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Needle in a haystack: Searching for threatened species using an acoustic observatory

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ABSTRACT

Monitoring threatened species is crucial for conservation, providing the necessary information on species distribution and abundance required to detect declines and evaluate the impact of conservation actions. Passive acoustic monitoring networks, such as the Australian Acoustic Observatory (A2O), have significant potential to aid the monitoring of vocal threatened species by collecting continuous data across many locations in a cost-effective manner. We analysed over 2 million hours of acoustic recordings collected as part of the A2O from 63 sites between 2019 and 2022 to determine the site presence of 74 threatened species. Using the existing deep-learning model BirdNET to detect species belonging to classes within the model, and embeddings search for species outside the model, we successfully detected 41 out of the 74 threatened target species at a minimum of one A2O location, with some broadly distributed threatened species detected at more than ten sites. Threatened species belonging to all three threatened categories (i.e., Vulnerable, Endangered, Critically Endangered), and all three broad taxonomic groupings (i.e., birds, frogs, mammals) were found within A2O recordings, and the majority of sites searched (83%) detected at least one threatened species. We provide information on the distribution of detections for all target species, an evaluation of classification performance for all species within the existing BirdNET model, as well as easy-to-use linear classifiers trained on BirdNET embeddings for all threatened species detected, which have improved performance over the standard BirdNET model. We conclude that acoustic monitoring networks such as the A2O, powered by deep-learning models, can serve as an important tool for monitoring threatened species.

1. Introduction

Worldwide, biodiversity loss is increasing (Ceballos et al., 2020), as is the number of threatened species (Butchart et al., 2010; Luedtke et al., 2023; Regan et al., 2015), necessitating urgent conservation action. Effective monitoring is vital for such action, to detect changes in the distribution and abundance of threatened species through time, providing useful data for managers to make informed decisions and evaluate intervention efforts (Stephenson et al., 2022). However, information on the distribution and abundance of threatened species is often limited and incomplete (Robinson et al., 2018). Threatened species can be difficult to monitor effectively, with the ability to detect a species at a location dependent on the interplay between their abundance, their detectability, and sampling effort. Scalable approaches such as passive acoustic monitoring have significant potential to aid in monitoring threatened species by continuously capturing data simultaneously at many locations (Schwarzkopf et al., 2023; Sugai et al., 2019).

Passive acoustic monitoring is now a powerful tool for detecting and monitoring vocal fauna due to recent advances in battery, storage, and automated processing techniques (Ross et al., 2023). Modern audio recorders can be deployed for extended periods of time (e.g., years) and record 24 h a day, allowing high temporal resolution data collection at many locations concurrently (Roe et al., 2021). These recordings can be stored indefinitely, forming a permanent record that can be interrogated later (e.g., for new species of interest, or with enhanced analysis tools). Additionally, they are a non-invasive method that does not require an observer to be present in the field, outside of device deployment and servicing visits. These features make it well suited for tackling the challenges associated with monitoring threatened species (Wood et al., 2023), however, challenges still remain in extracting useful information from long-duration recordings.

Until recently, most acoustic studies still used manual methods of

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analysis for processing their data (Sugai et al., 2019), however rapid advancements in automated recognition techniques for processing audio recordings now allow automated or semi-automated approaches for detecting species vocalisations. CNN-based call recognisers have emerged as highly effective tools for detecting species vocalisations from spectrograms (e.g., Eichinski et al., 2022; Ruff et al., 2020), and multi-species recognisers such as BirdNET (Kahl et al., 2021) and Perch (van Merriënboer et al., 2025) have made it much easier for large acoustic datasets to be rapidly analysed for many species. These advanced tools combined with continuous recordings can contribute significantly to threatened species monitoring, with CNN-based call recognisers increasingly used to detect and monitor a range of threatened vocal fauna (e.g., Allen-Ankins et al., 2024; Clink et al., 2025; Duarte et al., 2024; Shiu et al., 2020; Zhong et al., 2021). However, threatened species often do not have trained recognisers available to use for their detection, and even when available they are often trained on limited data with unknown performance when deployed in new monitoring efforts across their distribution. With biodiversity in many regions of the world declining, understanding how passive acoustic monitoring coupled with advanced analytic tools can be used to facilitate threatened species monitoring is essential.

