Detection of threatened floodplain bird species using Artificial Intelligence

Acoustic monitoring at sites across the north and north-west of Victoria provides valuable data for threatened species management

Biodiversity Flood Recovery Update, June 2024

Key Messages

- Monitoring and detection of rare bird species over vast areas can be enhanced by using passive audio monitoring linked with Artificial Intelligence (AI) identification systems.
- Clear calls of threatened and common bird species were recorded across a variety of floodplain habitats in northern Victoria to train AI recognisers to detect these calls.
- Accurate and efficient detectors were developed for Powerful and Barking Owls, Regent and Superb Parrots and Pink Cockatoos.

Project Background

The floodplain influenced regions of north and north-western Victoria cover about half of the state, the majority of this land is privately owned. Monitoring and detecting rare and threatened birds over this vast area can be difficult, expensive and complicated due to variability in access (such as land tenure and flood conditions). Passive audio monitoring offers an efficient and scalable solution to gather the necessary data to inform management decisions. This project lays the foundations of an audio detection system by commencing widespread monitoring across varied floodplain landscapes and developing an Artificial Intelligence (AI) bird call recognisers to cost-effectively process the large dataset of audio collected.

Listening for target species: All hours, all sites

This project focused on detecting the Barking Owl *(Ninox connivens),* Powerful Owl *(Ninox strenua)*, Pink Cockatoo *(Lophochroa leadbeateri)*, Regent Parrot *(Polytelis anthopeplus)* and Superb Parrot *(Polytelis swainsonii),* all of which are typically found in treed habitats.

Figure 1: Bolton Nature Conservation Reserve, Robinvale-Sea Lake Road. Credit: Peter Griffioen, Arthur Rylah Institute

Recording locations adjacent to open areas also had the potential to detect open country species such as Plains-wanderer *(Pedionomus torquatus)*, Bush Stone-curlew *(Burhinus grallarius)* and Brolga *(Antigone rubicunda)*.

Inexpensive programmable audio recorders allowed scheduled audio monitoring at 47 sites spread across the floodplains of Victoria (Figure 1). Sites were chosen on criteria including the likelihood of recording target species, coverage of a mixture of floodplain vegetation types, inclusive of both public and private land, vehicle accessibility and coverage of areas that may be marginal habitat for some species. Fifteen sites were monitored with Songmeter Mini recorders with remaining sites using Audiomoth recorders. All recorders were setup to record five minutes every fifteen minutes across the day and night during May 2024. The Songmeters were able to record for 30 days but the Audiomoths were limited by battery exhaustion to 7-10 days of recording. Even though six Audiomoth recorders experienced hardware issues, the project still collected 1.67TB of audio data across 55,000 files.

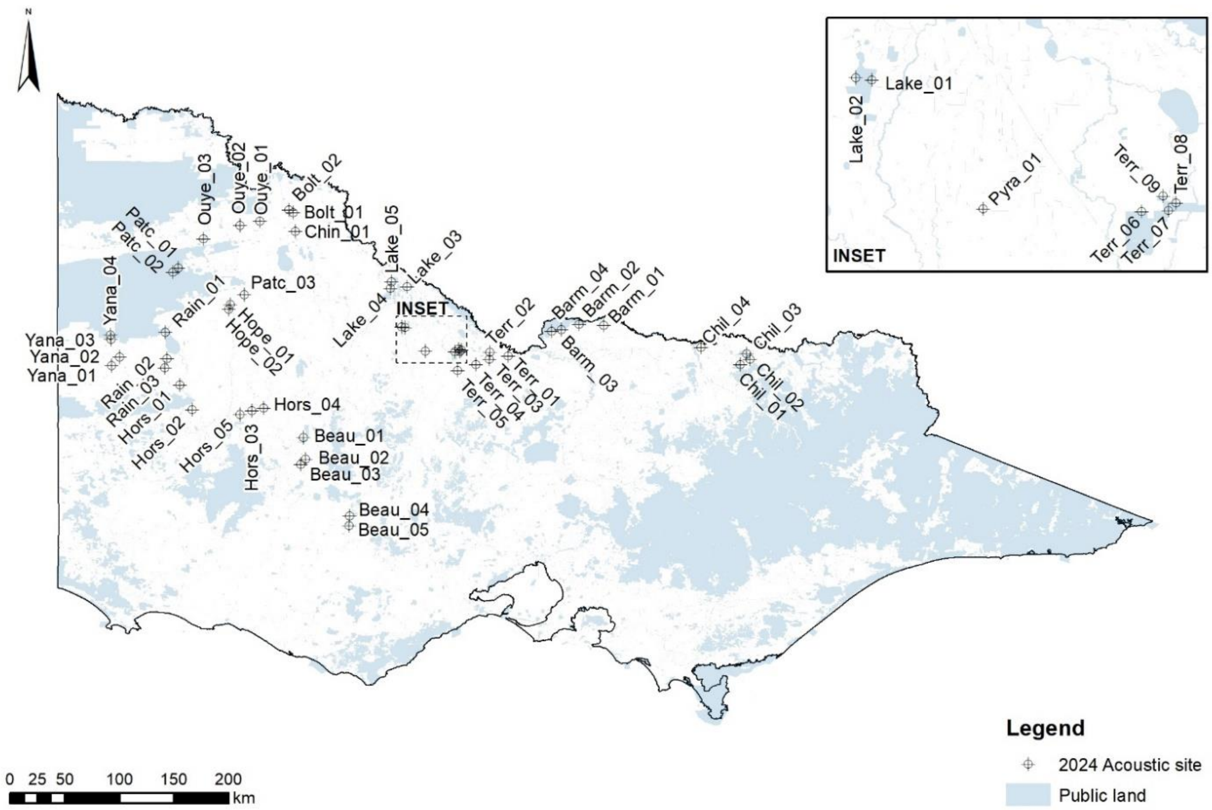

Figure 2: Observation sites chosen for floodplain species audio data collection and monitoring.

