if the calls recorded were from known individuals with transmitters.

RESULTS

We determined the accuracy of manual and MFCC methods in identifying individual great gray owls using 14 individuals recorded across 26 ARUs and 4 years (Figure 1). The manual spectral analysis method of classification was based on 5 variables (calling rate, high frequency, starting frequency, note duration, and frequency range) following the removal of 7 collinear variables. We chose variables based on demonstrated variability among calls and lack of collinearity ($r = 0.6$). The mean predicted probability of correctly identifying an individual great gray owl at the ARU level using the spectral analysis method was 77.2% based on 70% training data and 30% test data with k -fold cross validation across 10 runs with training and test data including all individuals used in the analysis (Figure 3A). When we adjusted our discriminant analysis to 40% training data and 60% test data across the classification accuracy was 69.4%. Discriminant analysis results indicated that, on average, 92% of the difference in individuals could be described by 2 linear discriminant functions. Overall, 77% of the difference could be described by linear discriminant function 1 (LD1), with 15% described by linear discriminant function 2 (LD2; Figure 3A). Note duration, calling rate, and starting frequency were the variables that contributed the most to the 2 discriminant functions based on discriminant function standardized coefficients (Table 2).

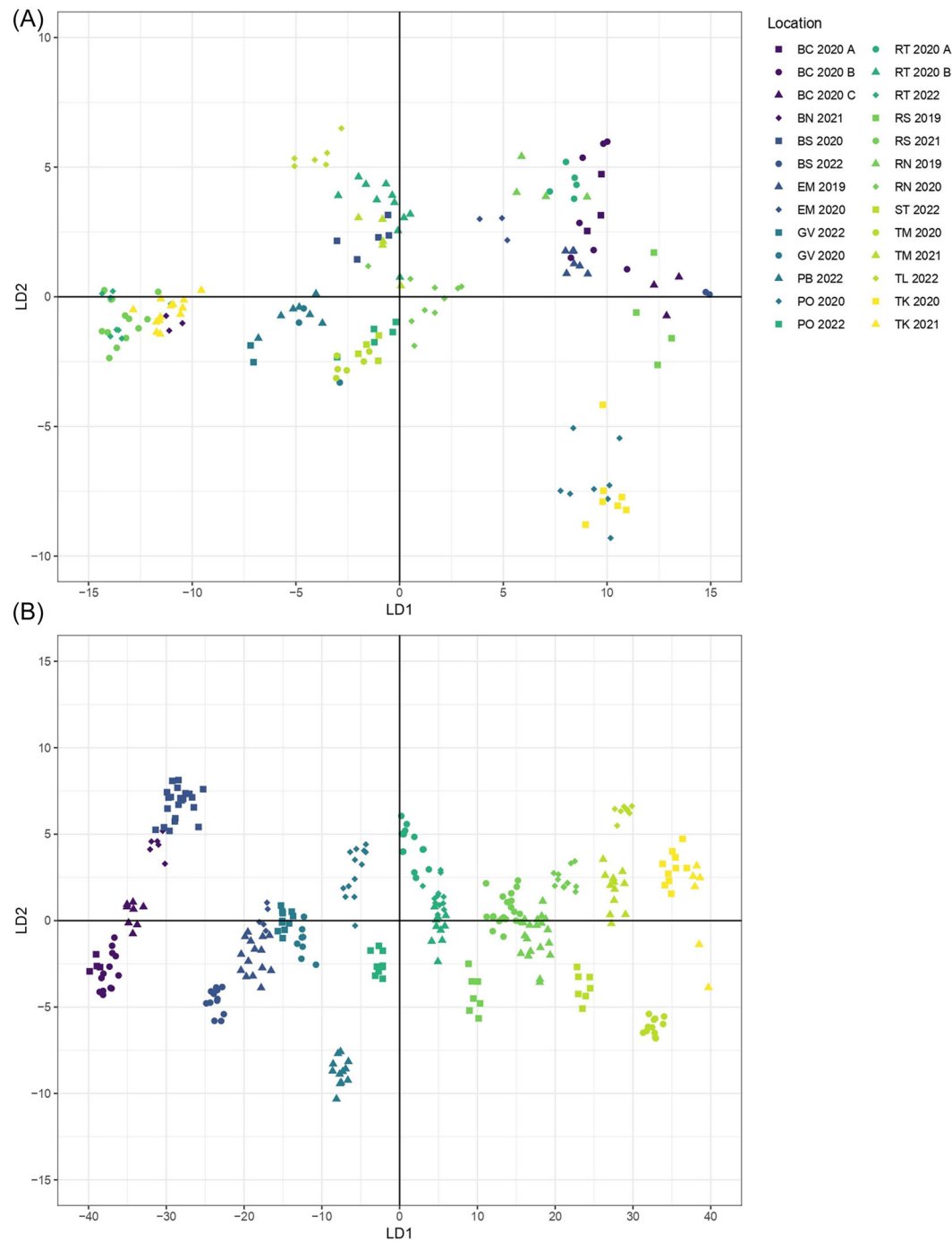


FIGURE 3 Linear discriminant functions 1 (LD1) and 2 (LD2) for discriminant analysis of great gray owl territorial calls using the (A) spectral analysis method and (B) mel-frequency cepstral coefficients method for 26 unique autonomous recording units (ARUs) located within known great gray owl territories within the Greater Yellowstone Ecosystem, USA during 2019–2022. Each symbol represents a unique deployment identification (ID) including the territory ID (first 2 letters), year of deployment, and unique ARU deployment (last letter if provided) for that territory. Clustering of points indicates that individuals match and are being identified accurately using the method, whereas non-clustered points indicate that individuals are not being identified accurately using the method.