Australia's biodiversity is in rapid decline and the country has one of the worst records for recent extinctions in the world (Dielenberg et al., 2023; Ritchie et al., 2013; Woinarski et al., 2019). The number of species listed as threatened in Australia has increased by 54% since 2000, while the abundance of threatened species show an average decline of 59% in the same period (van Dijk et al., 2025). Despite this, biodiversity monitoring in Australia is still very limited, and determining the trends for many threatened species remains problematic (Murphy and van Leeuwen, 2021). With much of Australia's natural environment remote and inaccessible, long-term monitoring surveys can be difficult and expensive, making acoustic monitoring a promising tool for gathering data on Australia's vocal threatened species such as birds, frogs and mammals. A continental-scale sensor network, the Australian Acoustic Observatory (A2O), was started in 2019 to continuously capture audio in various natural environments around Australia (Roe et al., 2021), and while not designed to target specific species, a previous study identified significant potential to detect and monitor many of the country's threatened vertebrate species (Schwarzkopf et al., 2023). However, despite having collected over 200 years of audio data to date, the potential for the A2O to enhance threatened species monitoring remains unrealised. The aims of this study were to: 1) determine which vocal threatened vertebrate species could be detected within the A2O and at which sites; 2) evaluate the performance of existing recognition models for threatened species; and 3) use any collected labelled data for detected threatened species to train new recognition models.

2. Methods

2.1. Audio data study locations

The Australian Acoustic Observatory (A2O) comprises numerous sites around Australia with locations varying from relatively undisturbed habitat, to grazed and peri-urban areas. Each site has four acoustic recorders with at least 500 m between each. The acoustic recorders used by the A2O are solar-powered devices from Frontier Labs (https://www.frontierlabs.com.au/solar-bar), and record continuously in mono at 16-bit, 22.05 kHz, stored locally on SD cards in 2-h FLAC files. Further details on the recorders and site setup can be found in (Roe et al., 2021). Audio data was obtained from the A2O website (https://data.acousticobservatory.org/). A total of 63 sites were analysed (Fig. 2), with audio data spanning the period Feb 2019 – Apr 2022. In total, over 2 million hours of audio recordings were analysed. The range of available data per site differed greatly due to differences in deployment dates and servicing schedules (mean = 558 days, range = 177–1235 days).

2.2. Target species

Vocal vertebrate species were selected using the EPBC Act List of Threatened Fauna (https://www.environment.gov.au/cgi-bin/sprat/public/publicthreatenedlist.pl), Australia's primary environmental legislation. A total of 74 species were selected, consisting of 13 frogs, 3 mammals, and 58 birds. The threatened status of the species included 6 listed as Critically Endangered, 29 listed as Endangered, and 39 listed as Vulnerable (Supporting Information A). Species were selected based on having known, species-specific vocalisations, and whether they were expected to occur in the broad habitat types in which specific A2O sites were located. For example, we excluded some birds such as seabirds, and waterbirds, that are unlikely to occur at A2O sites. To determine which A2O sites to search for each target species, we used distribution layers from the Species of National Environmental Significance and selected marine and cetacean species – indicative habitat models (https://www.dcceew.gov.au/; accessed 30th August 2024) which provides spatial layers for each threatened species, corresponding to areas that 'likely contain suitable habitat' and areas that 'may contain suitable habitat'. For simplicity these two categories are hereafter referred to as 'higher' quality habitat sites and 'lower' quality habitat sites respectively, however it should be noted that it is likely that in many instances a specific site may not be located in suitable habitat for a particular species. All A2O sites with audio recordings falling in either of the two areas were searched for each species (Fig. 1).

2.3. Audio analysis methods

Two audio analysis methods were used to determine site presence of each target species (Fig. 1), both involving the deep-learning model BirdNET (https://github.com/birdnet-team/BirdNET-Analyzer; Kahl et al., 2021). The latest version of BirdNET (i.e., v2.4) has been trained on many Australian bird species, including a number of our target species, and so for these species we used the existing model, run at default settings (sensitivity = 1, min_conf = 0.1, overlap = 0). For those target species not within BirdNET v2.4 (i.e., all frogs, all mammals, the remaining birds), we utilized the embeddings from the model and an example call to conduct a similarity search (Allen-Ankins et al., 2025). This method involved calculating the Euclidean distance between the embeddings for every 3-s of audio within our dataset, and the embeddings from an example call. Embeddings were generated using BirdNET's 'embeddings.py' script and result in a text file containing the embeddings vector for each 3 s of audio (i.e., a single vector for the example call and many vectors per 2-h recording). This allows a large amount of audio to be ranked by its similarity to an example call and help guide validation effort to where a detection of the target species is most likely. Other similarity metrics could be employed like cosine similarity or dot-product, as well as more complex manifold-aware search approaches. We used Euclidean distance as it required no assumptions of the underlying relationship between embeddings around the example calls used, was computationally simple to perform on multiple recordings simultaneously, and has been successfully used with BirdNET embeddings (Allen-Ankins et al., 2025; McGinn et al., 2023).