Linking calls to species

Upon recovery of the recorders at the end of May 2024, a 20-minute bird survey was conducted at each site by an ornithologist. These surveys aid the identification of common bird calls present on the recordings. Threatened target species were not detected during these on-site surveys, although this was to be expected given their rarity. Post-survey, bird calls were manually identified by careful inspection of spectrograms and listening to selected recordings collected over the month. High-quality calls were identified for the Superb and Regent Parrots, Pink Cockatoo and the Barking and Powerful Owls. This call set was boosted with a handful of calls for each species from ARI's bird-call library for model training. Calls of several common species were also identified such as the Laughing Kookaburra, Yellow-throated Miner and Restless Flycatcher. A 'non-target sounds' category included calls from non-target bird and mammal species, human-induced and other environmental sounds. All calls were sampled into 1.5 second exemplars and these formed the training data for the AI call recogniser.

Figure 2: 20-minute bird surveys were conducted at each site.
Credit: Peter Griffioen, Arthur Rylah Institute.

AI Model Design

The AI ‘deep learning’ call recogniser was developed by ARI using Google TensorFlow software. The recogniser is an ensemble of three convolutional neural networks (CNN) specifically trained to recognise target sounds and is very similar in design to that model used to recognise threatened Eastern Bristlebird calls (Griffioen and Francis 2022).

Three different designs of CNN were trained using 70% of the call samples. These call samples included the field recordings and calls from the ARI sound library. A test subset of 30% of the samples, that were a good representation of the target species, were withheld to test model performance.

Figure 3: Superb Parrot silo mural, Picola Victoria. Credit: Peter Griffioen, Arthur Rylah Institute

Sound files recorded in the field contain a lot of variation and are likely to present sounds or combinations of sounds not present in the training and test data. The resultant ensemble model was then passed over a subset of the field files to gauge model performance. False positives were fed back into the model as new training data. In this way the model development is an iterative process. The model performance for each species for the 30% holdout test data is given Table 1.

Table 1: Call samples used to train the AI model and the average true-positive accuracies achieved by the ensemble model for each species. False positives in the holdout test data were zero between species except between Regent and Superb Parrots where it was 8.6% and 10.4% respectively.

Species	Samples	Model Accuracy
Barking Owl	85	64.4%
Brolga	51	78.8%
Bush Stone-curlew	99	45.6%
Pink Cockatoo	222	99.9%
Plains-wanderer	18	77.8%
Powerful Owl	144	91.7%
Regent Parrot	119	93.0%
Superb Parrot	81	77.8%
Non-target sounds	198,834	99.9%

ARI’s custom model application software processed the field sound files, applying the call recogniser model and reporting on detections. This software, running on a powerful workstation, ‘listens’ to approximately 200 seconds of sound per second making detection of target species far more efficient than humanly possible.

Results and Implications

The model application software processed the 55,000 field files in 23 hours. The model was successful in detecting Powerful Owls, and Barking Owls in Chiltern area, Pink Cockatoos and Regent Parrots at Patchewollock and Ouyen, and Superb Parrots at Barmah Forest and Terrick Terrick National Park surrounds. The model did not detect any Brolga, Bush Stone-curlew or Plains-wanderer in field recordings at any site. It is notable that these three species had very little training data for the model.

The model currently has a high false-positive rate on field data across some species at some sites. That is, that the model identifies a sound as a target species when it is not. This indicates that further training of the model is required to improve the detection accuracy of some target species. For the species already being detected in the field recordings, this is generally a case of training the model to ignore false-positive-triggering sounds. For the species not being detected, more training calls are required to detect these species, if indeed they are present in the recordings.

To manage false-positive detections, the audio detection validation software ARIEL developed by ARI (https://zenodo.org/records/10681701 helps scientists quickly validate detected calls. The software allows the rapid location of detected call within the files, it provides a spectral depiction of the call, an estimate of the model’s confidence of detection, and allows the scientist to listen to the call to validate the detection.

This project added 2320 bird call sound exemplars of target species, common birds and other noises to the ARI audio database. These new exemplars enabled the model to identify more calls at sites in addition to those that provided training data. These valuable additions will improve model accuracy across a variety of sound recognition projects.

The model developed here is but the beginning of a system to automatically detect bird species over vast areas. Given the project implementation constraints, the brief field-work timeframe and sampling prior to the breeding season, this may have limited the amount and variety of calls recorded. A longer and seasonally stratified approach would likely result in significant increase call additions. Spatial coverage could also be intensified or more targeted.

With more and better data, these models will improve over time to provide more accurate results for more species. There is an axiom in mathematical modelling which is “the best model is the latest model”. Later versions of the model presented here can be passed over the field call files collected here to provide more identifications of the target and other species.

Acknowledgements

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Further reading

Griffioen, P. and Francis L. (2022). Developing Eastern Bristlebird Call Recognition Software. Unpublished Report for the Department of Agriculture, Water and Environment. Arthur Rylah Institute for Environmental Research, Department of Environment, Land, Water and Planning, Heidelberg, Victoria.

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