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RESEARCH ARTICLE

Sensors versus surveyors: Comparing passive acoustic monitoring, camera trapping and observer-based monitoring for terrestrial mammals

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Abstract

1. Mammals play vital roles in ecological communities, but many are in rapid decline worldwide. Comprehensive monitoring of mammal populations is crucial for effective conservation, but large-scale monitoring presents significant challenges. Remote sensing techniques such as passive acoustic monitoring offer viable and effective solutions for surveying animal communities. While passive acoustic monitoring has shown promising results for birds, its application in mammal biodiversity assessments has received little testing.
2. In this study, we compared passive acoustic monitoring (combined with BirdNET embeddings) to traditional observer-based monitoring and camera trapping for assessing terrestrial mammal biodiversity over multiple years across an extensive spatial scale in eastern Australia. Using embeddings from the BirdNET deep learning model, we efficiently analysed a cumulative total of 317,410 h of continuous audio data, recorded at a sampling rate of 22 kHz (effective up to 11 kHz), from six sites, successfully detecting all 17 target vocal mammal species. Given the inherent inability of passive acoustic monitoring to detect non-vocalising species or those vocalising outside this frequency range, we considered the mammal community in two ways: (i) entire mammal community and (ii) vocal mammals only.
3. For detecting species in the entire mammal community, observer-based monitoring performed the best, followed by camera trapping and then passive acoustic monitoring. However, when focusing on vocal mammals only, all methods showed comparable performance for the same 28-day survey period, with passive acoustic monitoring demonstrating significantly better performance when leveraging long-term audio data. Additionally, we found a significant positive correlation between species richness of vocal mammals and that of the entire mammal community, suggesting that vocal mammal richness may serve as a proxy for overall mammal biodiversity. Furthermore, PAM's effectiveness was not influenced by

common life-history traits, suggesting PAM may be a broadly applicable survey tool for vocal mammals.

4. Despite the benefits, the inability of passive acoustic monitoring to detect non-vocal mammals necessitates a combined approach with other survey methods such as camera trapping or observer-based monitoring to achieve a comprehensive assessment of terrestrial mammal biodiversity. This combined approach is likely to enhance future biodiversity monitoring, offering a more detailed understanding of ecosystems and supporting effective conservation practices.

KEYWORDS
artificial intelligence, bioacoustics, biodiversity assessment, deep learning model, ecoacoustics, machine learning, remote sensing, survey methods

1 | INTRODUCTION

Globally, mammal populations are in decline, with more than 25% of species threatened with extinction due to habitat alteration, introduced species and many other anthropogenic pressures (Ceballos et al., 2015; Hoffmann et al., 2010). This decline is particularly concerning in Australia, which has experienced over one-third of the global modern mammal extinctions (Woinarski et al., 2015). Many Australian mammals are endemic, with highly restricted ranges, and play vital roles in ecological communities as predators, grazers, ecosystem engineers and even pollinators (Holt et al., 2013; Lacher Jr. et al., 2019). Therefore, monitoring mammal biodiversity and detecting further declines in populations is crucial, necessitating comprehensive, large-scale monitoring efforts (Schmeller et al., 2015; Woinarski et al., 2011).

A variety of methods have been developed for surveying and monitoring mammals, many of which rely on direct observation or capture in the field (Eyre et al., 2018; Hoffmann et al., 2016), hereafter referred to as observer-based monitoring (OBM). For example, drift fences, coupled with pitfall traps, funnel traps, and Elliott or Sherman traps have been effectively used across many studies to capture small mammals (e.g. Amori & Luiselli, 2011; Brenner et al., 1992; Nicolas et al., 2010; Tasker & Dickman, 2001). Cage traps are commonly employed for medium-sized mammals (e.g. Garden et al., 2007; Thompson & Thompson, 2007), while spotlighting and thermal cameras have proven to be effective for detecting nocturnal and arboreal mammals (Burt et al., 2021; Catling et al., 1997; Doggart et al., 2006; Vinson et al., 2020). While all these methods are effective for detecting a range of mammals across various habitats, they are limited in their spatiotemporal coverage due to high manual labour requirements (Kitzes & Schricker, 2019), and can cause disturbance to the environment and potential harm to trapped animals (Stephens & Anderson, 2014).

More recently, remote sensing has enabled the long-term and large-scale monitoring of many mammals (Leyequien et al., 2007; Rodofili et al., 2022). Techniques such as satellite imagery, unoccupied aerial vehicles (UAVs) and camera traps have all been employed to effectively survey and monitor mammals (Linchant et al., 2015; McCallum, 2013; Wang et al., 2019). Camera trapping is a widely adopted method that allows for continuous, non-invasive observations of some wildlife, which is critical for answering questions related to population ecology, animal behaviour, conservation and wildlife management (Meek et al., 2015; O'Connell et al., 2011). Camera traps have been used across a broad spectrum of mammals, including many medium to large-sized species (Bridges et al., 2004; Claridge et al., 2010; Moolman et al., 2019; Wegge et al., 2004), and they have proven highly useful for studying cryptic and nocturnal species (Kelly, 2008; Vine et al., 2009). Furthermore, camera trapping has been more effective for detecting some medium-sized and small mammals compared with observer-based methods (De Bondi et al., 2010; Dundas et al., 2019), while reducing ongoing costs and the need for experts in the field.

Passive acoustic monitoring (PAM) is another remote sensing technique that has recently gained increased interest for detecting terrestrial vertebrates (Sugai et al., 2019). This method utilises automated recording units (ARUs) or automated sound recorders programmed to operate on a predefined sampling schedule to gain information on vocal fauna (Blumstein et al., 2011; Rhinehart et al., 2020). While most PAM research on mammals has focused on bats (Sugai et al., 2019), a wide range of other species have been successfully detected using PAM, including primates (Heinicke et al., 2015; Kalan et al., 2015; Wood, Barceinas Cruz, & Kahl, 2023), elephants (Wrege et al., 2017), deer (Enari et al., 2017), wolves (Barber-Meyer et al., 2020; Garland et al., 2020; Suter et al., 2017), koalas (Whisson et al., 2023), possums (Penman et al., 2005) and gliders (Whisson et al., 2021). A significant challenge associated with PAM is the amount of audio data it collects, which is often too extensive for manual processing (Rempel et al., 2005; Swiston & Mennill, 2009). To effectively manage and analyse large acoustic datasets, it is essential to integrate automated acoustic analysis workflows, which enable PAM to be applied across extensive temporal and spatial scales.

Automated acoustic analysis methods have been rapidly advancing in recent years, particularly through the application of machine learning, which has dramatically improved processing times and detection accuracy (Brodie et al., 2020; Ghani et al., 2023; Kahl et al., 2021; Priyadarshani et al., 2018). BirdNET is one such machine learning model, using deep artificial neural networks (DNNs), capable of identifying thousands of species within extensive audio recordings,

and has been successfully applied to detect a wide range of bird species (Bota et al., 2023; Kahl et al., 2021; Manzano-Rubio et al., 2022; Toenies & Rich, 2021; Wood et al., 2022). This large acoustic model is regularly being extended to include even more species from different vertebrate classes (BirdNET v2.4 includes 41 anurans and seven mammals), and with recent updates, BirdNET has been able to successfully identify several species of frogs (Bota et al., 2024; Pérez-Granados et al., 2023; Wood, Kahl, et al., 2023), a primate (Wood, Barceinas Cruz, & Kahl, 2023), and wolves and coyotes (Sossover et al., 2023). In addition to detecting the classes present in a pre-trained model, the embeddings from deep learning models can be used to search target vocalisations. These embeddings are numerical representations of acoustic signals learned by a model that capture essential features of a call and map them into a high-dimensional space. By comparing the embeddings of a user-provided example call to those in an unknown audio dataset, target vocalisations can be discovered even from just a single example call (Allen-Ankins et al., 2025; Ghani et al., 2023). While the use of BirdNET embeddings seems promising for detecting novel sound classes within unknown audio recordings and has been able to distinguish between different call types of the same species (McGinn et al., 2023), their utility for mammal biodiversity assessments has not been explored.

