Assessing drivers of nocturnal bird detection and diversity in the Western Arc of the Lockyer Valley

Photo Credit: Kingston Tam

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July 2025

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Background

Bird diversity sampling is an effective proxy for measuring overall ecosystem health due to the sensitivity of birds to environmental changes and their ease of detectability (Smits & Fernie, 2013). Bio-acoustic recorders have emerged as an effective, non-invasive method of monitoring wildlife over long periods of time with little operational input (Frommolt & Tauchert, 2014; Zwart et al., 2014) and are especially effective at detecting cryptic species such as nocturnal birds (Zwart et al., 2014). With the use of bio acoustic recording equipment (audio moths) and machine learning algorithms (BirdNET), nocturnal bird species present in the western arc of the Lockyer Valley were identified across several Lockyer Uplands Catchment Inc (LUCI) properties. Here, we continue monitoring the nocturnal bird community to understand how community structure and species diversity vary as well as what environmental, temporal and spatial variables are driving the detection of these species.

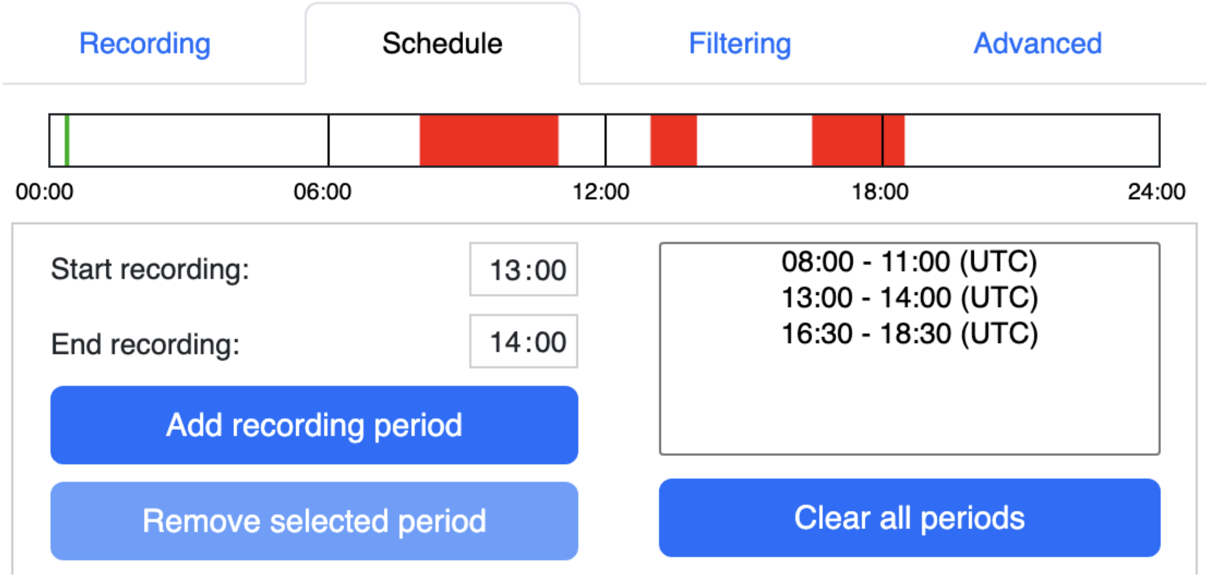
Aims

1. To collect presence/absence data on nocturnal bird species as means to augment LUCIs ongoing Bird Survey project.
2. To collect presence/absence data on Powerful Owls (*Ninox strenua*) as a component of Birdlife Australia's' Powerful Owl project in Southeast Queensland
3. To assess what variables may be influencing nocturnal bird diversity
4. To assess what variables are influencing species detections

Methods

Programming

Audio moths were programmed to record for a total of 6 hours every night; 3 hours at dusk, 1 hour in the middle of the night and 2 hours at dawn. The moths also had the gain set to high and cyclic recording was turned off to ensure they recorded for the full period they were programmed for rather than sampling this period. Figure 1 and Figure 2 show how the audio moths were programmed in the audio moth configuration application.