For the target species for which we conducted similarity search using embeddings, we obtained example vocalisations from a number of different sources including our own call library, xeno-canto (https://xeno-canto.org/), and iNaturalist (https://www.inaturalist.org/). The number of example calls used for each target species ranged from 1 to 4, depending on the availability of example calls for each species and amount of variation within those available example calls. All audio analysis was conducted using a High Performance Computer (servers running Intel Xeon Gold 6148/6248 CPUs). This allowed the large number of recordings to be processed in a parallel fashion (e.g., up to 100 at a time) such that >1000 files could be processed per hour. A full list of target species, number of sites searched, and search method used can be found in Supporting Information A.

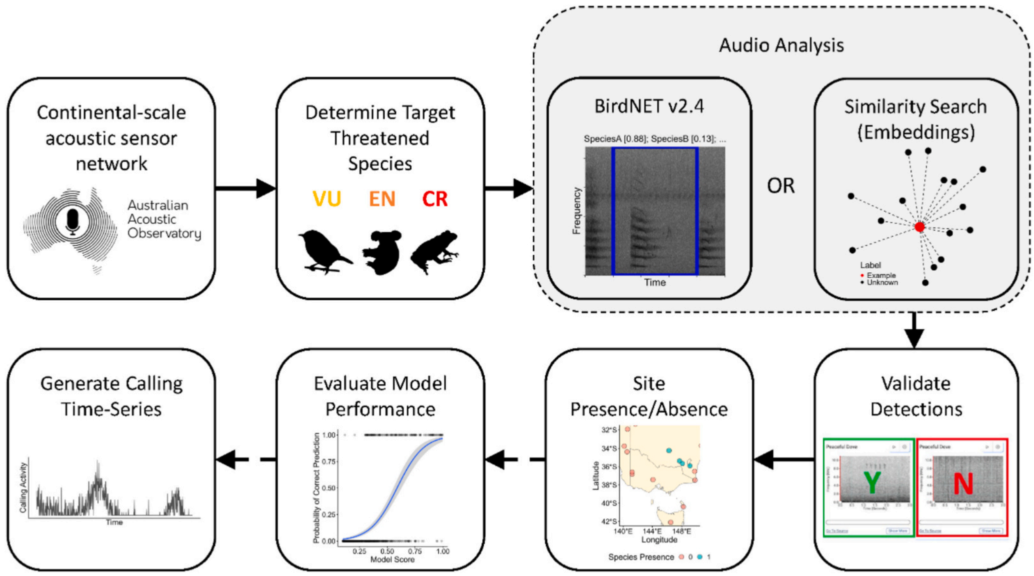

Fig. 1. General overview of the workflow used to detect threatened vocal species in the audio recordings of the Australian Acoustic Observatory (A2O) sensor network. The primary aim was to determine presence-absence of each target species at A2O sites; however, we also evaluate the detection performance for the analysis methods used and present example calling activity time-series that can be derived from such data.

2.4. Validation method and evaluation

For each species within the existing BirdNET v2.4 species list, 400 apparent detections were validated between confidence level 0.1 and 1.0 per site. This amount of validation is likely excessive to establish site presence-absence alone, but was done to thoroughly evaluate the performance of the existing model for each threatened species. For species for which we used similarity search using embeddings, the 20 lowest-distance samples per site were validated. Validations were carried out using Kaleidoscope Lite (Wildlife Acoustics, https://www.wildlifeacoustics.com) for playback of audio and viewing spectrograms of each potential detection (i.e., BirdNET detections across confidence range, lowest-distance embeddings search results). Each segment was inspected and marked as 'TRUE' or 'FALSE' for the target species.

A generalised-linear mixed-effects model with a binomial link function was fit to all validated BirdNET detections with confidence score as a fixed effect and an uncorrelated random intercept and random slope within species (e.g., Thompson et al., 2025). The same was done for all validated embeddings search detections with Euclidean distances as the fixed effect. In addition, the performance of detection methods for each individual species was visualized by plotting the relationship between true-positives, false-positives, and either confidence score for BirdNET species, or Euclidean distance for species for which we used embeddings searches.