Here, we compared the performance of PAM in combination with BirdNET embeddings to traditional observer-based monitoring methods and camera trapping for assessing terrestrial mammal biodiversity. We evaluated the effectiveness of this remote sensing approach by examining: (i) species richness, (ii) community composition, (iii) species accumulation and (iv) time investment. To account for PAM's inability to detect non-vocal species, we structured our comparisons in two ways: first for the entire mammal community, and second for only vocal mammals. This dual analysis provides a more nuanced assessment of PAM's effectiveness, both on its own terms and as part of a comprehensive survey strategy.

2 | MATERIALS AND METHODS

2.1 | Study sites

This study was conducted within a broader project assessing the efficacy of PAM for terrestrial vertebrate biodiversity surveys throughout Australia. We selected six existing sites located in open eucalypt woodland (Figure 1a), where acoustic recording units (ARUs) were previously deployed as part of the Australian Acoustic Observatory

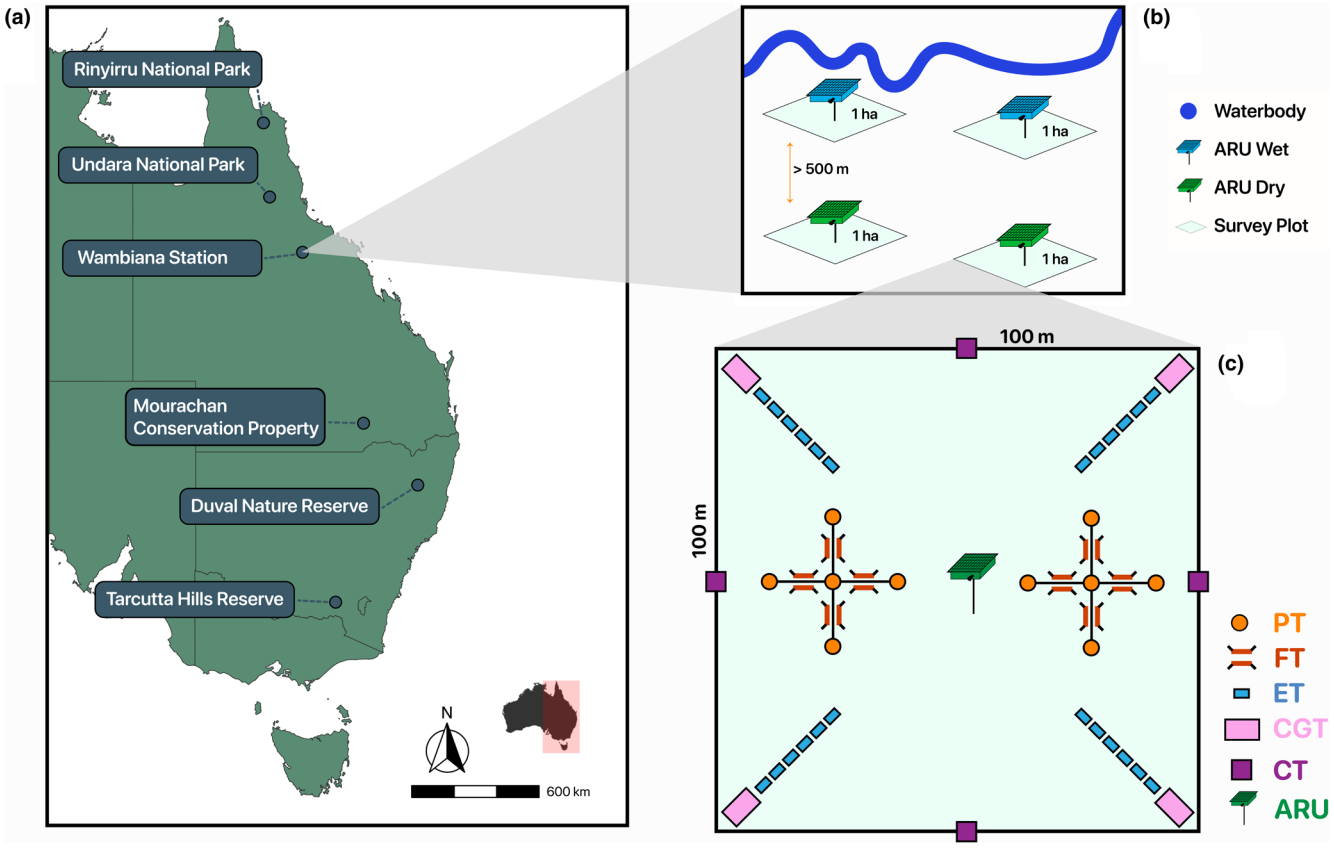

FIGURE 1 Schematic of (a) the six study sites throughout eastern Australia with (b) a diagram of the acoustic design for each site and (c) a summary of the survey methods employed at each survey plot (four per site) to target mammals within a 1 ha plot near each acoustic recording unit (ARU; adapted from Hoefer et al., 2024). At each site, four ARUs were installed in a comparable habitat type, with two positioned within 50 m of a body of water (ARU Wet—blue) and two more than 500 m away from a water source (ARU Dry—green). Abbreviations used: PT = pitfall trap, FT = funnel trap, ET = Elliott trap, CGT = cage trap, CT = camera trap.

project (Roe et al., 2021). All six sites were situated within natural reserves (Rinyirru National Park: 15.044° S, 144.243° E; Undara National Park: 18.187° S, 144.540° E; Duval Nature Reserve: 30.402° S, 151.625° E) or private properties without public access (Wambiana Station: 20.531° S, 146.113° E, Mourachan Conservation Property: 27.779° S, 149.032° E—Australia Zoo, Tarcutta Hills Reserve: 35.369° S, 147.697° E—Bush Heritage). We established a 1-ha survey plot, with each plot edge within 50 m of an ARU, resulting in four survey plots (2×'wet' [within 50 m of a body of water], 2×'dry' [at least 500 m from a waterbody]) per site (Figure 1b). Hereafter, we use the term 'site' to refer to the six reserves or private properties, and 'plot' to denote the four 1-ha areas surveyed within each site. We conducted observer-based monitoring (OBM), camera trapping and PAM simultaneously at each plot over a 7-day period per survey trip. Each survey trip lasted eight calendar days, although survey days have been considered as one of the seven 24 h periods (12 pm–12 pm) used in the analysis.

2.2 | Observer-based monitoring (OBM)

We conducted observer-based surveys to detect terrestrial mammals in Australian spring/summer (September–November) and autumn/winter (April–August) in 2021 and 2022 at each site, except for Mourachan and Duval, which were inaccessible during spring 2021 due to high rainfall (Table 1). To sample the mammal community, we used six different OBM methods within each plot (spatial arrangement shown in Figure 1c): (i) pitfall traps, (ii) funnel traps, (iii) Elliott traps, (iv) cage traps, (v) nocturnal active area searches (spotlighting) and (vi) incidental encounters (i.e. animals observed while not conducting active searches or checking traps).

Our trapping array within each plot consisted of 2 drift fences, 24 Elliott traps and 4 cage traps. Each 30-cm high drift fence was arranged in a cross design with four 10-m arms. Along these arms, we placed five 20-L pitfall traps (one at the centre and one at the end of each arm), and two funnel traps (positioned midway along each arm; Thompson & Thompson, 2007). For each funnel trap, we attached smaller additional fences or 'wings' at the openings to broaden the funnel and enhance capture efficiency (McKnight et al., 2013). Shade cloth was used to cover all funnel traps, while wet sponges were placed within every pitfall and funnel trap to mitigate desiccation and overheating of the trapped animals (McDiarmid et al., 2012). Elliott and cage traps were arranged in a line, 5-m apart, originating from every corner and extending towards the centre of the plot, each placed alongside a tree or log near vegetation cover (Friend, 1978; Tasker & Dickman, 2001). Each Elliott and cage trap was baited with peanut-butter-oat balls to attract mammals (Garden et al., 2007). When temperatures were low at the southern sites, Elliott traps were placed inside opened plastic bags and cotton wool was inserted into each trap to provide protection against the cold (Tasker & Dickman, 2001).