TABLE 2 Standardized discriminant function coefficients by variable for manual spectral analysis of territorial calls of great gray owls in the Greater Yellowstone Ecosystem, USA, during 2019–2022.

Variable	Discriminant function 1	Discriminant function 2
Calling rate	−0.4647	−0.8046
High frequency	0.0600	−0.2657
Starting frequency	0.6845	−0.2129
Note duration	1.0320	−0.4172
Frequency range	−0.5219	0.3620

The mean predicted probability of correctly identifying an individual using the automated MFCC method at the ARU level was 97.6% based on 70% training data and 30% test data across a total of 10 runs (Figure 3B). When we adjusted our *k*-fold cross-validation to be based on 40% training data and 60% test data across 10 runs the classification accuracy was 95.5%. Discriminant analysis results indicated that an average of 93% of the difference could be described by linear discriminant function 1 (LD1), with 3% described by discriminant function 2 (LD2, Figure 3B).

Referencing the plotted discriminant analysis results and utilization of posterior probabilities from discriminant analysis allowed us to confirm that calls from each unique individual owl (based on resighting or tracking tagged birds or ARUs deployed within arrays on the same territory) were grouped together across space and time, using MFCC analysis (Table 1, Figure 3B). We used the timing of movements of tagged birds compared to the timing of ARU deployments to verify if a particular individual was present near a given ARU when a call was detected. We also used ARUs deployed within an array on a known territory to verify if an individual would be detected across multiple ARUs.

We used groups of ARUs from the same territory location known to contain calls from the same individual to run another test of the accuracy of the MFCC method for determining vocal individuality at the unique individual owl level. The classification accuracy was 97.6% with 70% training data and 30% test data with a 97.4% classification accuracy using 40% training data and 60% test data across 10 runs. Discriminant analysis of territorial calls based on groups of ARUs from the same territory location across space and time, where each group represented a single unique individual owl, indicated that an average of 93% of the difference could be described by linear discriminant function 1 (LD1) with 4% described by linear discriminant function 2 (LD2, Figure 4).