To determine how search method, threatened status, taxonomic class, and habitat quality affected the probability of detecting a species at an A2O site, we fit a generalised-linear mixed effects model with a binomial link function with detected status (1 = detected, 0 = undetected) as the response variable, and threatened status (i.e., Critically Endangered, Endangered, Vulnerable), search method (i.e., BirdNET, Embeddings), taxonomic class (i.e., Birds, Mammals, Frogs), and number of years of available audio as fixed effects and a random intercept for species. Models were fit using the lme4 package in R (Bates et al., 2015) and effects were plotted using the *ggeffects* package (Lüdecke, 2018).

2.5. Custom recogniser training

To improve automated recognition capabilities for Australia's threatened species, the labelled data from the validation process was used to train new recognisers for all species with at least 30 positive detections. The 1024-length embeddings vectors from BirdNET v2.4 were used as the predictor features and the labels (1 = true-positive, 0 = false-positive) as the response to fit a binomial generalised-linear model for each species with the *bayesglm* function from the arm R package (version 1.11–2; Gelman and Su, 2020). This approach of training a linear classifier on the embeddings was chosen over training a model through the BirdNET application as it is computationally efficient and can take advantage of the precomputed embeddings from the similarity search to allow for rapid inference. For each species, data were split into train and test sets at a 70:30 ratio. Performance of the custom-trained recognisers were evaluated on the test set. For species already present in BirdNET v2.4, a comparison was made between our model and the existing model using the area under the precision-recall curve (PRAUC), with paired mean difference in PRAUC between methods determined using 5000 bootstrap resamples, with bias-corrected and accelerated confidence intervals. All validated audio and the resulting models are available at https://doi.org/10.5281/zenodo.17172660.

3. Results

A total of 41 out of the 74 threatened target species were detected at one or more A2O site (Fig. 2). Some threatened species with wide distributions were found at many A2O sites (e.g., Southern Whiteface – 21 sites, Blue-winged Parrot – 11 sites). Nearly all A2O sites searched (52/63) had at least 1 threatened species detected (Fig. 2), and the average number of species detected per site was 2.19 (range: 0–11). Maps showing the detection-non-detection locations for each individual species can be found in Supporting Information B. The proportion of species searched for that were detected declined with increasing listing status (Vulnerable = 0.64, Endangered = 0.48, Critically Endangered = 0.33; Fig. 2).

The probability of detecting a species at a location was significantly affected by the search method used and the habitat quality of the site for the species, but not by taxonomic class or the amount of audio available. The odds of detecting a species at a location were ~ 19 times lower when using Embeddings Search than when using BirdNET (OR = 19.7, 95% CI [4.7, 82.5]), and the odds of detecting a species at a location were ~ 6 times lower (OR = 6.55, 95% CI [3.38, 12.7]) if the location was in the 'lower' habitat quality region. Detection performance plots for each individual species can be found in Supporting Information B.

3.1. Validation effort to determine site presence

For both methods, very few validations were required to determine species presence. For the BirdNET model, 83 out of 102 (81%) instances of site presence (i.e., each occurrence of a species being detected at a single site), had positive detections as the returned sample with the highest confidence score. This increased to 88% (90/102) after validating the top 3 detections, and 95% (97/102) after validating the top 10 detections. For embeddings search, 26 out of 36 (72%) instances of site presence had positive detections as the most similar returned sample (i.e., the sample with the lowest Euclidean distance to the example call). This increased to 86% (31/36) after validating the top 3 detections, and 94% (34/36) after validating the top 10 detections.

3.2. Performance of detection methods

The probability of a detection from BirdNET being correct increased with confidence score (odds ratio = 44.2, 95% CI [15.8, 124]; $p < 0.001$; Fig. 3A). The median probability of correct detection at a confidence score of 0.99 for the 33 species was 0.83. The performance of BirdNET was species-specific with higher random intercept variance ($\tau_{00} = 12.9$) and random slope variance ($\tau_{11} = 5.3$) than residual variance ($\sigma^2_\varepsilon = 3.3$). Similarly for embeddings search, the probability of a detection being correct increased with decreasing Euclidean distance (odds ratio = 12.3, 95% CI [4.3, 35.6]; p < 0.001; Fig. 3B), with much higher random intercept variance ($\tau_{00} = 1218$) and random slope variance ($\tau_{11} = 5.4$) than residual variance ($\sigma^2_\varepsilon = 3.3$).

