Passive acoustic monitoring outperforms observer-based methods for Australian frog communities

Sebastian Hoefer[1], Slade Allen-Ankins[1], Donald T McKnight[1,2], Eric J Nordberg[1,3], and Lin Schwarzkopf[1]

[1] College of Science and Engineering, James Cook University, Townsville, 4814 QLD, Australia

[2] Savanna Field Station, La Democracia, Belize District, Belize

[3] School of Environmental and Rural Science, University of New England, Armidale, NSW, Australia

Corresponding author: sebastian.hoefer@my.jcu.edu.au - ORCID: 0000-0001-7143-7777

Monitoring Australian frog biodiversity

Abstract

Effective biodiversity monitoring is fundamental for evaluating conservation status and detecting population declines, yet traditional observer-based monitoring (OBM) is often constrained by high costs and logistical challenges resulting in limited spatial and temporal coverage. Passive acoustic monitoring (PAM) offers a scalable alternative, but its efficacy for frog biodiversity assessments remains largely unexplored. In this study, we compared the effectiveness of PAM (combined with BirdNET embeddings) to OBM for assessing frog biodiversity across six open eucalypt woodland sites in eastern Australia. Using embeddings from the BirdNET deep-learning model, we efficiently analysed over 300,000 hours of continuous audio data, detecting 34 frog species. While OBM proved more effective over short-term (28-day) periods due to visual detections, long-term PAM significantly outperformed OBM in total species richness, detecting 48% more species overall. We found that frog activity was highly seasonal, with species accumulating fastest during spring and summer. Financially, PAM was far more cost-effective for long-term monitoring, costing approximately 5 times less than OBM by the end of the study. However, we found that monitoring methods were complementary rather than interchangeable. Consequently, we propose a hybrid monitoring design with short-term targeted OBM surveys to capture the species and individuals that are difficult to detect acoustically, and long-term PAM deployment to capture the full breadth of acoustic diversity. This integrated approach maximises the strength of both monitoring methods, ensuring comprehensive and cost-effective frog biodiversity assessments.

Keywords

Bioacoustics; Ecoacoustics; Biodiversity assessment; Survey methods; Machine learning

Introduction

Effective biodiversity monitoring is fundamental for evaluating the conservation status of species, assessing the success of management action, and detecting potential future population and species declines (Scheele et al., 2019; Schmeller et al., 2015). Traditionally, biodiversity is surveyed using a variety of field-based methods (e.g., Eyre et al., 2018; Heyer et al., 1994; Lindenmayer et al., 2014; Magurran & McGill, 2010; Thompson et al., 1998) which have inherent limitations. Observer-based monitoring (OBM) requires substantial financial, time, and labour investments, and can be ineffective for rare or cryptic species (Gibb et al., 2018). As a result, OBM is often limited in its spatial and temporal coverage, potentially leaving critical gaps in our understanding of ecosystem health.

Remote sensing has been used across various groups of terrestrial vertebrates to overcome some of these limitations (e.g, Pimm et al., 2015). Among these, passive acoustic monitoring (PAM) has proven particularly effective for surveying vocalising species (Hoefer et al., 2023; Sugai et al., 2019). By deploying autonomous recording units (ARUs), data can be collected continuously over long durations and broad spatial scales, substantially reducing time investment, especially for long-term monitoring (Hoefer et al., 2023, 2025; Sugai et al., 2019). Despite its advantages, the application of PAM has historically been hindered by the difficulty of processing vast volumes of audio data, and long-term continuous PAM data is lacking and available from only a few large-scale sensor networks (Cretois et al., 2026; Darras et al., 2024; Roe et al., 2021; Ross et al., 2018). Most acoustic monitoring studies have relied on manual analysis, restricting recording schedules to short snapshots of expected activity (Hoefer et al., 2023), which risks missing species that vocalise at unexpected times or seasons (Callaghan & Rowley, 2020; Taylor et al., 2017), or with delayed responses following environmental triggers (Brodie et al., 2021). Many species could be declining so rapidly that they may disappear completely before such declines are detected (Skerratt et al., 2007), emphasising the urgent need for the continuous, long-term monitoring. Recent advances in automated acoustic analysis, specifically deep learning models and Convolutional Neural Networks (CNNs), now enable the efficient processing of long-term continuous datasets (Ghani et al., 2023; Kahl et al., 2021; Priyadarshani et al., 2018). BirdNET is a deep learning model that has shown promise in detecting various species (Bota et al., 2023; Doohan et al., 2026; Sethi et al., 2024; Sossover et al., 2023; Wood et al., 2022, 2023). Despite being trained primarily for birds, the use of BirdNET embeddings allows for the detection of species from a single example call, offering potential for broader biodiversity assessments (Allen-Ankins et al., 2025; Ghani et al., 2023; Hoefer et al., 2025).

Frogs represent an ideal model system to evaluate PAM as an effective long-term monitoring method. They are among the most threatened groups of terrestrial vertebrates and have experienced rapid declines globally (Cox et al., 2022; Luedtke et al., 2023), driven by habitat loss, climate change, and disease (Alford & Richards, 1999; Collins, 2010; Sodhi et al., 2008). Because nearly all frogs produce species-specific vocalisations for reproduction, they are well suited for acoustic surveys. While PAM has proven effective for detecting various frog species in previous studies (Acevedo & Villanueva-Rivera, 2006; Barnes & Quinn, 2023; Gunzburger, 2007; Madalozzo et al., 2017; Melo et al., 2021), the potential of leveraging advanced deep learning tools like BirdNET for frog biodiversity assessments remains largely unexplored.

In this study, we compared the performance of PAM combined with automated detection using BirdNET embeddings to in-field observer-based monitoring efforts for assessing frog biodiversity. We compared the performance between the methods for: a) species richness, b) community composition, and c) survey effort and d) cost. Additionally, we investigated a seasonal sampling bias for PAM.

Material And Methods

Study Sites

This study was conducted at six sites within open eucalypt woodlands in eastern Australia (Fig. 1A), situated within national parks (Rinyirru, Undara, Duval) or on private properties with no public access (Wambiana, Mourachan, Tarcutta). These are the same sites and survey plots described in Hoefer et al. (2025). At each site, we established four 1-ha survey plots, each associated with an acoustic recording unit (ARU; Fig. 1B). Observer-based monitoring (OBM) and passive acoustic monitoring (PAM) were conducted simultaneously within each plot for seven days per survey trip. ARUs recorded audio continuously during and between survey trips.