The MFCC method also identified the same unique individual owl across space and time. For example, in the case of ARU deployments BC_2020_A, B, and C, the 3 ARUs were deployed approximately 600 m apart within the same territory during the same weeklong period (Figure 1). We confirmed that a GPS-tagged great gray owl was present near the 3 ARUs throughout the deployment period. The MFCC method identified the territorial calls recorded on all 3 ARUs as being from the same unique individual owl (1 – BC 2020 A, B, and C; Figures 3B, 4). In another example, ARU deployments EM 2019, EM 2020, GV 2020, and GV 2022 were arrayed across 3 seasons and 2 unique territories. Using GPS movement data from one great gray owl, we confirmed this individual regularly moved between the EM and GV territories in all survey years, suggesting it was likely in the vicinity of all 4 ARUs. Utilizing the MFCC method of call analysis, we determined that this same unique individual owl was detected and identified on all 4 ARUs (Figure 3B), which we classified as individual 4 – EM 2019, 2020, and GV 2020, 2022 (Figure 4). Finally, in a third example, the MFCC methods grouped calls from deployments RS 2021 and RN 2019 and RN 2020 as the same individual. A tagged individual was present in the area of RS 2021 and RN 2020. That owl was tagged a week after the RN 2019 ARU deployment but also had locations in the vicinity of RN 2019 once tagged, suggesting it likely occurred in the area of RN 2019 before being tagged. We determined that the same

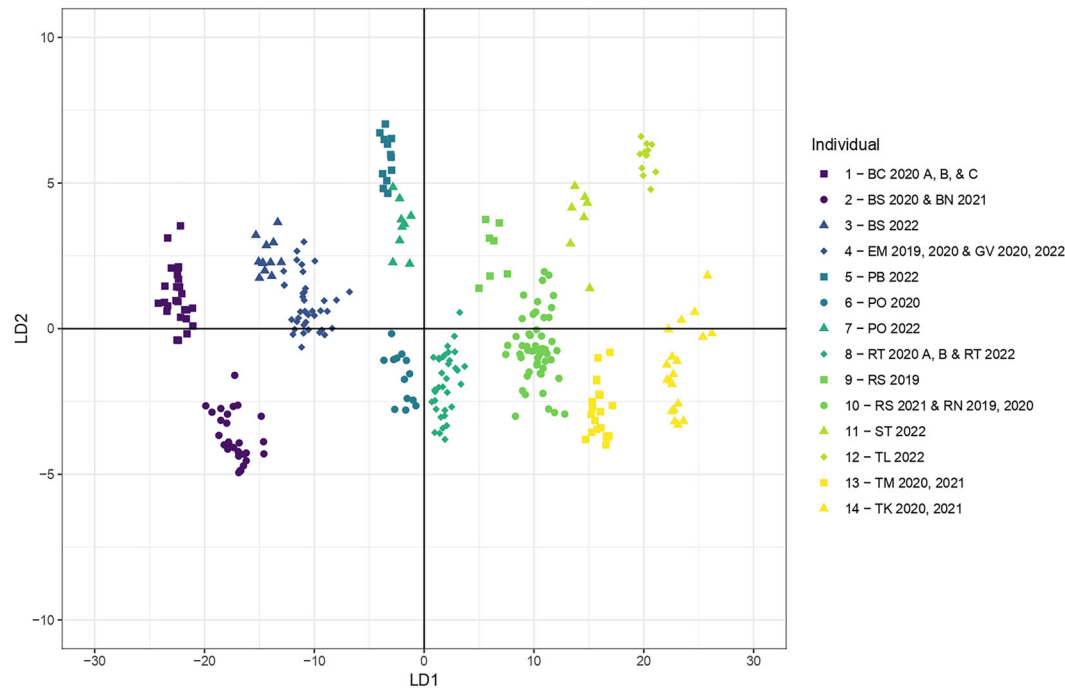


FIGURE 4 Linear discriminant functions 1 (LD1) and 2 (LD2) for discriminant analysis of great gray owl territorial calls using the mel-frequency cepstral coefficient method with territorial calls from 14 unique individual owls (compiled from groups of autonomous recording units [ARUs]) in the Greater Yellowstone Ecosystem, USA during 2019–2022. Each symbol represents a unique deployment identification (ID) including the territory ID (first 2 letters), year of deployment, and unique ARU (last letter if provided) for that territory. Clustering of points indicates that individuals match and are being identified accurately using the method, whereas non-clustered points indicate that individuals are not being identified accurately using the method.

unique individual owl was detected on all 3 ARUs based on MFCC analysis of calls (Figure 3B), and we classified this individual as 10 – RS 2021 and RN 2019, 2020 (Figure 4).