Using the more than 37,000 labelled apparent detections (of which over 14,000 were true-positive vocalisations) we developed new recognisers for 33 threatened species using logistic regression models trained on BirdNET v2.4 embeddings and the mean performance (i.e., PRAUC) on the test data was 0.96. For the 23 detected species that already existed within the BirdNET v2.4 classifier (only 23/33 detected BirdNET species had at least 30 positives for model training), the paired mean difference between the custom models and the original BirdNET classifier was 0.171 (95% CI [0.101, 0.285]; Fig. 4). Custom trained recognisers for each species can be found at https://doi.org/10.5281/zenodo.17172660.

Using the detection performance estimated from the generalised linear mixed-effects model, we extracted all BirdNET detections with a greater than 80% probability of being correct, and plotted time series for a broadly distributed endangered species, the Pink Cockatoo, and a collection of species detected at a single site, the Kangaroo Island A2O site, which is home to a large number of listed threatened species (Fig. 5).

4. Discussion

Passive acoustic monitoring has enormous potential to contribute to threatened species monitoring. Here, we show how a large-scale acoustic sensor network (i.e., the Australia Acoustic Observatory), despite being deployed without an explicit focus on detecting threatened species, is nevertheless able to detect a large number of vocal threatened taxa, indicating significant potential in monitoring Australia's threatened species. All three vertebrate taxonomic groups for which we searched (i.e., birds, frogs and mammals) were detected within the sensor network, as well as all categories of threatened status listings (i.e., critically endangered, endangered, and vulnerable). Additionally, existing acoustic detection methods detected the majority of species with little validation effort. However, we also provide new recogniser models trained on the embeddings of the deep-learning model BirdNET, for enhancing acoustic monitoring capabilities for Australia's threatened species.

We successfully detected a greater proportion of the ‘Vulnerable’ listed species that we searched for than those belonging to ‘Endangered’ and ‘Critically Endangered’ categories. This suggests that acoustic sensor networks with broad spatial distributions such as the A2O are likely to be most useful for monitoring threatened species that are in lower concern categories as those species typically have larger distributions that increase their chance of being located at one or more sensors. Additionally, being detected at multiple sites increases the usefulness of any trends detected in the data collected, with concurrent declines (or increases) at multiple sites more likely to represent broader trends in the species population than those same trends detected at only a single site. However, there is still value to detecting presence or absence of threatened species even at a single location. Verifying