All plots were surveyed by two teams of two trained observers familiar with the local fauna. To minimise observer bias, the observers in each search team were rotated, as was the order in which plots were surveyed during each survey trip. Funnel and pitfall traps were checked twice daily. Elliott and cage traps were checked early in the morning prior to sunrise to alleviate stress on nocturnal mammals, and they were closed during daylight hours. Each captured mammal was marked with a veterinary-grade pink antiseptic spray (Chloromide™) before release, to ensure any recaptured mammals within the survey trip were not mistaken for new captures. Mammals recaptured within a survey period were removed from the data for community analyses. Nocturnal active area searches, or spotlighting, were conducted by two observers every day after sunset. For 15 min, the entire plot was searched, and all individual mammals detected visually or aurally were recorded.

All mammals were collected, handled and released in accordance with the protocols approved by the James Cook University Animal Ethics Committee (A2727), QPWS (Queensland Research Permit P-PTUKI-100066861 and WA0033038) and NSW Government (New South Wales Scientific Licence SL102511).

2.3 | Camera trapping

Four camera traps (Campark T85) were installed in each plot, mounted on trees approximately 50 cm above the ground and oriented towards the plot's interior (Figure 1c). Each unit was baited with sardines and peanut-butter-oat balls and configured for high sensitivity, capturing a sequence of three photographs and one 10-s video upon activation. Deployment was restricted to coincide with OBM survey periods due to equipment constraints.

2.4 | Camera trap data analysis

We analysed all available camera trapping data using the MegaDetector image recognition algorithm (Beery et al., 2019) and Timelapse2 (Greenberg, 2022a). There were three stages of analysis to generate species-level identification. In the first stage, we classified images as either 'wildlife' or 'non-wildlife' using the MegaDetector for each site and each survey. In Stage 2, we validated 'non-wildlife' classifications to ensure misclassifications are identified and corrected if necessary, following the workflow described in the Timelapse Image Recognition Guide (Greenberg, 2022b). To decrease the likelihood of failing to detect mammals in our camera trap data, we used a more conservative confidence threshold of 0.5 (Timelapse2 default: 0.8) to validate 'wildlife' classifications. In the final stage, all images classified as 'wildlife' were identified and labelled to species level by an expert observer.

2.5 | Passive acoustic monitoring

We conducted passive acoustic monitoring to assess its effectiveness for evaluating mammal biodiversity in Australia. Each ARU

TABLE 1 Summary of survey durations across six study sites, including the total number of days for field surveys, camera trapping days and the number of days of acoustic recordings during the survey period and for all available audio data.

Site	First survey	Second survey	Third survey	Fourth survey	Total number of survey days	Total number of camera trapping days	Total acoustic recordings (survey period) in days	Total acoustic recordings (all audio) in days
Rinyirru	14 June 2021–21 June 2021	8 October 2021–15 October 2021	7 August 2022–14 August 2022	23 October 2022–30 October 2022	112	441	98	1297
Undara	3 June 2021–10 June 2021	29 September 2021–6 October 2021	8 May 2022–15 May 2022	13 October 2022–20 October 2022	110	448	84	1660
Wambiana	5 July 2021–12 July 2021	10 November 2021–17 November 2021	12 June 2022–19 June 2022	28 September 2022–5 October 2022	112	448	97	3280
Mourachan	9 May 2021–16 May 2021	NA	19 June 2022–26 June 2022	2 November 2022–9 November 2022	84	336	60	1956
Duval	18 April 2021–25 April 2021	NA	28 April 2022–5 May 2022	12 November 2022–19 November 2022	70	273	65	2122
Tarcutta	29 April 2021–6 May 2021	18 October 2021–25 October 2021	8 May 2022–15 May 2022	22 November 2022–29 November 2022	112	434	109	2910

Note: Total survey days are expressed as the number of survey days per site (max 28 days) multiplied by the four survey plots. Total camera trapping days represent the total number of days all 16 camera traps were active at each site.

(Frontier Labs Solar BAR) was a self-contained, weather-sealed unit comprising a charge controller, battery, solar panel and recorder. The units were equipped with an external omnidirectional microphone (Primo EM172: 80 dB SNR, −28 dB sensitivity at 1 kHz) and mounted on a star picket with sufficient clearance to prevent wildlife damage. Audio was recorded continuously in mono at a 16-bit depth and 22.05 kHz sampling rate, using FLAC lossless compression. Recordings were stored as 2-h files on dual 512 GB SD cards (see Roe et al., 2021 for full specifications). This setup allowed for up to 12 months of uninterrupted data collection, at which point the SD cards were replaced and recording resumed.

2.6 | Acoustic data analysis

We used the BirdNET-Analyzer (Kahl et al., 2021) to gain information about the presence of vocal mammals in our audio recordings. Specifically, we created feature embeddings via BirdNET, which are numerical representations of sound data as vectors in a multidimensional space (Allen-Ankins et al., 2025; Ghani et al., 2023; McGinn et al., 2023), to search for novel sounds in our audio recordings. For this, we selected up to three example calls for each of the 17 Australian mammals that produce vocalisations within the human audible frequency range (Rosenfeld & Hoffmann, 2021), and for which we were able to attain audio samples of their characteristic calls (hereafter referred to as 'vocal mammals'), which resulted in 46 example calls (Table S1). Eastern grey kangaroos and common wallaroos were grouped as 'macropod' and grey-headed flying-fox, little red flying-fox and black flying-fox were grouped as 'fruit bat'. While we were able to obtain example calls of these individual species, we were unable to differentiate the individual species during validation. The 46 example calls were subsequently used to examine the acoustic data collected during the same 7-day periods when other survey methods were in use (PAM during survey period: 12,303 h) and to examine all acoustic data available (PAM all audio: 317,410 h). We created feature embeddings for our six survey sites using all acoustic data available in the A2O data repository (Roe et al., 2023) and for the 46 example mammal calls following the instructions in the BirdNET-Analyzer Github repository (https://github.com/kahst/BirdNET-Analyzer). We then calculated the Euclidean distances between feature embeddings of the mammal example calls and the unknown audio in the acoustic dataset. Finally, we extracted the top detection (single lowest Euclidean distance) for each example call for every day of recording at each survey site and used Kaleidoscope (https://www.wildlifeacoustics.com/products/kaleidoscope) to both aurally (sound clip) and visually (spectrogram) verify and confirm species detections (199,604 detections). We found that lower Euclidean distances typically corresponded to true positive detections (Figure S1), justifying our use of the single lowest daily distance for identifying species presence. To quantify this relationship, we determined the probability that a randomly chosen true positive detection would have a smaller Euclidean distance than a randomly chosen false positive detection for the same example call. Across all example calls, this probability averaged 78%, confirming that true positives generally yielded lower Euclidean distances.