Observer-based Monitoring (OBM)

We conducted observer-based surveys to detect frogs as part of the overall observer-based monitoring efforts to detect all terrestrial vertebrates (mammals: Hoefer et al., 2025, reptiles: Hoefer et al., 2024, birds: Doohan et al., 2026), therefore, survey periods were identical. Briefly, each site was surveyed for seven-day periods up to two times a year, for two years. Some sites were intermittently inaccessible, so the exact survey effort per site varied (Table 1). To sample the frog community, we employed five OBM methods within each plot (Fig. 1C): i) pitfall traps, ii) funnel traps, iii) arboreal cover boards, iv) nocturnal active area searches (spotlighting), and v) incidental encounters (detections of animals while not actively searching or checking traps). Protocols for trapping and active searches followed those described in Hoefer et al. (2024, 2025). Frog detections recorded in this study represent observations rather than individual counts, as individuals were not permanently marked, thus we were unable to distinguish between different individuals across multiple encounters.

Passive Acoustic Monitoring (PAM)

We conducted passive acoustic monitoring following the protocol described in Hoefer et al. (2025). We used Frontier Labs Solar BARs equipped with external omnidirectional microphones (Primo EM172), recording continuously in mono at 16-bit and a 22.05 kHz sampling rate.

Acoustic Analysis

To detect frog vocalisations, we generated feature embeddings for the target species and all available audio data using the BirdNET-Analyzer (Kahl et al., 2021). We selected 115 example calls representing 50 Australian frog species with predicted ranges overlapping the study sites (Cutajar et al., 2022; Table S1). We compared OBM results against two acoustic datasets, audio data collected during only during the 7-day survey periods (12,303 hours) and all available audio data (317,410 hours). Hereafter, we will use the term "short-term PAM" to refer to PAM using audio data matching only the survey period, and "long-term PAM" for PAM using all available audio data. We calculated Euclidean distances between the feature embeddings of the example calls and the unknown audio dataset and extracted the top detections (lowest Euclidean distances) for each example call per day at each survey site. These potential detections (251,315 total) were aurally and visually verified to species level. Consistent with Hoefer et al. (2025) in mammals, lower Euclidean distances were highly predictive of true positives in the target frog example calls (Fig. S1), justifying the use of the lowest daily distance to confirm species presence.

Statistical Analysis

All statistical analyses were conducted in the R statistical environment (R Core Team, 2023; v.4.5). Our reproducible code and the data for our analyses can be accessed here: https://doi.org/10.5281/zenodo.18490757. We excluded data from survey plots where acoustic recorders collected less than 70% of the total possible amount of audio data, due to battery or SD card malfunctioning (Table S2). For species richness, we explored the relationship between the total number of species per survey plot for each assessment method using hierarchical Bayesian models with a Poisson distribution and weakly informative priors in the *brms* package (Bürkner, 2017). We compared several candidate models and selected the final model based on LOO information criterion values (Vehtari et al., 2017) and validated the best model *via* DHARMa residuals (Hartig, 2022). Finally, we used post-hoc pairwise comparisons to make specific inferences on the value of the different assessment methods for detecting high frog species richness. To gain information on the similarity of the frog community sampled by each assessment method, we performed nonmetric multidimensional scaling (nMDS) based on Jaccard (presence-absence) dissimilarities and conducted pairwise permutational analysis of variance using the packages *vegan* (Oksanen et al., 2022) and *pairwiseAdonis* (Martinez Arbizu, 2020). Each unique combination of site and plot was treated as a separate data point in the analysis, with assessment method as the main factor of interest. To evaluate the sampling effort necessary at each site, we constructed species accumulation curves for the 28-day survey period and all available audio recording days, using the *iNEXT* package (Hsieh et al., 2016). Additionally, we investigated a seasonal sampling bias in species accumulation by splitting the audio data and species detections into four seasons: Summer (Dec-Mar), Autumn (Mar-Jun), Winter (Jun-Sep), and Spring (Sep-Dec).

Cost Analysis

To evaluate the financial efficiency of each method, we calculated the cumulative costs (AUD) associated with OBM and PAM over the duration of the study. Costs included the purchase cost of all necessary equipment (e.g., ARUs, SD cards, drift fences, traps) and operational costs (accommodation, transportation, food, observer salaries during deployment, active surveys, and data processing and analysis). We tracked these costs across the four survey periods to quantify how financial investment for each method accumulated over time.

Results

Over the course of this study, we detected and identified 35 species of Australian frogs across eight genera and four families (Table S3). Passive acoustic monitoring using all available audio data (long-term PAM) detected the highest number of species across all study sites, (34 detected out of 50 potential species based on predicted ranges from the Australian Frog Atlas; Cutajar et al. 2022) and recorded 13,577 observations. In comparison, OBM detected 23 species (2,834 observations), while PAM using audio recordings matching only the survey period (short-term PAM) detected 21 species (540 observations). Within OBM methods, spotlighting recorded the highest numbers of species (19) and observations (2155), followed by pitfall traps (18 species, 419 observations), incidental encounters (17 species, 263 observations), and funnel traps (16 species, 210 observations). Arboreal cover boards were the least effective, detecting only two species, *Litoria rubella* (two observations), and *Platyplectrum ornatum* (one observation; Table S3; Fig. S2)

Species richness

The maximum total species richness varied among sites but followed a latitudinal trend with an increase in the number of detected frog species from South to North (Table S4). For the matching survey period (28 days), OBM detected significantly more species on average than PAM (1.7x more species, 95% highest density interval [HDI]: 1.26-2.20; Fig. 2). OBM also recorded higher total numbers of frog species compared to short-term PAM at four sites (Tarcutta, Mourachan, Wambiana, Rinyirru), whereas short-term PAM detected more species than OBM at two sites (Duval, Undara; Table S4). When all available audio data was considered, PAM detected significantly more species on average than OBM (1.65x more species, 95% HDI: 1.33-2.05) and short-term PAM (2.8x more species, 95% HDI: 2.12-3.58). Long-term PAM recorded the highest species richness at all six survey sites, which was also the highest total species richness (i.e., total richness of all methods combined) at five sites, and only at Rinyirru OBM detected three species not found via PAM (*Limnodynastes terraereginae:* five observations, *Litoria inermis:* one observation, and *Platyplectrum ornatum:* 116 observations; Table S4). Across all sites, long-term PAM detected 12 unique frog species not detected by OBM, three of which were also detected in short-term PAM, while OBM detected one species (*Limnodynastes terraereginae*) not recorded by PAM at any site (Table S3). This species was exclusively detected in pitfall traps (two observations) and funnel traps (three observations) at Rinyirru.