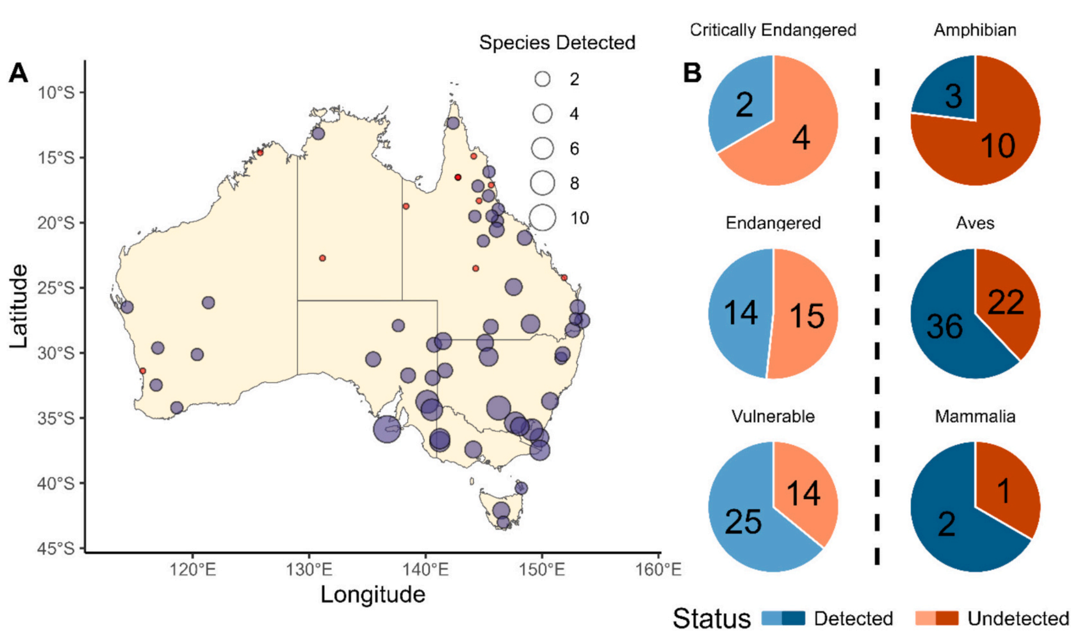

Fig. 2. A) The location of Australian Acoustic Observatory sites ($n = 63$) searched with the size of points scaled by the number of threatened species successfully detected there. Red points indicated sites where no threatened species were detected. B) Detection status of the number of target species ($n = 74$) belonging to different threatened categories and taxonomic groups. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

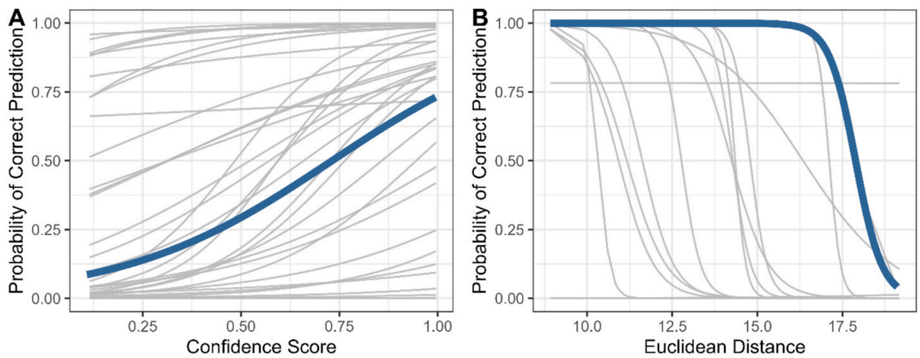

Fig. 3. Probability of correct prediction as a function of A) confidence score from BirdNET for 33 species, and B) Euclidean distance from embeddings search for 14 species. Models fit using a binomial generalised linear mixed effects model with an uncorrelated random intercept and random slope within species. The blue lines represent the fixed effects predictions, while the grey lines represent the species-specific predictions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

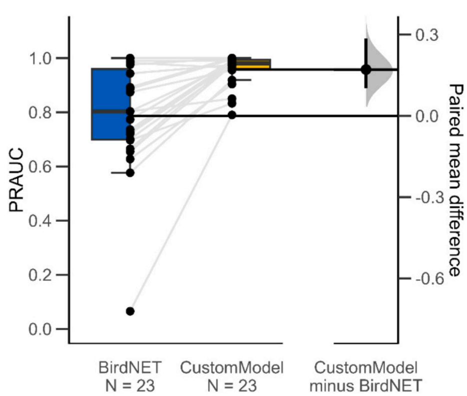

Fig. 4. Performance comparison (area under the precision-recall curve - PRAUC) on test data for 23 species between custom models (i.e., glms) trained on BirdNET embeddings and equivalent BirdNET model. Paired mean difference in PRAUC between methods determined using 5000 bootstrap resamples, with bias-corrected and accelerated confidence intervals.

presence at a site, particularly if this presence is at a new or understudied location, could be followed with further survey effort and even potential protection of the habitat, if it turns out to be an especially important area for the species. Likewise, failure to detect a species at a location where it was expected could be followed with more investigation, to identify if the species is actually absent from the area.

Species were more likely to be detected at A2O sites when they fell within ‘higher’ quality habitat areas than ‘lower’ quality habitat areas for that species, however there were still numerous instances of detections in those ‘low’ quality areas. The usefulness of a large sensor network such as the A2O is that sites are continuously recording, even outside the typical distribution for a particular species, opening the possibility of detecting species where they previously were not known (e.g., Stock, 2025). While we did not search outside the provided geographic ranges for each species, those recordings exist and could be analysed in the future. As acoustic monitoring becomes a more standard ecological monitoring method, the amount of available audio in both temporal and spatial dimensions that could be searched for any particular threatened species will only increase, and open acoustic dataset sharing has enormous potential to contribute to threatened species monitoring.