2.7 | Statistical analysis

All statistical analyses, conducted for all mammals and vocal mammals only, were performed in the R statistical environment (R Core Team, 2024; v4.3.2). To compare species richness across assessment methods, we employed hierarchical models within a Bayesian framework. Using the *brms* package (Bürkner, 2017), we modelled the total species count per survey plot as a function of the assessment method, assuming a Poisson distribution and weakly informative priors. For model fitting, we used three chains, each with 5000 iterations, a thinning rate of 5 and a 1000-iteration warmup period. The final model was chosen from several candidates based on the LOO information criterion (Vehtari et al., 2017). Convergence was confirmed (all Rhat <1.05), and the model was validated with DHARMa residuals (Hartig, 2022). To determine specific differences between methods, we performed post hoc pairwise comparisons on the model estimates. We encountered ARU and camera trap failure over the course of the study. To enable a fair comparison of the methods, we excluded data from plots for surveys where either the acoustic recorder collected less than 70% of the possible full audio data or more than one camera trap failed (Table S2). Initially, we analysed the individual OBM methods separately for species richness comparisons against camera trapping and PAM. However, aside from spotlighting, which performed better than the other OBM techniques, the differences among the individual OBM methods were not significant. Moreover, comprehensive mammal surveys typically involve deploying multiple techniques rather than relying on a single method. Consequently, the individual OBM methods were combined into one category for the subsequent analyses. To determine whether specific mammal characteristics affect their detectability via PAM, we explored the relationship between the likelihood of detection and six common traits (Table S3). The traits selected for analysis were adult mass, dispersal distance, home range extent, lifestyle (fossorial or above-ground), daily activity pattern and volant capacity (flying or non-flying). Trait information was primarily compiled from the COMBINE and HomeRange databases (Broekman et al., 2023; Soria et al., 2021), with data for species not included in these resources being extracted from a field guide to Australian mammals (Van Dyck et al., 2013).

2.8 | Community composition and species accumulation curves

We evaluated community differences between assessment methods using nonmetric multidimensional scaling (nMDS) on Jaccard dissimilarities (presence-absence), followed by pairwise permutational analysis of variance (*vegan* and *EcolUtils* packages; Oksanen et al., 2022; Salazar, 2022). To assess sampling effort, we constructed species

accumulation curves (*vegan* package) for both the 28-day surveys and all available acoustic recordings. We also calculated the time required for PAM to equal the vocal mammal richness detected by OBM, using randomised day-order permutations to generate robust estimates.

2.9 | Time investment

We estimated the time investment required for each method to generate species inventories, providing an important proxy for financial costs in mammal biodiversity assessments. While each day of sampling with OBM required less than 24 h of active searches and live animal trapping, observers spent the full 24 h on site in the field. Therefore, we calculated the time investment for OBM by multiplying the 24-h periods spent in the field by the total number of survey days (28) across each of the six survey sites and added the time needed for setup and takedown of all traps. For PAM and camera trapping, we calculated the time needed to analyse and validate the 317,410 h of audio recordings and approximately 100,000 images, respectively. For both methods, we used timestamps embedded in the validation files created during data analyses, and therefore, the time of analysis could be easily calculated. For validation, we used stopwatches to accurately record the time required to validate acoustic and camera trapping data. We also added the time needed for the initial setup and regular maintenance of PAM and the setup and takedown of camera traps.

3 | RESULTS

Across the six sites, we identified a total of 45 species of mammals, of which 17 were classified as 'vocal mammals' (Table S4). For all mammals combined, OBM recorded the highest species richness (45/45 species), followed by camera traps (25/45 species), PAM using all available audio (17/45 species) and PAM using audio matching the survey period only (13/45 species). Overall, OBM detected 11 unique species not detected by any other method (Table S4). The highest number of vocal mammals were detected by PAM using all audio (17/17 species) and OBM (17/17 species), followed by PAM using audio recorded only during the survey period (13/17 species), and camera traps (11/17 species). The maximum total species richness achieved varied among survey sites and did not follow a strict latitudinal trend (Table 2). However, species richness was highest at the most southern sites, with Tarcutta (24 total mammals/14 vocal mammals) and Duval (19 total/11 vocal) recording the highest number of species, followed by Wambiana (19 total/11 vocal), Undara (18 total/9 vocal), Mourachan (16 total/9 vocal) and Rinyirru (16 total/9 vocal).

3.1 | Species richness

3.1.1 | All mammals

Over the same 28-day survey period, OBM detected significantly more species on average than PAM (2.46× more species, 95% highest density interval [HDI]: 1.85–3.12) and camera traps (1.44× species, 95% HDI: 1.15–1.77; Figure 2). PAM recorded significantly fewer species than camera traps during this period (0.58× species, 95% HDI: 0.43–0.74). When all available audio data were used, PAM detected significantly more species than when PAM was limited to the survey period only (2.13× species, 95% HDI: 1.62–2.72), but did not differ significantly from OBM (0.86×, 95% HDI: 0.69–1.04) or camera traps (1.25x species, 95% HDI: 0.99–1.52).

3.1.2 | Vocal mammals only

Considering vocal mammals only, over the same 28-day survey period, OBM detected significantly more species than camera traps on average (1.46× more species, 95% HDI: 1.05–1.87; Figure 2). However, there was no significant difference in the average number of species detected by OBM compared with PAM (1.34× species, 95% HDI: 0.99–1.74). Similarly, no significant difference was found between PAM and camera traps (1.08× species, 95% HDI: 0.79–1.43). Using all available audio data, PAM identified significantly more vocal mammal species than OBM (1.58× species, 95% HDI: 1.24–1.98), camera traps (2.29× species, 95% HDI: 1.73–2.93) and

TABLE 2 Maximum total species richness, number of days to reach the maximum total species richness, the percentage of total richness achieved after 28, 90, 180 and 365 days of passive acoustic monitoring (PAM) of vocal mammals at each survey site, as well as the mean value across all sites.

Site	PAM (maximum total richness)	Days to max total richness	PAM proportion of max richness			
			28 days	90 days	180 days	365 days
Tarcutta	13	968	0.66	0.78	0.86	0.94
Duval	10	676	0.72	0.86	0.91	0.95
Mourachan	7	782	0.68	0.86	0.89	0.92
Wambiana	10	760	0.79	0.91	0.96	0.99
Undara	7	771	0.50	0.75	0.86	0.92
Rinyirru	9	487	0.61	0.79	0.87	0.96
Average (all sites)	9	741	0.66	0.82	0.89	0.95