Community composition

Non-metric multidimensional scaling (NMDS) at the plot level indicated broad overlap in the species assemblages detected by all methods (Fig. 3A). A global PERMANOVA stratified by site indicated a significant effect of assessment method on community composition (Jaccard, $R^2 = 0.06$, $P < 0.001$). Pairwise comparisons with Holm's correction yielded significant differences between OBM and short-term PAM ($R^2 = 0.035$, $P_{adj} = 0.003$), OBM and long-term PAM ($R^2 = 0.056$, $P_{adj} = 0.003$), and short-term PAM and long-term PAM ($R^2 = 0.056$, $P_{adj} = 0.003$).

Pairwise Jaccard dissimilarity analysis showed an average dissimilarity of 0.55 between OBM and short-term PAM at the plot level (Fig. 3B), which was higher than the average spatial turnover between plots within a site (0.45). Methodological dissimilarity varied by site, ranging from an average of 0.30 at Tarcutta to > 0.65 at Undara and Rinyirru (Fig. 3C; Fig. S3).

Survey effort

Over our 28-day survey period, species accumulation curves for the total number of species reached an asymptote at only two sites (PAM at Tarcutta after 11 days and OBM at Duval after 13 days; Fig. 4). For this short-term period, OBM accumulated species more rapidly than PAM at all sites. Neither OBM nor PAM alone detected all species present at four of the sites within 28 days. Only at the two southernmost sites did a single method detect all species: PAM at Duval and OBM at Tarcutta.

Using all available audio data, PAM reached a maximum frog species richness at an average of 12 species across all sites, ranging from six at Tarcutta to 16 at Rinyirru (Table 2). To reach this maximum richness required on average 447 days of PAM, ranging from 386 days at Undara to 528 days at Duval. Short-term PAM (28 days), captured only 66% of the maximum total species richness on average, with a variability of 25% across sites. Extending sampling to 90 days increased the average proportion of the species detected to 84%, reducing variability to 12% across sites. After 180 days, the average proportion reached 93% (maximum variability = 8%), and following a full year (365 days) of recording, PAM detected 98% of the maximum total species richness with 4% variability between sites.

Species accumulation curves of long-term PAM did not approach an asymptote at any site (Fig. 5). The number of days needed for PAM to match the frog species richness obtained by OBM varied at each site but took, on average, 93 days (Tarcutta: 387 days; Duval: 10 days; Mourachan: 40 days; Wambiana: 19 days; Undara: 35 days; Rinyirru: 68 days; Table S5). When splitting the audio data and species detections into four seasons, summer and spring sampling were the most effective (Fig. 5). Across all sites, summer sampling accumulated species the quickest and detected the most species (33), followed by spring (29), autumn (26) and winter (21). However, some species were only detected in one season at some sites. Six species were detected only during summer (Mourachan: *Cyclorana verrucosa*; Undara: *Cyclorana brevipes*, *Limnodynastes grayi*; Rinyirru: *Cyclorana brevipes*, *Litoria latopalmata*, *Litoria pallida*), and two species only in spring (Duval: *Limnodynastes dumerilii dumerilii*; Mourachan: *Limnodynastes grayi*), but no species was exclusively detected during winter or autumn sampling.

Financial cost

The cumulative financial investment differed substantially between OBM and PAM over the duration of the study (Fig. 6). PAM required an initial investment of approximately AUD 35,000, nearly three times that of OBM (~AUD 12,000), due to the purchase of autonomous recording units, batteries, SD cards, and deployment costs. However, operational costs for OBM increased rapidly during each survey period due to fieldwork expenses (e.g., accommodation, travel, field gear, and staff salary), surpassing the total cost of PAM during the first survey trip in May 2021. In contrast, PAM costs increased only 1.5-fold over the course of this study, to cover ongoing maintenance, data processing, storage, and analysis. By the end of the study in December 2022, the total investment for OBM reached approximately AUD 250,000 (a 21-fold increase), roughly five times the final cost of PAM (~AUD 50,000).

Discussion

We compared the performance of passive acoustic monitoring (PAM) to observer-based monitoring (OBM) for frog biodiversity assessments across a range of open eucalypt woodlands in Eastern Australia. Using feature embeddings from the BirdNET deep-learning model, we analysed over 300,000 hours of continuous audio recordings from six sites and detected 34 species of frogs. This method required only a single example call per species, without the need to build individual recognisers which demand a high time investment and in-depth knowledge (Priyadarshani et al., 2018). Across all sites, we detected the most frog species (34) using long-term PAM (i.e., PAM using all available audio data) which was 48% higher than using OBM (23 species) and 62% higher than *via* short-term PAM (i.e., PAM using the audio time period matching the survey period only: 21 species).

Short-term vs long-term detection dynamics

During the 28-day survey period, OBM proved more effective than PAM by accumulating species more quickly and recording the highest richness at most sites. The ability of OBM to detect species both visually and aurally, as opposed to aural detection only *via* PAM, lead to generally higher species richness observed with OBM in the short-term. Visual detections have been noted as a significant factor in the superior performance of OBM for detecting some species of birds (Alquezar & Machado, 2015; Haselmayer &

Quinn, 2000; Hutto & Stutzman, 2009; Vold et al., 2017). However, OBM alone did not detect all species present, suggesting that a combination of OBM and PAM may be the most comprehensive strategy for short-term monitoring of frogs. However, when extending the recording period to include all available audio data, PAM significantly outperformed OBM and short-term PAM in terms of species richness. Similar findings have been reported in studies on birds, where long-term PAM was more effective than short-term monitoring (Klingbeil & Willig, 2015; Kułaga & Budka, 2019).