While this study focused primarily on detection and non-detection of threatened taxa, we also present examples of the detailed temporal information available for threatened species that cannot be obtained with manual survey methods. The continuous nature of the data collected by acoustic recorders reduces or removes entirely the chance of missing a species by not surveying at the correct time. The time-series of detections for species detected at the Kangaroo Island site show that each species had activity peaks at different times of the year, suggesting they could be missed by manual survey methods if their timing was not right. This is particularly important for threatened species that move significant distances through the landscape, such as nomadic or migratory species. While an increase or decrease in acoustic detections does not always mean a change in abundance, the vocal activity rates of different taxa, including birds and frogs, typically correlate positively with abundance (Nelson and Graves, 2004; Pérez-Granados et al., 2019), suggesting a drop a detections can be a useful proxy for a decline. A decline in a time-series of acoustic detections for a threatened species at a single monitoring site, or even a few monitoring sites, might not be enough evidence to conclude a species is declining more broadly. However, this information could be useful for triggering further monitoring efforts nearby to those sites, or across the species' distribution whether by manual survey or additional deployment of acoustic sensors. For example, the two northernmost time-series for the nomadic Pink Cockatoo (*Cacatua leadbeateri*), show a decrease in detections through time, while the southern sites show an increase in detections. This type of information could be useful for guiding further monitoring to understand if the bird is declining in an area, or used to help understand the site conditions that influence their nomadic movements (e.g., Rowley and Chapman, 1991). Studies targeting specific species with specific aims (e.g., detecting a decline) will benefit from a carefully designed study that considers the appropriate number of sites required to achieve desired outcomes (Teixeira et al., 2024). However, data from broadly distributed, long-term monitoring efforts such as the A2O can contribute to initiatives such as the Threatened Species Index (https://tsx.org.au/; Bayraktarov et al., 2021), where data from disparate sources can be leveraged to understand trends in threatened species more broadly.

Existing deep-learning models (i.e., BirdNET) and embeddings searches proved remarkably successful at finding threatened species in a large acoustic dataset. Both detection methods reliably returned instances of the target species as the best, or nearly best, detection at a site (assuming the full validation effort detected the species there at all), allowing very little validation effort to be expended to determine presence or absence of species relative to the enormous scale of the data. However, that validation step was still crucial, evidenced by BirdNET returning high confidence detections for species at sites that turned out to be all false-positives, and the high inter-specific variation in the intercepts and slopes of the relationship between confidence score and probability of correct detection (Doohan et al., 2026; Thompson et al., 2025). For the species that had low probability of correct detection even at high BirdNET confidence scores, it is likely that additional recogniser model improvement would be necessary for obtaining reliable estimates