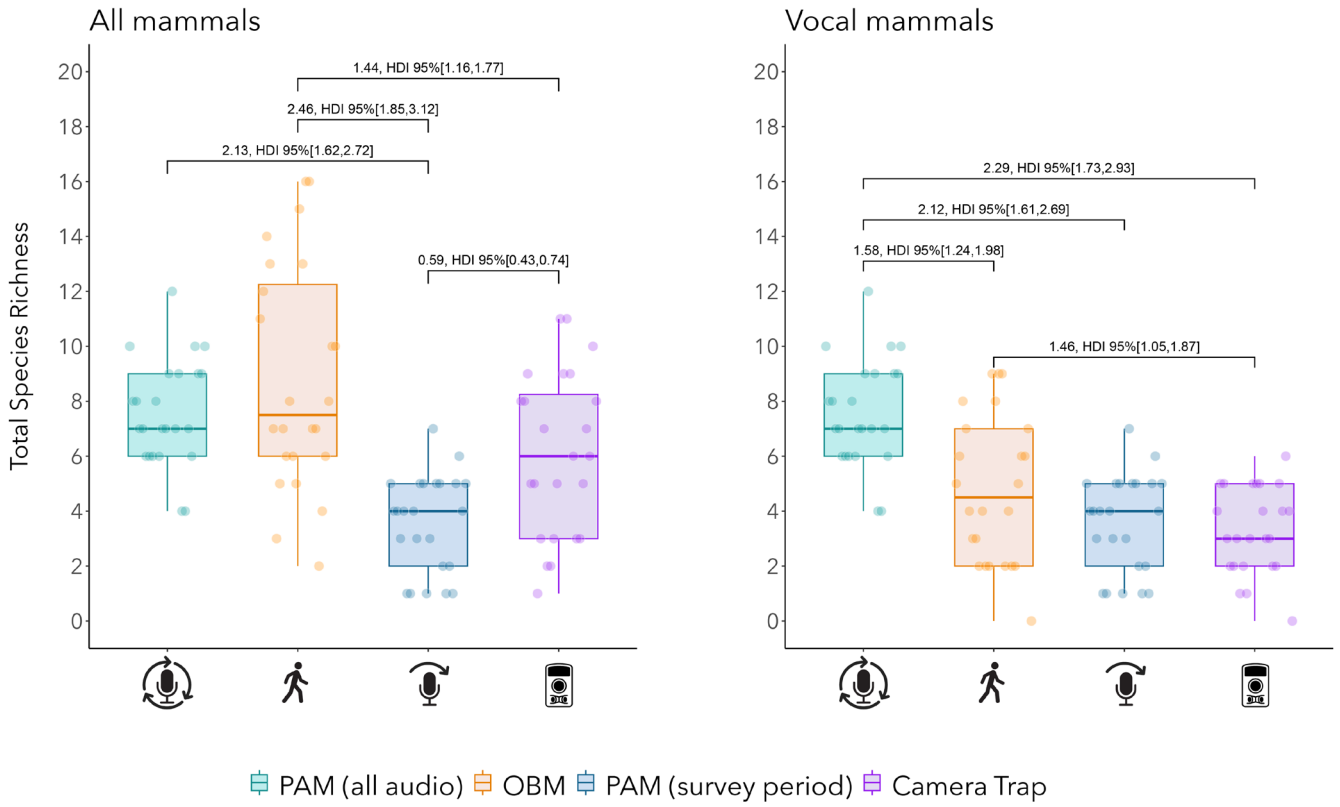

FIGURE 2 Total species richness for all mammals (left) and vocal mammals only (right) as captured by each assessment method: Passive acoustic monitoring using all available audio (PAM [all audio], green with microphone icon with three arrows), observer-based monitoring (OBM, orange with human icon), passive acoustic monitoring with audio from only the survey period (PAM [survey period], blue with microphone icon with one arrow) and camera trapping (purple with camera trap icon). Jittered points indicate species richness per survey plot. Average fractional differences and 95% Highest Density Intervals, signifying statistical significance, are displayed above the boxplots. Vocal mammals constituted 42% of all mammals in this study.

PAM using audio data only recorded during the survey period (2.12× species, 95% HDI: 1.61–2.69). A Pearson's correlation test revealed a significant, moderately positive relationship between the species richness of vocal mammals detected via PAM and the species richness of the entire mammal community detected via OBM ($r_{22}=0.46$, $R^2=0.21$, p-value = 0.02; Figure S2).

3.2 | Community composition

3.2.1 | All mammals

Mammal communities surveyed via OBM were significantly different from those sampled through PAM during the same 28-day survey period (Jaccard index, $R^2=0.216$, p-value = 0.015; Figure 3). However, communities surveyed by OBM did not differ significantly from camera traps (Jaccard, $R^2=0.145$, p-value = 0.212), nor from PAM for all audio (Jaccard, $R^2=0.199$, p-value = 0.057). Camera traps recorded significantly different assemblages compared with both PAM over the survey period (Jaccard, $R^2=0.327$, p-value = 0.016) and PAM for all audio (Jaccard, $R^2=0.331$, p-value = 0.006). Notably, PAM using all audio and PAM over the survey period captured similar mammal communities (Jaccard, $R^2=0.109$, p-value = 0.291).

3.2.2 | Vocal mammals only

For the communities of vocal mammals only, OBM sampled a similar suite of species compared with PAM during survey period (Jaccard, $R^2=0.115$, p-value = 0.698), PAM with all audio data (Jaccard, $R^2=0.06$, p-value = 0.698) and camera traps (Jaccard, $R^2=0.178$, p-value = 0.296; Figure 3). The only significant difference in mammal communities sampled was between camera traps and both PAM for all audio (Jaccard, $R^2=0.295$, p-value = 0.045), and PAM over the survey period (Jaccard, $R^2=0.306$, p-value = 0.03). The assemblages of vocal mammals did not differ significantly between PAM all audio and PAM over the survey period only (Jaccard, $R^2=0.109$, p-value = 0.698).

3.3 | Species accumulation

Passive acoustic monitoring reached its maximum total species richness at an average of nine species across all sites, ranging from

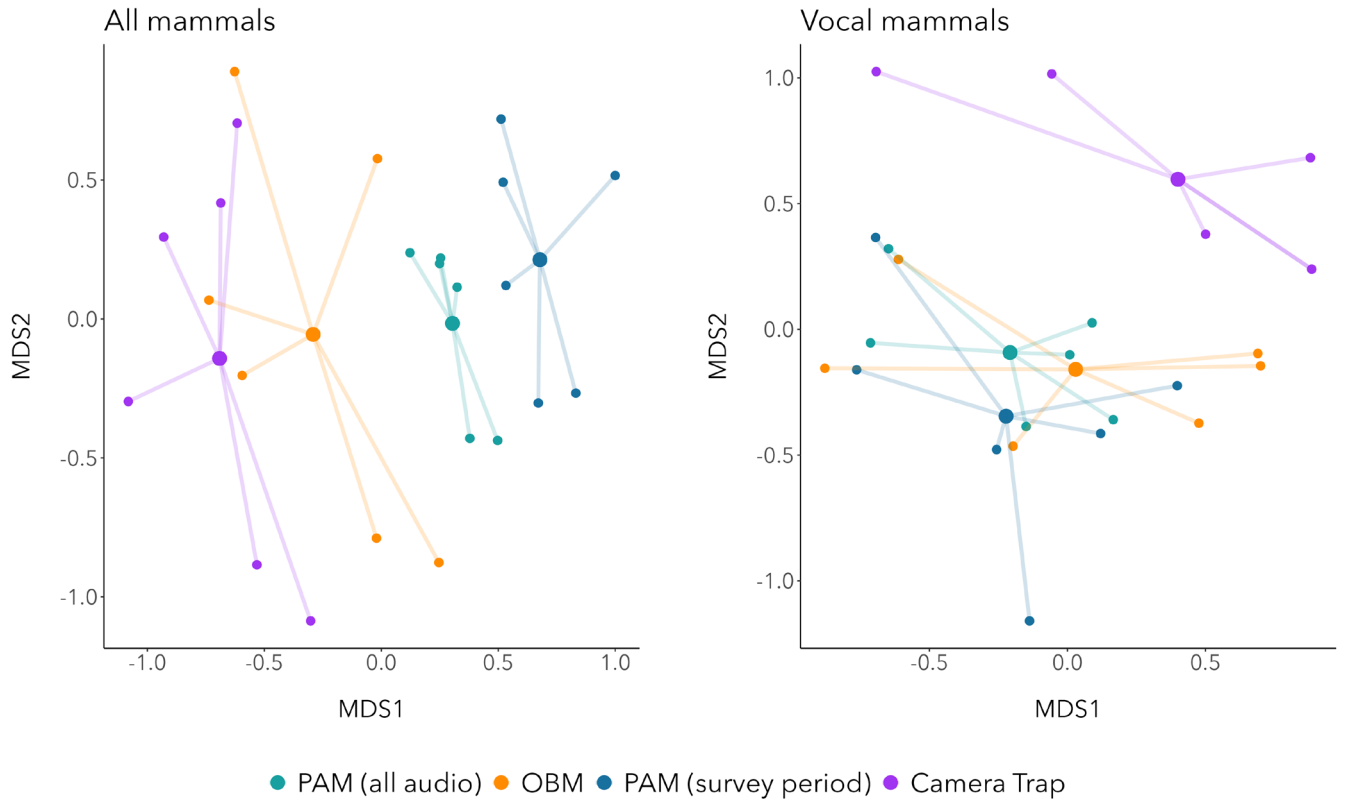

FIGURE 3 Nonmetric multidimensional scaling (NMDS) ordination of mammal communities (all mammals [left] and vocal mammals only [right]) based on Jaccard dissimilarity (presence-absence) captured by the different assessment methods at each survey site. Each point represents a survey site, and larger points mark the centroids for every assessment method, with connecting lines to individual sites belonging to each method.

seven (Undara and Mourachan) to 13 species (Tarcutta; Table 2). It took on average 741 days to reach this maximum total richness, with a range of 487 days (Rinyirru) to 968 days (Tarcutta). After 28 days of sampling, we captured 66% of the maximum total species richness on average, with a high variability of 29% across sites (Table 2). After 90 days of recording, the average proportion was 82% and the maximum variability (i.e. the difference between the best- and worst-performing sites for the proportion of total species richness detected) decreased to 16%. After 180 days of sampling, the average proportion was 89% and maximum variability between sites decreased to 10%. After 365 days of recordings the average proportion of the maximum total species richness at a site was 95% and the maximum variability between sites was 7%.