Technological feasibility and sampling completeness

Utilising PAM for extended monitoring periods resulted in the highest species richness at all sites, indicating that this is the most effective approach for quantifying overall frog biodiversity. In the short-term (28 days), PAM detected only 66% of the total possible frog species richness, whereas after 365 days, this increased to 98%, demonstrating the substantial benefits of long-term PAM. Reaching maximum species richness required substantial sampling effort (average 447 days), highlighting that short-term surveys likely underestimate biodiversity. With recent technological advancements, it is feasible to collect and store long-term continuous audio data (Aide et al., 2013; Rhinehart et al., 2020), and using deep-learning models like BirdNET allows for efficient analysis of these extensive acoustic datasets, further enhancing the practicality and effectiveness of long-term PAM.

Cost-efficiency and scalability

Beyond its ecological effectiveness, PAM demonstrated a clear advantage in temporal scalability and cost-efficiency. While OBM benefited from lower initial startup costs, the cumulative expense of personnel and travel resulted in a significantly higher financial investment over time. By the end of the study, the total cost of OBM was approximately five times greater than that of PAM, reflecting a 21-fold cost increase for OBM compared to only a 1.5-fold increase for PAM. This aligns with findings from monitoring of cryptic birds (Williams et al., 2018), which similarly demonstrated that extending PAM duration does not proportionally increase costs relative to site visits. While total costs will vary depending on specific project requirements such as site accessibility, maintenance schedules, and personnel renumeration, PAM represents the most financially viable strategy for the continuous monitoring required to detect rare, cryptic, or weather-dependent species.

Seasonality and sampling effort

Frogs primarily vocalise for reproductive purposes (Duellman & Trueb, 1994; Gerhardt, 1994) and since breeding is closely associated with rainfall, increased precipitation typically triggers heightened calling activity (Brodie et al., 2025; Hauselberger & Alford, 2005; Xie et al., 2017). Thus, restricting monitoring to short periods of time may increase the risk of missing rainfall events that trigger breeding calls. In our study, restricting the acoustic monitoring period for PAM to only 28 days resulted in missing 13 species of frogs that we were detected in long-term PAM. Similarly, recording schedules that capture only parts of the day or night may fail to detect unexpected calling activity from some species or individuals (Callaghan & Rowley, 2020).

We found that species detection was most rapid and species richness highest during spring and summer, which aligns with periods of more frequent and intense rainfall. Notably, six species were only detected in summer and two only in spring, while no species were unique to autumn or winter. However, as opportunistic calling can occur during sporadic rainfall in cooler months, we recommend continuous 365-day sampling to capture those stochastic events. Where year-round monitoring is constrained, deploying PAM in early spring offers the best compromise to capture the rapid accumulation of species associated with increasing seasonal rainfall.

Community composition and method complementarity

While global analysis indicated a broad overlap in species assemblages, fine-scale analysis revealed that PAM and OBM function as complementary rather than interchangeable methods. We found a significant dissimilarity between methods employed at the same location, which was driven by systematic detection biases inherent to each survey approach. Previous studies have shown that OBM and PAM can detect different species, and, in particular, visual detections represent an advantage of OBM (Darras et al., 2019). However, since vocalisation is essential for successful reproduction in most frog species, frogs should eventually vocalise, providing the opportunity for detection *via* PAM. In some cases, frogs with short or quiet calls may remain undetected because their calls could be masked by other species, or environmental noises such as rain, wind, or even anthropogenic sounds (Luther & Gentry, 2013; Pijanowski et al., 2011). In fact, OBM proved essential for detecting three species (*Limnodynastes terraereginae*, *Litoria inermis*, *Platyplectrum ornatum*) at Rinyirru that were physically present and were observed in traps and visually during active searches but remained acoustically unavailable. Possibly, the noisy, insect-dominated soundscape at this site reduced the probability of acoustically detecting these species, highlighting the challenge of PAM transferability across different habitats, as some environments may pose greater difficulties for species detection (Hill et al., 2013; Kułaga & Budka, 2019).

However, acoustic masking is not the only potential cause for these detection failures. Unlike mobile observers who can actively search diverse microhabitats, ARUs are stationary and limited by their detection radius (Darras et al., 2016; Yip et al., 2017). Consequently, species breeding in ephemeral pools or temporary water bodies just outside the recorder's range may be missed by PAM but be detected by observers covering a broader area. This highlights that recorder placement and spatial sampling design are critical considerations when designing acoustic monitoring programs (Browning et al., 2017; Sugai et al., 2020).

Conversely, PAM was more effective for detecting cryptic species easily missed during in-person surveys, or difficult to identify morphologically. PAM presented an advantage over OBM for differentiating among species within the genera *Crinia* and *Uperoleia*, which were often impossible to identify visually. Additionally, PAM provided valuable information on seasonal activity in frogs, helping to identify optimal periods for effective monitoring. While in-person survey efforts remain necessary for non-vocal species or those vocalising outside recorder sampling rates (e.g., Hoefer et al., 2025), detection rates for vocal species could be further improved by refining the embeddings search strategy. Using a larger, more diverse set of example calls could better capture regional call variations, while verifying a greater number of high-scoring detections, rather than just the single top hit, could increase the likelihood of detecting rare, quiet, or acoustically masked species. Ultimately, the development of more robust deep-learning recognisers, trained on diverse call examples from various geographic regions, could significantly enhance the detection of difficult-to-detect species in complex soundscapes.

Conclusion

This study demonstrated that passive acoustic monitoring (PAM) combined with BirdNET feature embeddings was highly effective for assessing frog biodiversity in open eucalypt woodlands across Eastern Australia. By analysing over 300,000 hours of continuous audio recordings with minimal training data, we successfully detected 34 frog species. Our results highlight that neither PAM nor OBM is sufficient to detect every species in isolation. While long-term PAM was superior for generating complete species inventories and capturing opportunistic breeders during stochastic rainfall events, it is limited to detecting vocalising males. OBM remains essential for capturing non-vocal demographics (females and juveniles) and species masked by complex soundscapes. While the most useful and effective OBM method will depend on the target region, fauna, and budget, spotlighting emerged as the most efficient complement to PAM in our study, offering a high number of detections for both arboreal and ground-dwelling species at a fraction of the cost of trapping. Overall, integrating long-term PAM with targeted OBM methods offers the most comprehensive approach to frog biodiversity monitoring, enhancing our understanding of ecosystems and supporting effective conservation practices.