DISCUSSION

Automated MFCC methods were more accurate at differentiating territorial calls of individual great gray owls than was manual spectral analysis. Mel-frequency cepstral coefficient methods had a mean classification accuracy of 97%, whereas spectral analysis only correctly identified individuals approximately 77% of the time. The MFCC classification accuracy also held true when we used groupings of territorial calls that represented a single unique individual owl with calls recorded on multiple ARUs across territories or years. Based on the accuracy of the MFCC method, as compared with the spectral analysis method, we recommend that future studies utilize the MFCC method to identify individuals based on territorial calls.

Mel-frequency cepstral coefficient methods achieved 97% accuracy when applied to calls from known individuals grouped across territories; however, there were some instances in which the MFCC method misclassified calls. One of the misclassification instances may be explained by the possibility that the same individual moved between adjacent territories between years due to the close proximity of the territories, but we did not have a tagged owl in the area to confirm whether movements occurred. Other misclassifications have no apparent

explanation based on proximity or timing and may represent actual classification errors. The misclassifications lacking a clear explanation may be the result of similarities in call features between the 2 individuals for the misclassified calls, or instances with smaller sample sizes, as 2/3 of the misclassification instances included individuals with 15 or fewer calls. If so, a different individual may have passed through the area from a neighboring territory, and the ARU recorded its territorial call. However, the fact that we were able to obtain a high level of accuracy even with an average of only 16 territorial calls per ARU (min–max = 7–31) across 26 ARUs and 14 unique individual owls indicates that relatively small sample sizes are sufficient for classifying individuals of great gray owls with the MFCC method based on calls captured passively.

We found that manual spectral analysis of territorial call characteristics of great gray owls had a limited classification accuracy for identifying individuals across space and time. Less than 80% of the territorial calls were classified correctly using manual classification, with variation within and across seasons. Our classification rates were less than the 93% classification rate that Rognan et al. (2009) found within a season and more than the 71% accuracy found across seasons by Rognan et al. (2009). Such variability reinforces the need for automated approaches with objective feature extraction (Knight et al. 2024). Spectral analysis methods involved first identifying high-quality calls and then measuring 12 different spectral characteristics by hand for each call. The spectral analysis method has a degree of human error involved and may explain the lower classification rates we found with manual spectral analyses.

Identifying individuals across years and territories has been demonstrated for other species, including western screech-owls (*Megascops kennicottii*; Tripp and Otter 2006), African wood-owls (*Strix woodfordii*; Delport et al. 2002), Eurasian eagle-owl (*Bubo bubo*; Grava et al. 2008), and Queen Charlotte northern saw-whet owl (*Aegolius acadicus brooksi*; Holschuh and Otter 2005). However the call differentiation for those species used the spectral analysis approach that typically has required hand measuring individual call characteristics in a spectrogram, which can be time consuming. In our study, the entire process of manual spectral analysis took 2.5–3 hours per ARU, whereas the entire process of the MFCC method took only 1.5–2 hours per ARU. Although the MFCC method was more time-efficient compared to the spectral analysis, both the MFCC and spectral analysis methods nonetheless required a certain amount of preprocessing time. Preprocessing first involves identifying great gray owl territorial calls, which was done using automated species-specific classifiers built in Kaleidoscope that identify potential calls from the entire week's worth of audio data. After an output of potential great gray owl calls was provided using Kaleidoscope, trained biologists and volunteers verified territorial calls from the provided output because classifiers are imperfect at identifying calls (Knight et al. 2017, Marchal et al. 2021). Although other tools already exist for identifying great gray owl calls (e.g., BirdNET; Kahl et al. 2021, McGinn et al. 2023), we have found that the use of our species-specific classifier in Kaleidoscope detects great gray owls in some cases where BirdNET fails to detect the species within the same audio recordings, particularly in instances where few calls are recorded or the calls are distant. The next step required locating high-quality calls from previously identified calls so that call characteristics could be adequately measured. On average, only ca. 30% of the great gray owl calls that were verified on the ARUs were of high enough quality to be used in both spectral analysis and MFCC analysis methods. Using only high-quality calls does have the potential to reduce detection of individuals, including additional owls within a territory if those owls were too distant from the ARU to be recorded with a high signal-to-noise ratio, but it was necessary for comparing the 2 methodologies of individual identification.