Species accumulation curves of PAM did not approach an asymptote at any survey site, except for Wambiana where the maximum species richness was accumulated after 760 of 1235 days (Figure S3). The number of days required to reach equal vocal mammal species richness to OBM at each survey site varied greatly, from 12 to 676 days (Tarcutta: 320 days; Duval: 676 days; Mourachan: 88 days; Wambiana: 17 days; Undara: 175 days; Rinyirru: 12 days; Figure S3). The number of days required to match camera trap varied less, ranging from 9 to 35 days (Tarcutta: 9 days; Duval: 12 days; Mourachan: 17 days; Wambiana: 12 days; Undara: 35 days; Rinyirru 12 days). None of the tested mammal traits, including adult mass (p-value = 0.6), dispersal distance (p-value = 0.66), home range extent (p-value = 0.8), lifestyle (p-value = 0.74), daily activity patterns (p-value = 0.89), or volant capacity (p-value = 0.94) significantly affected detection probability via PAM (Figure S4).

Species richness accumulation over the 28-day survey period revealed that OBM detected the greatest richness for all mammals, and more quickly, followed by camera traps and PAM (Figure S5). For vocal mammals only, OBM accumulated greater species richness at four sites and did so more quickly, while PAM accumulated species more quickly and reached greater final numbers at two sites. A combined remote sensing approach with PAM and camera traps offered quicker accumulation and higher species numbers than OBM at four sites for vocal mammals and achieved higher richness at one site for all mammals.

3.4 | Time investment

The time required to conduct each survey type and process data varied greatly. By considering the time required to actively conduct surveys, analyse and validate data at each site using each survey method, OBM was more time intensive than PAM or camera trapping. OBM required the greatest time investment for conducting surveys and collecting data in the field (observers spent 24 h in the field, totalling 4032 h over

the survey period; Table S5), whereas processing the data was done following collection and completed within the same 24-h daily time investment. In contrast, PAM and camera trapping required an initial short time investment for installation and setup (PAM: 12 h, camera trapping: 64 h), as well as additional brief visits for maintenance (SD card and battery changes) but required the greatest time investment for processing and validating the collected data (PAM: 299 h, camera trapping: 181 h). For each day of sampling and data processing with OBM, observers spent 24 h in the field to generate a species list. In comparison, each day of sampling and processing data required 0.02 h (1.2 min) for PAM and 1.1 h (66 min) for camera trapping. Therefore, the time investment per survey day for PAM and camera traps amounted to less than 0.1% and 4.6% of OBM's time, respectively, with PAM taking 1.8% of the time required by camera traps. With 4032 h of OBM (45 species detected), 299 h of PAM (17 species), and 181 h of camera trapping (25 species), detection of each individual species took 90 h for OBM, 18 h for PAM and 7 h for camera trapping.

4 | DISCUSSION

We compared the efficacy of PAM to OBM and camera trapping for assessing terrestrial mammal biodiversity in eastern Australia. Using embeddings from the BirdNET deep learning model, we efficiently analysed a cumulative total of 317,410 h of continuous audio data (equivalent to 36 years) from six sites, successfully detecting all 17 target vocal mammal species. Given the inherent inability of PAM to detect non-vocalising species, we structured our comparisons in two ways: first, for the entire mammal community to understand each method's overall contribution, and second, for vocal mammals only to evaluate PAM within its capability. For the entire mammal community, the greatest species richness was detected by OBM (45 species), followed by camera traps (25) and PAM (17). For vocal mammals only, PAM detected at least equal numbers of species and identified a similar suite of the community compared with other survey methods while only requiring a fraction of the time investment. The time needed to capture more than 95% of the total species richness possible with PAM varied across sites, but on average, required 365 days of sampling. The species richness detected via PAM reflected the overall species richness, as sites with higher vocal mammal species richness also exhibited higher overall species richness. Furthermore, PAM's effectiveness for detecting vocal fauna was not significantly influenced by common life-history traits which suggests that PAM may a broadly applicable survey tool for vocal mammals.

4.1 | Species richness

This study showed that all survey methods conducted in the 28-day survey period detected similar species richness of terrestrial vocal mammals. However, the species richness detected by long-term recordings of PAM was significantly greater than all other survey methods conducted over the 28-day survey period. It is well established that species richness is an important metric when assessing biodiversity and the overall health of an ecosystem (Gotelli & Colwell, 2001; Tilman et al., 2006). Similarly, long-term monitoring generally results in the detection of greater species richness (e.g. long-term camera trapping for medium- to large mammals (Mashintonio et al., 2022), or longer duration live animal trapping for small mammals (Conard et al., 2008)). It is therefore unsurprising that long-term data from PAM significantly outperformed all other methods for species richness (see also Klingbeil & Willig, 2015; Kułaga & Budka, 2019 for reports in other terrestrial vertebrates). This is likely because although shorter overall recording periods and non-continuous daily sampling schedules can effectively detect some species (Shirose et al., 1997; Thompson III et al., 2002), long-term, continuous audio recordings provide the advantage of detecting additional cryptic or infrequently vocalising species (Digby et al., 2013; Gibb et al., 2018; Klingbeil & Willig, 2015). Indeed, we detected six species in the long-term PAM data which may be considered cryptic or nocturnal, and were not detected by any other survey method at some sites (e.g. squirrel gliders [*Petaurus norfolcensis*], sugar gliders [*P. breviceps*], common brushtail possums [*Trichosurus vulpecula*]). Although we designed sampling for all methods to capture multiple seasons and times of day, the six species detected exclusively by long-term PAM at some sites emphasise that as technological advancements and innovations in autonomous audio recorders progress, the collection of more audio data is achievable and desirable (Aide et al., 2013; Rhinehart et al., 2020). For the monitoring data collected only within the survey period, all methods detected comparable numbers of vocal mammal species, and it is therefore plausible that greater species richness may also be achieved with longer sampling periods for OBM and camera trapping.

4.2 | Community composition

While species richness is a fundamental aspect of biodiversity, relying solely on this metric is unlikely to provide adequate ecological information (Brown et al., 2001; Fleishman et al., 2006). Considering species richness without broader community data prevents understanding of important impacts on communities, such as native species replacements by invasive species, changes in species interactions and reductions in species performing specific functional roles within the community, which are critical for understanding ecosystem processes and stability (Tilman et al., 1997). Community composition, which includes the variety of species within a community, provides an additional perspective by highlighting the community structure and identifying potentially important species contributing to ecosystem functionality and health (Díaz & Cabido, 2001). This metric may be particularly important in the context of effective conservation action, where failing to identify keystone species may risk the health of an ecosystem (Power et al., 1996).

While PAM and OBM detected similar assemblages of vocal mammals in this study, the overall community similarity decreased

when non-vocal mammals were considered, as these are inherently missed by PAM. Other studies have also shown that PAM may detect a different part of the community compared with observer-based methods (Acevedo & Villanueva-Rivera, 2006; Lintott et al., 2013; Wheeldon et al., 2019). This is most obviously due to the simple limitation of PAM to detect non-vocal species and species with vocalisations indetectable by the recorders (e.g. outside of the sampling rate of the recorder or vocalising at low decibels), or those that vocalise infrequently. Indeed, the 28 species detected by OBM that were not detected by PAM are not known to produce vocalisations, vocalise in ultrasonic frequencies, or vocalise very infrequently (Menkhorst & Knight, 2011; Rosenfeld & Hoffmann, 2021). However, for species that do vocalise, PAM can detect arboreal species difficult to detect without specialised camera trapping (Moore et al., 2021). This highlights how each method provides unique and complementary data: PAM was most effective for detecting arboreal and elusive species (e.g. gliders and foxes), camera trapping proved particularly useful for detecting ground-dwelling cryptic species (e.g. feral cats and pigs), and OBM was necessary for capturing small non-vocal mammals (e.g. rodents and dasyurids). Recording at higher sampling rates could lead to additional detections of mammals vocalising in ultrasonic frequencies, which remained undetected by PAM in this study. In our case, such an approach might have captured an additional two bat and six rodent species previously detected only by OBM, and could potentially have recorded further species missed by all survey methods.