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Author Contributions

Sebastian Hoefer: Conceptualisation; methodology; fieldwork and data collection; acoustic data processing and analysis; positive detection verification; formal analysis; investigation; designing figures; writing original draft; reviewing and editing manuscript. **Slade Allen-Ankins:** Supervision; acoustic data processing and analysis; reviewing and editing manuscript. **Donald T. McKnight:** Supervision; methodology; fieldwork and data collection; reviewing and editing manuscript. **Eric J. Nordberg:** Supervision; methodology; fieldwork and data collection; reviewing and editing manuscript. **Lin Schwarzkopf:** Supervision; conceptualisation; funding acquisition; reviewing and editing manuscript.

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.18490757.

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Tables

Table 1. A summary of survey durations across six study sites, including total number of days for field surveys (days x number of plots per site), as well as the number of days of acoustic recordings during the survey period and for all available audio data. The total number of days between sites differed due to inaccessibility because of weather and battery or SD card malfunctioning.

Site	First survey (2021)	Second survey (2021)	Third survey (2022)	Fourth survey (2022)	Total number of survey days	Total acoustic recordings (survey period) in days	Total acoustic recordings (all audio) in days
Rinyirru	14 – 21 Jun	8 – 15 Oct	7 – 14 Aug	23 – 30 Oct	112	98	1297
Undara	3 – 10 Jun	28 Sep – 5 Oct	8 – 15 May	13 – 20 Oct	110	84	1660
Wambiana	5 – 12 Jul	10 – 17 Nov	12 – 19 Jun	28 Sep – 5 Oct	112	97	3280
Mourachan	9 – 16 May	NA	19 – 26 Jun	2 – 9 Nov	84	60	1956
Duval	18 – 25 Apr	NA	28 Apr – 5 May	12 – 19 Nov	70	65	2122
Tarcutta	29 Apr – 6 May	18 – 25 Oct	8 – 15 May	22 – 29 Nov	112	109	2910

Table 2. Maximum total species richness, number of days to reach the maximum total species richness, the percentage of total richness achieved after 28 days, 90 days, 180 days, and 365 days of passive acoustic monitoring (PAM) of frogs at each survey site, as well as the average 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
Rinyirru	16	476	0.60	0.78	0.88	0.96
Undara	15	386	0.54	0.82	0.95	1
Wambiana	12	405	0.67	0.88	0.96	0.99
Mourachan	13	499	0.64	0.83	0.93	0.99
Duval	10	528	0.74	0.85	0.92	0.98
Tarcutta	6	387	0.79	0.90	0.95	0.99
Average (all sites)	12	447	0.66	0.84	0.93	0.98

Figures

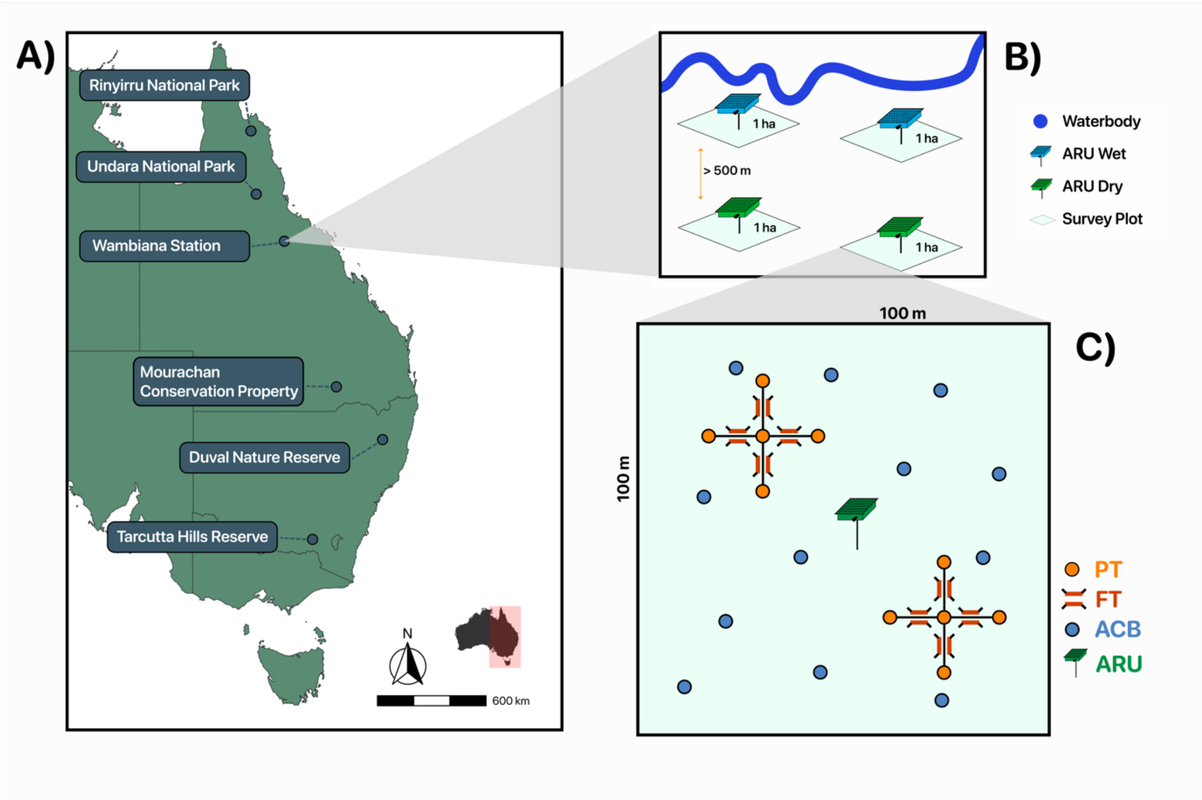

Figure 1. Illustration of (A) the six study sites throughout eastern Australia, (B) the acoustic design layout for each site and, (C) a summary of the survey methods used at each of the four survey plots (1 ha area each) per site to target frogs (adapted from (Hoefer et al., 2024). At each site, four Autonomous Recording Units (ARUs) were installed in similar habitat types, with two recorders placed within 50 m of a body of water (ARU Wet – blue) and two recorders placed more than 500 m away from any water source (ARU Dry – green). Abbreviations used: PT = Pitfall Trap, FT = Funnel Trap, ACB = Arboreal Cover Board, ARU = Automated Recording Unit.