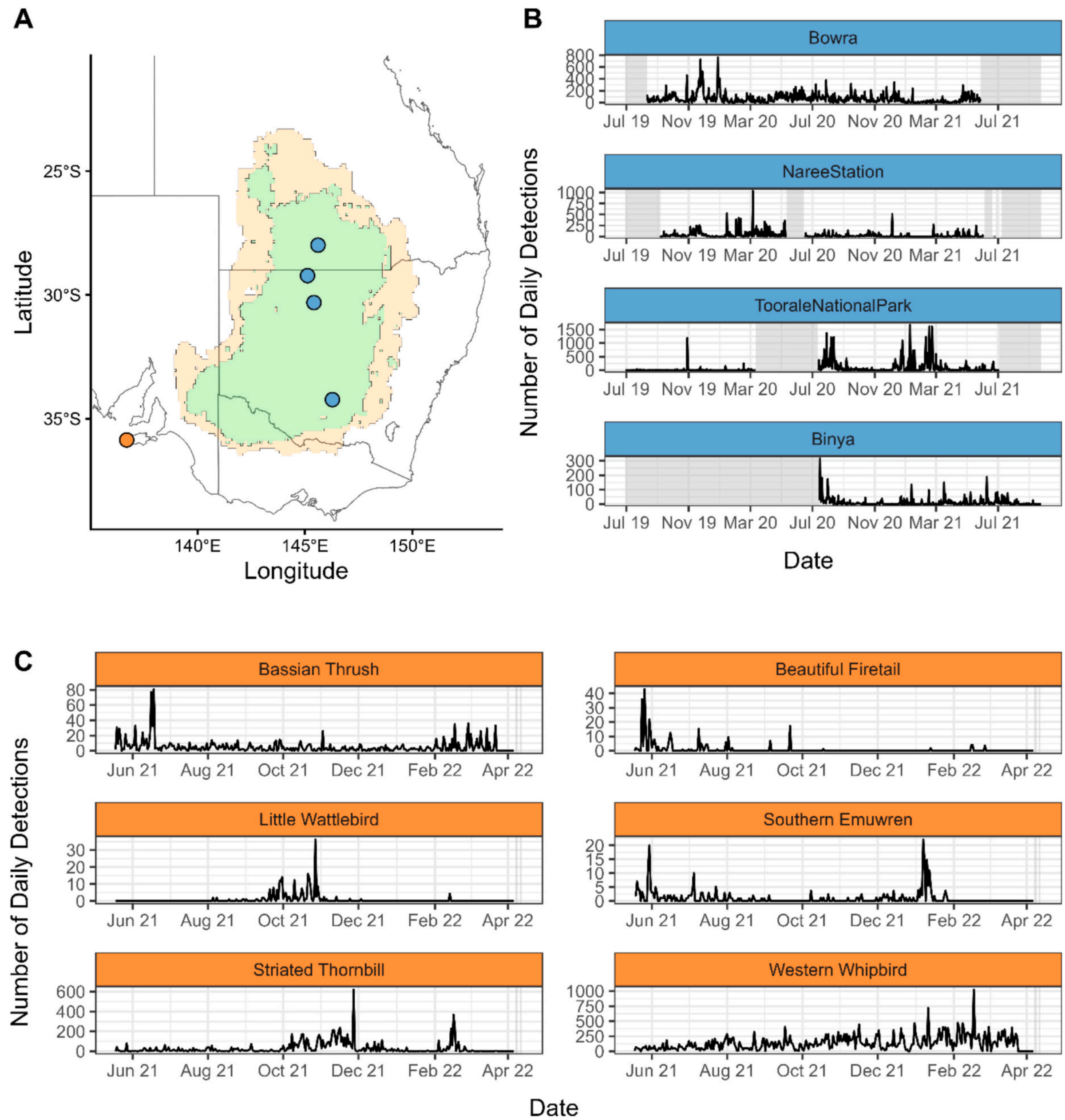

Fig. 5. A) selection of A2O sites with detections of the endangered Pink Cockatoo (blue circles) overlayed on their potential distribution range (green = 'higher' quality habitat region, tan = 'lower' quality habitat region) and the Kangaroo Island A2O site (orange circle), B) time-series of daily detections of Pink Cockatoo at the selected A2O sites arranged north to south, and C) time-series of daily detections of six threatened species detected at the Kangaroo Island A2O site. All detections are derived from BirdNET output with a confidence score exceeding an 80% probability of being correct for the respective species. Grey bars on time-series represent missing audio data. Number of detections scaled to account for variation in amount of recording available per day. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of calling activity. This is one of the strengths of passive acoustic monitoring datasets; this data from earlier points in time is still available for future interrogation once such models exist. Despite being trained almost exclusively on birds, the embeddings from BirdNET detected both threatened frogs and mammals using as little as a single example vocalisation, and models trained on those embeddings showed high predictive performance. Although, where possible, search results would benefit from using multiple example calls that represent the variation in a species vocal repertoire to increase chances of detection. The development of large bioacoustics models (e.g., BirdNET, Google Perch) that are effective for generalising to new call types, species, and distinct taxonomic classes (Dumoulin et al., 2025; Ghani et al., 2023), has made the development of recognisers for new tasks much quicker and easier. These models can allow effective detection and monitoring of threatened species, which typically have very little available labelled recordings to train recognisers with, giving managers an easy-to-use tool in threatened species conservation.

5. Conclusion

We show how the continental-scale acoustic sensor network, the Australian Acoustic Observatory (A2O), was able to detect a wide range of Australia's vocal threatened species including birds, frogs and mammals. Acoustic monitoring networks such as the A2O have great potential to provide long-term information on the presence and activity of threatened species over a wide area and can help fulfilling the monitoring obligations of many threatened listed species. Additionally, through thorough evaluation of the performance of existing recognisers (i.e., BirdNET) for available threatened species, as well as training new recognisers on top of the existing model embeddings, we provide essential information and tools to allow improved detection reliability for monitoring threatened species acoustically.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2026.103850.

CRediT authorship contribution statement

Slade Allen-Ankins: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Paul Roe:** Writing – review & editing, Funding acquisition, Conceptualization. **Lin Schwarzkopf:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Lin Schwarzkopf reports financial support was provided by Anglo American Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data and R codes that support the findings of this study are available at the public repository on Zenodo (https://doi.org/10.5281/zenodo.17172660), and supplementary tables and figures of this article.

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