Although camera trapping identified the fewest vocal mammal species of all methods, the assemblage of vocal mammals it captured varied significantly from that detected by PAM. Notably, camera trapping detected cats (*Felis catus*) and pigs (*Sus scrofa*) at certain sites where PAM did not. This is likely because camera traps were baited, which attracted cats and pigs and facilitated detection. Given that these animals do not vocalise as readily and frequently as other terrestrial mammals, detecting them solely through sound is likely to pose a significant challenge. However, increasing the number of call examples used within BirdNET analyses, particularly from a variety of different regions, could enhance detection rates. Vocalisations of the same species can vary regionally due to dialects and different call types (Henry et al., 2008; Luís et al., 2021), and thus constructing a robust, trained recogniser with a variety of call examples may yield more reliable detections of cats and pigs.

4.3 | Species accumulation

The 28-day survey period used in this study followed the recommendations of survey guidelines for OBM and camera trapping for terrestrial mammals in the region (Eyre et al., 2018). However, there is currently no consensus on the optimal deployment duration for PAM, and most studies vary widely in the overall deployment and daily sampling period for acoustic recorders (Hoefer et al., 2023; Sugai et al., 2019, 2020; Wood et al., 2021). While shorter deployment periods may reduce maintenance demands (i.e. changing SD cards and batteries), this can lead to less complete species inventories (Klingbeil & Willig, 2015; Kułaga & Budka, 2019; Wimmer et al., 2013). We found that for the short-term (28-day) monitoring period, OBM was most effective, as it accumulated the greatest species richness and at a faster rate than any other method alone. However, a remote sensing approach with combined PAM and camera trapping achieved similar species richness. The combined strengths of camera trapping and PAM (i.e. the ability of camera traps to detect non-vocalising species and the ability of PAM to detect arboreal species and species from any direction) may allow similarly effective biodiversity assessments compared with traditional OBM, while offsetting time and financial investment involved with survey efforts.

Sampling over short periods of time may risk missing species that vocalise seasonally, rarely vocalise, or are cryptic (Digby et al., 2013; Zwart et al., 2014), and some species detections may be masked by anthrophony, geophony or even other biophony (Pijanowski et al., 2011). We found that continuously sampling with PAM for 28 days led to an average detection of only 60% of all vocal mammals, compared with 95% of the total species richness detected by PAM after 365 days. Furthermore, with prolonged sampling, the variability of total species richness detected across the six sites dropped from 29% to 7%, highlighting that long-term acoustic monitoring reduced differences in detection rates across sites. Given its temporal and spatial scalability, deploying ARUs for extended periods is crucial for achieving comprehensive species inventories. However, continuous year-round recording generates vast amounts of audio data, which can pose significant challenges for data storage (Teixeira et al., 2024). For instance, the approximately 32 TB of acoustic data from this study could incur local storage costs exceeding A$1500, while cloud storage providers might charge well over A$1000 per month (Naldi & Mastroeni, 2013). In our case, data storage costs were mitigated as all acoustic data used are publicly and freely available through the Australian Acoustic Observatory (Roe et al., 2023). Furthermore, Ecosounds, developed by the same research group, offers a free repository facilitating the management, access, visualisation and analysis of environmental acoustic data (Towsey et al., 2018). However, if long-term monitoring is not feasible due to these or other constraints, combining short-term PAM with camera trapping or targeted OBM may be the most effective way to detect the greatest number of terrestrial mammal species using remote methods.

4.4 | Time investment

A critical consideration for any biodiversity assessment is the resource investment required to effectively detect species present. The amount of time needed is a reasonable proxy of financial expenses and often acts as a constraint for comprehensive survey

efforts (Gardner et al., 2008). Therefore, reducing the time required by personnel to detect species in an area is not only desirable but vital for long-term biodiversity monitoring (Darras et al., 2019). For vocal mammals, we found that long-term PAM, in combination with BirdNET embeddings significantly decreased the time needed to conduct species inventories, with at least equal detection performance compared with OBM and camera traps for vocal species.

This study allowed us to analyse a cumulative total of 36 years of continuous audio recordings (24 ARUs × 6 sites × hours of available audio data for each ARU; Table S2) and compile species lists in less than 2 weeks, with each 24 h of continuous audio recordings only requiring about 1 min to analyse. compared with OBM, this represented less than 0.1% of the time required (when considering OBM in terms of total necessary in-field days) and only 2% of the time needed for camera trapping. These significant time savings could considerably reduce costs, particularly for large-scale, long-term biodiversity assessments. We acknowledge that our acoustic analyses were conducted in a high-performance computing (HPC) environment providing enhanced computational resources over conventional local machines. Therefore, analyses attempting to handle similar volumes of audio data and mammal example calls on conventional computers will require an increased time investment.

4.5 | Limitations and future directions

One inherent limitation of PAM is its inability to detect non-vocal mammals, leading to incomplete assessments of mammal diversity. This limitation is well-documented across various studies, emphasising the restriction of PAM to vocalising species (e.g. Alquezar & Machado, 2015; Farmer et al., 2009; Haselmayer & Quinn, 2000; Hutto & Stutzman, 2009). While this is an obvious drawback of PAM, it is important to recognise that all monitoring methods have inherent constraints. For example, observer-based monitoring, which relies on field-based human observers, is limited by the availability of experts, logistical challenges and financial resources, often making it impractical over extensive spatial and temporal scales (Darras et al., 2019; Kitzes & Schricker, 2019; Rhinehart et al., 2020). Similarly, camera trapping, although capable of capturing non-vocal fauna, is restricted by its limited field of view, and typically targets ground-dwelling species. Likewise, emerging methods like eDNA sampling can detect a wide range of non-vocal species from environmental samples but often provide limited information on abundance or behaviour and are sensitive to issues of DNA transport and degradation (e.g. Harrison et al., 2019; Thomsen & Willerslev, 2015). Some studies have found a positive correlation between the species richness of vocal and non-vocal species (Alcocer et al., 2022; Allen-Ankins et al., 2023; Botero-Cañola et al., 2024), suggesting that detecting vocal species alone may be sufficient to infer overall species richness. Consequently, changes in vocal species richness could serve as indicators of shifts in overall species diversity.

Automated recording units allow for continuous data collection over extended periods without human presence, which is especially beneficial during or after extreme weather events, when accessing field sites may not be possible (Darras et al., 2019). However, much like camera traps, this also makes ARUs susceptible to theft and vandalism, which can be mitigated with the use of safety locks, camouflage and secure mounting techniques (Meek et al., 2019). Additionally, technological failures in ARUs can pose substantial challenges. Given that these devices are often deployed in remote locations and monitored only periodically, any malfunction due to battery depletion, memory card failure, or environmental damage can result in significant data loss until the next scheduled maintenance visit. In fact, this project experienced significant data loss at some sites (e.g. ~50% at Rinyirru) due to corrupted SD cards and unexpected battery depletion or malfunction. Furthermore, ARUs are limited to sampling within a single location and microhabitat, much like camera traps and live animal trapping, whereas field observers can move and assess multiple habitats during a survey. To achieve similar coverage across diverse habitats with PAM, a greater number of audio recorders would be necessary, which would significantly increase costs.