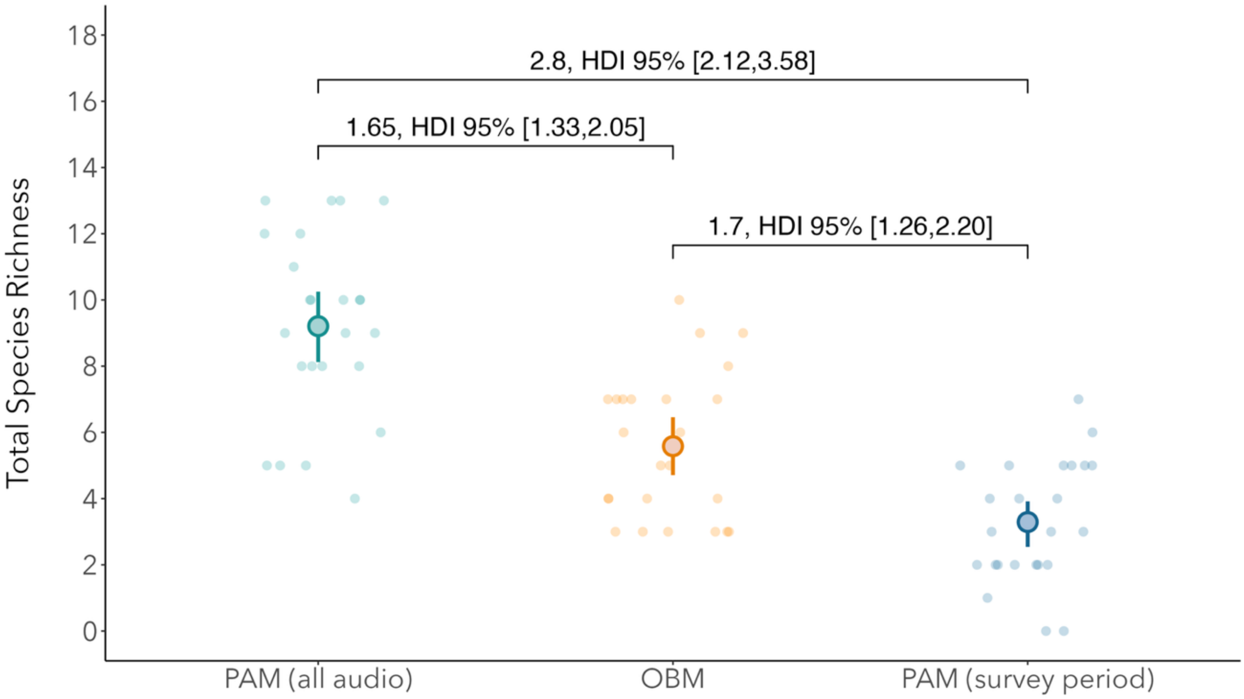

Figure 2. Total species richness of frogs for each survey plot at each site detected by each survey method: passive acoustic monitoring using all available audio data (green), observer-based monitoring (orange), passive acoustic monitoring using only audio data matching the survey period (blue). Points and error bars represent the mean ± 95% confidence intervals. The average fractional difference and 95% Highest Density Intervals (HDI) are shown above the points, indicating statistical significance.