Once we identified high-quality calls, we clipped them to the length of the full territorial call for MFCC methods, then we ran the calls through the automated process of MFCC feature extraction. The process of clipping calls and extracting MFCC features requires less time than the manual spectral analysis and reduces human inaccuracy by automating the method in which features are extracted. The automated MFCC method for identifying individuals not only increases the efficiency and accuracy of the process but also makes it more transferable to other species. The transferability of the automated MFCC method is because MFCC features can easily be extracted from a vocalization regardless of its unique characteristics by measuring the amplitude of the vocalization across overlapping frames of a predefined length and frequency range. Therefore, the use of MFCCs can be used for distinguishing individuals of other species, including those with more complex calls than *Strix* owls, if MFCC

feature extraction is done within a time window that accurately reflects the complexity of the call using a band pass filter that encompasses the frequency range of the call (Clink et al. 2018).

We determined that the automated method using MFCC features and passively collected ARU data is highly effective for identifying great gray owls in our study area using territorial calls. Passive acoustic monitoring of species has become widely used in the field of ecology, replacing more invasive methods of studying wildlife and minimizing impacts to species (Tosa et al. 2021, Ross et al. 2023). Applying individual identification using vocalizations will allow researchers to understand more about behaviors and monitor the abundance of species (Bristow et al. 2022) using passive methods, as well as help inform the occupancy and landscape use of species (Appel et al. 2023). Demographic metrics can also be calculated if ARUs are properly spaced for the species' detection radius, so individuals are not double-counted. The accuracy of population demographic metrics, particularly survival, is also based on the assumption that calls of individuals remain stable over the time period of the study (Knight et al. 2024). Use of the automated MFCC method with passively collected audio data holds particular merit for secretive, rare, or sensitive wildlife that may be difficult to monitor using other methods (Willacy et al. 2015, Bobay et al. 2018), and for other species for which call characteristics can be used to identify unique individuals. The combined use of passive audio recording and MFCC analysis to identify individuals can inform ecological questions related to individual behaviors, occupancy, and population dynamics and trends.

MANAGEMENT IMPLICATIONS

The use of passively collected audio data and automated audio analysis methods has important implications for monitoring individuals of a species across large areas and multiple years. Identifying individuals using automated MFCC methods provides spatiotemporal data on individuals that previously could only be collected through more resource-intensive methods of tagging and tracking individuals. The ability to identify individuals of a species across multiple territories and years using a noninvasive approach based on analysis of vocalizations can strengthen long-term species monitoring. Identifying individuals can also bolster existing large-scale passive acoustic monitoring efforts to determine trends in species occupancy due to the additional ability to track individuals within monitored populations. The use of automated MFCC methods to differentiate individuals using territorial calls can provide information on population dynamics, territory occupancy, and behaviors that can be used to guide conservation and management actions for a species, while minimizing disturbance to individuals.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

ETHIC STATEMENT

All animal handling and sampling procedures adhered to the Guidelines to the Use of Wild Birds in Research (Fair et al. 2023). All birds were banded under the following permits: Bird Banding Lab Permit No. 24140, Wyoming Game and Fish Department Permit No. 33-1011, USDA Forest Service Special Use Permit No. JAC225202, and Grand Teton National Park Permit No. GRTE-year-SCI-0005 (for years 2019–2022).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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