It is possible that the presence of bait at camera traps within each survey plot attracted species to the area, leading to their detection by the audio recorders and potentially boosting PAM performance as well as detections via all other methods. However, given that the ARUs were deployed continuously and over the long term, and that animals would need to have been nearby to detect the bait, it is highly likely that these species would have been detected by the ARUs even in the absence of bait. Furthermore, bait was deployed only during the 7-day OBM surveys, conducted twice per year over 2 years, yet most mammal detections occurred outside these OBM survey periods.

We also acknowledge that the performance of the embeddings search varied by example call and species (see Figure S1), and that improvement of the search calls used, or the development of a species-specific recogniser would result in steeper accumulation curves for PAM. In fact, many mammals have large repertoires of vocalisations, and more call examples could be considered for each species, potentially enhancing detection. Additionally, macropods and fruit bats had to be grouped because they could not be distinguished during data validation. Therefore, our findings on the performance of PAM for terrestrial mammal biodiversity assessments, compared with OBM and camera trapping, are likely conservative. These results may be further improved as additional call examples become available with the increased deployment of acoustic sensors.

Advancements in technology will continue to enhance the capabilities of PAM for terrestrial biodiversity assessments. For example, real-time data processing and wireless data transfer are developing quickly and can help mitigate data loss and reduce maintenance requirements, thereby increasing the autonomy of audio recorders (e.g. Aide et al., 2013; Mohaimenuzzaman et al., 2022, 2023; Wood et al., 2024). Similarly, improvements in battery and storage technology will enable collection of more audio data across broader frequency ranges, allowing for detection of a wider array of species, including those with ultrasonic vocalisations. Additionally, recorders

equipped with an array of time-synchronised microphones can capture more detailed spatial information about vocalisations, enhancing individual recognition and abundance estimates (Heath et al., 2024; Rhinehart et al., 2020), although moderately accurate abundance estimates can be made using calibrated calling activity (Pérez-Granados & Traba, 2021).

Automated acoustic analyses are crucial for advancing the effectiveness of large-scale, long-term passive acoustic monitoring. While PAM combined with BirdNET embeddings requires manual validation, this validated data can be used to build and train robust deep learning models, such as convolutional neural network (CNN) species recognisers (Ghani et al., 2023; McGinn et al., 2023). Our approach focused on surveying a broad range of species rather than targeting specific ones. Although building CNN recognisers for each species is possible, it is time-consuming due to the extensive data labelling required. Therefore, we opted for a quicker method more suited to broad surveying, focusing on detecting daily presence rather than detailed species vocal activity. While detecting an overall presence of species would have required even less manual validation, finer-scale analyses of calling activity would necessitate the development and use of reliable species recognisers. As more advanced recognisers are developed for a wider array of species and locations, PAM's ability to detect species will be enhanced. This will enable more reliable detection of both species that are currently difficult to distinguish and commonly vocalising species, making PAM even more effective at estimating species richness with minimal validation required. It is important to note that embeddings themselves do not constitute a standalone model and thus cannot be directly fine-tuned. Instead, embeddings act as a tool to extract specific species data from large acoustic datasets using only few example calls, which could then be used to build sophisticated models or recognisers and be assessed for recall and precision (Allen-Ankins et al., 2025).

By collecting call examples from diverse locations and times of year, CNN recognisers can significantly enhance the speed and accuracy of acoustic analyses (Sethi et al., 2024). These advanced deep learning models can differentiate between similar-sounding species (Allen-Ankins et al., 2024), reducing the need to group or omit species due to difficulties in call differentiating during validation. Despite the steep learning curve associated with analysing acoustic data using deep learning models, these tools are becoming increasingly user-friendly, with simple user interfaces and clear instruction manuals (Pérez-Granados et al., 2023; Wood et al., 2022; Wood, Barceinas Cruz, & Kahl, 2023). Over time, they will become more accessible, enabling a wide variety of users, including researchers, practitioners and citizen scientists, to apply them to audio recordings and gain valuable information about vocalising species.

5 | CONCLUSION

Here we show that passive acoustic monitoring in combination with BirdNET embeddings were an effective method for assessing the biodiversity of terrestrial vocal mammals in Australia. By analysing a cumulative total of 317,410 h (equivalent to over 36 years) of continuous audio recordings from six sites across eastern Australia, we demonstrated that the ability of PAM to detect vocal mammal species was at least equal to traditional methods, such as observer-based monitoring and camera trapping. Furthermore, its effectiveness for vocal fauna appears unbiased by common life-history traits, such as body size or home range, suggesting it is a broadly applicable tool for the species it can detect. PAM significantly reduced time investment compared with traditional methods, further emphasising its value in biodiversity assessments, especially over large spatial and temporal scales. The use of embeddings from deep learning models like BirdNET offers a low-cost and time-efficient method for exploring extensive acoustic datasets. Despite the benefits, the inability of PAM to detect non-vocal mammals necessitates the combination of PAM with other monitoring methods to provide the most comprehensive assessment of mammal biodiversity. Integrating methods leverages the strengths of each: PAM was most effective for arboreal and elusive species (e.g. gliders and foxes), camera trapping was highly useful for cryptic, ground-dwelling species (e.g. feral cats and pigs) and OBM was necessary for capturing small, non-vocal mammals (e.g. rodents and dasyurids). This combined approach will likely improve future biodiversity monitoring, offering a more detailed understanding of ecosystems and support effective conservation practices. Future research should aim to identify call features that influence the performance of deep learning model embeddings like BirdNET, informing the selection of high-quality example calls and improving overall detection performance.

AUTHOR CONTRIBUTIONS

Sebastian Hoefer and Lin Schwarzkopf designed the research concept with contributions from all authors. Sebastian Hoefer, Donald T. McKnight and Eric J. Nordberg conducted the fieldwork and collected the data, Sebastian Hoefer prepared and processed the camera trap data, Sebastian Hoefer and Slade Allen-Ankins prepared and processed the acoustic data, and Sebastian Hoefer conducted the statistical analysis. Sebastian Hoefer drafted the manuscript and figures with contributions from all authors.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210X.70169.

DATA AVAILABILITY STATEMENT

The data used in this study and the reproducible code for analyses can be accessed at: https://doi.org/10.5281/zenodo.17118352 (Hoefer et al., 2025).

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SUPPORTING INFORMATION

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

Figure S1. Probability of correctly predicting true positive detections based on the Euclidean distance for each of the 46 example calls across 17 vocal mammal species used in this study.

Figure S2. Relationship between species richness via PAM (passive acoustic monitoring) and species richness via OBM (observer-based monitoring) across six different study sites.

Figure S3. Species accumulation curves for passive acoustic monitoring (PAM) using all audio data available at six survey sites.

Figure S4. The relationship between the detection probability of vocal mammal species via passive acoustic monitoring (PAM) and six different life-history traits: (A) adult mass, (B) dispersal distance, (C) home range extent, (D) fossoriality, (E) daily activity cycle, and (F) volant capacity.

Figure S5. Species accumulation curves for mammal communities (all mammals [left] and vocal mammals only [right]) at six survey sites for each assessment method over up to 28 survey days.

Table S1. Overview of the number and source of the 46 example calls for 17 Australian vocal mammal species used in this study.

Table S2. Detailed summary of the survey dates, acoustic recording hours and camera trapping days (summed for all four camera traps) at a survey plot level across the six study sites.

Table S3. Common mammal traits and detectability in this study for 19 vocal mammal species. Trait information was compiled from the COMBINE and HomeRange databases (Broekman et al., 2023; Soria et al., 2021), with additional data from the Field Companion to the Mammals of Australia (Van Dyck et al., 2013).

Table S4. Mammal species detected via Observer-based monitoring (OBM) through pitfall traps (PT), funnel traps (FT), Elliott traps (ET), cage traps (CT), spotlighting (SL), and incidental encounters (IE); camera trapping; and passive acoustic monitoring (PAM) for both matching only the survey period, and all available audio data.

Table S5. Overall and 'Per day' time investment (in hours) to produce species lists via passive acoustic monitoring (PAM), observer-based monitoring (OBM), and camera trapping, as well as the time investment required per species detection for each method.

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