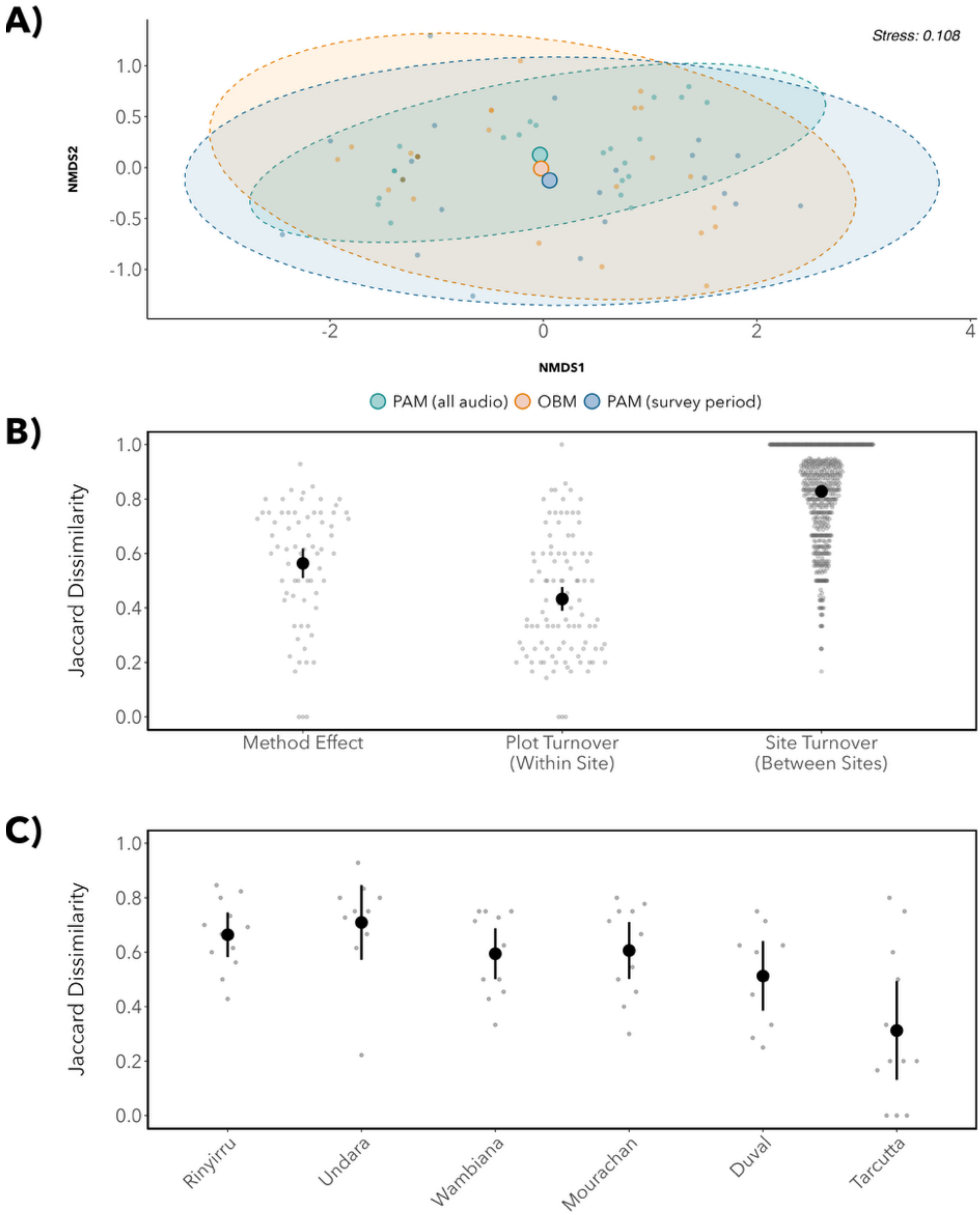

Figure 3. Community composition analysis comparing frog survey methods. (A) Non-metric multidimensional scaling (NMDS) ordination of frog communities based on Jaccard dissimilarity (presence-absence). Large points represent the centroids for each method, shaded regions indicate 95% confidence ellipses, and small points represent

individual survey plots. (B) Pairwise Jaccard dissimilarity values (1 = complete turnover, 0 = no turnover). Each point represents a single pairwise comparison: “Method Effect” = different methods (OBM, short-term PAM, and long-term PAM) at the same plot; “Plot Turnover” = different plots within the same site (using the same method); “Site Turnover” = different sites (using the same method). (C) Site-specific breakdown of the Jaccard dissimilarity between methods, showing the variation in method agreement across the six study sites. Black points and error bars represent the mean ± 95% confidence intervals.

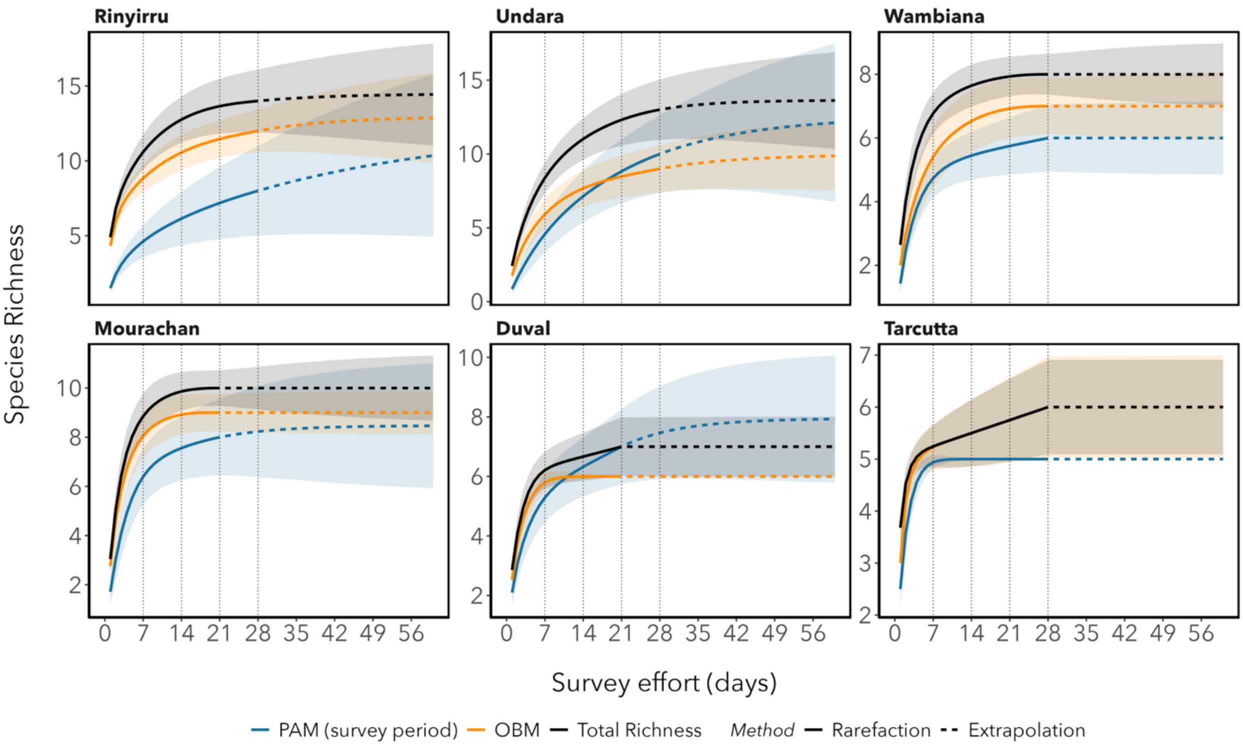

Figure 4. Species accumulation curves for frog communities at six survey sites for each assessment method over up to 60 survey days (28 days of rarefaction [solid lines], 32 days of extrapolation [dotted lines]). The coloured lines represent the different assessment methods: passive acoustic monitoring (blue), observer-based monitoring (orange), and all methods combined (total richness [black]). Shaded areas around each line corresponds to the 95% confidence intervals and dotted vertical lines mark the cumulative effort after each survey.

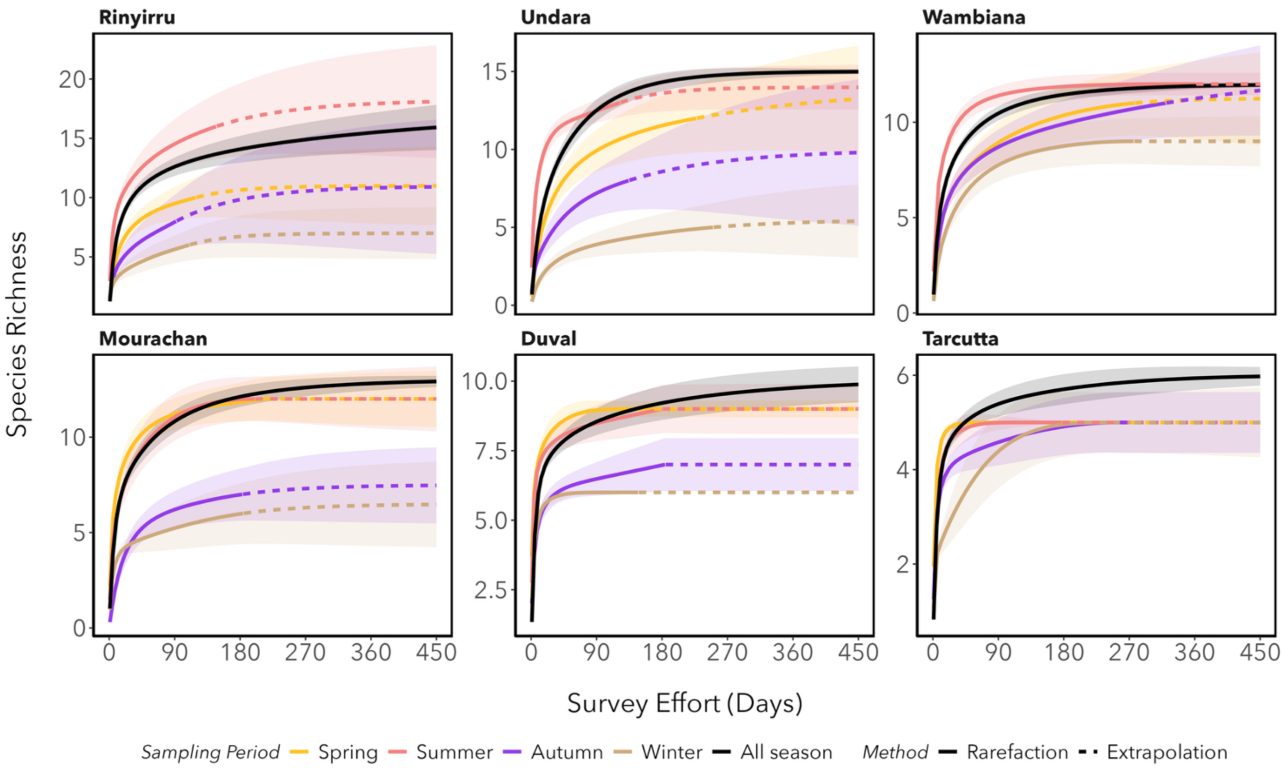

Figure 5. Species accumulation curves for frog communities at six survey sites for only passive acoustic monitoring (PAM). The coloured lines represent different sampling periods over the year: sampling only in spring (yellow), summer (red), autumn (purple), winter (brown), and sampling all seasons (all available audio data [black]). Solid lines represent rarefaction and dotted lines represent extrapolation. Shaded areas around each line corresponds to the 95% confidence intervals.

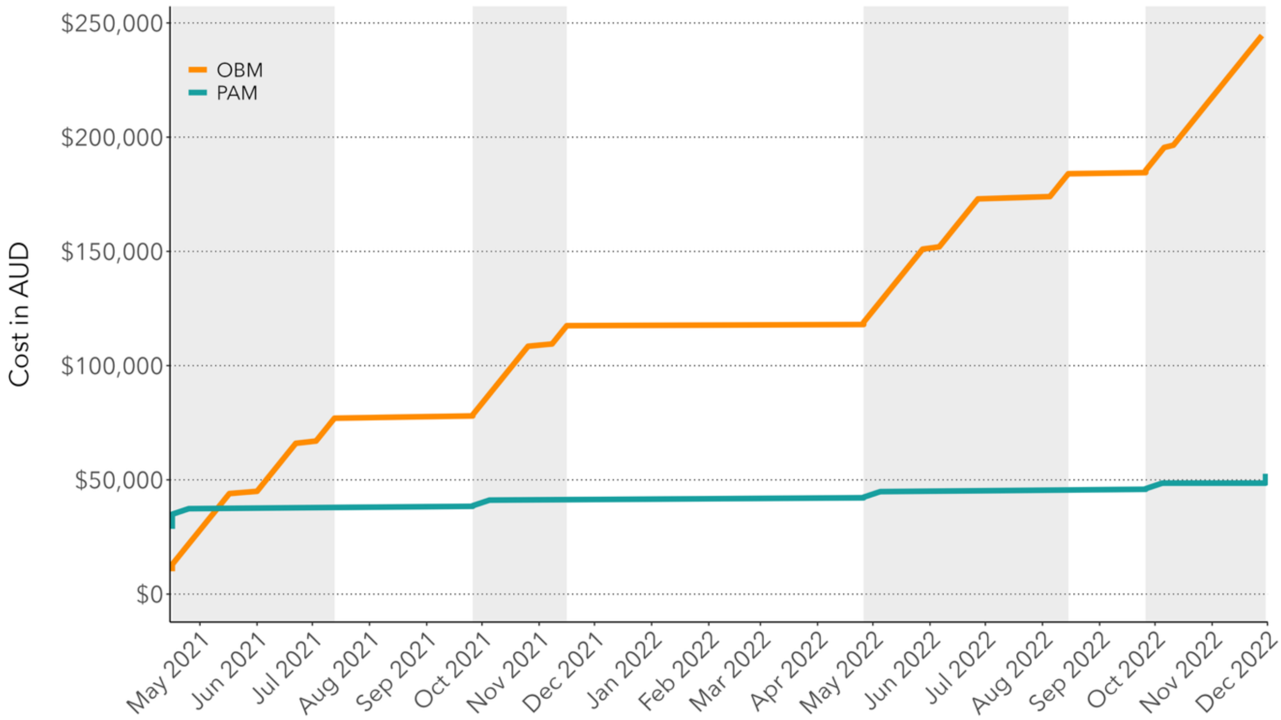

Figure 6. The rate of increase in total cost in Australian Dollar (AUD) for observer-based monitoring (OBM – orange) and passive acoustic monitoring (PAM – green) over the duration of this research. Costs included initial equipment purchases, deployment and fieldwork expenses (accommodation, transportation, salary, food), and compensation of staff for data analysis and validation. The grey bands represent the four survey periods during this research.