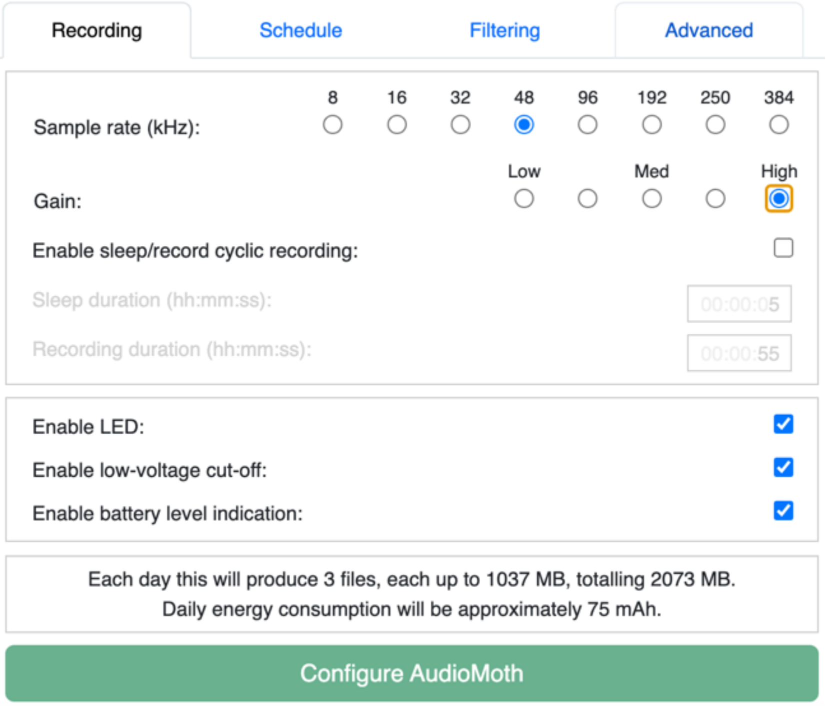


Start recording: 13:00

End recording: 14:00

08:00 - 11:00 (UTC)
13:00 - 14:00 (UTC)
16:30 - 18:30 (UTC)

Figure 1. The completed “Schedule” tab. Make sure your tab looks the same prior to uploading the data into your audiomoth.



Sample rate (kHz): 8 ○ 16 ○ 32 ○ 48 ● 96 ○ 192 ○ 250 ○ 384 ○

Gain: Low ○ ○ Med ○ ○ High ●

Enable sleep/record cyclic recording: ☐

Sleep duration (hh:mm:ss): 00:00:05

Recording duration (hh:mm:ss): 00:00:55

Enable LED: ☑

Enable low-voltage cut-off: ☑

Enable battery level indication: ☑

Each day this will produce 3 files, each up to 1037 MB, totalling 2073 MB.
Daily energy consumption will be approximately 75 mAh.

Figure 2. The completed “Recording” tab. Make sure your tab looks the same prior to uploading into your audiomoth.

Fieldwork

A total of 8 properties had bio acoustic surveys conducted in 2024. As the powerful owl was considered a priority species, the placement of audio moths was decided based on the presence of environmental characteristics associated with Powerful Owl habitat. These included the presence of waterways, gullies and dense canopy cover. Previous detection of powerful owls by landholders as well as the identification of powerful owl pellets and the remains of prey species such as possum tails and intestines at the base of trees was also used as selection criteria.

Once a site was selected within a property, audio moths were attached to trees at head height to avoid them being tampered with by animals and were set to record. The audio moths typically recorded for a month as that is the duration that the batteries could last and the memory cards would be able to continue to store audio files prior to becoming full. Once the audio moths were collected, the audio files were transferred to a computer for processing and analysis.

In total, 32 bioacoustics surveys were conducted between February and December of 2024.

Data processing

Audio files were analysed by BirdNET using 14 target species (the Powerful owl, Barn owl (*Tyto alba*), Australian owlet nightjar (*Aegotheles cristatus*), Southern boobook (*Ninox boobook*), Rufous owl (Ninox rufa), Barking owl (Ninox connivens), Australian masked owl (Tyto novaehollandiae), Sooty owl (Tyto tenebricosa), White-throated nightjar (Eurostopodus mystacalis), Spotted nightjar (Eurostopodus argus), Large-tailed nightjar (Caprimulgus macrurus), Tawny frogmouth (Podargus strigoides), Marbled frogmouth (Podargus ocellatus), and Australasian grass owl (Tyto longimembris)). All recordings with detections of these target species were then trimmed by BirdNET into ten second audio files. These shorter files were manually assessed in Raven Lite to determine whether BirdNETs detections were true detections or false positives.

All true detections were recorded and transformed into a survey by species presence-absence matrix. This matrix was further transformed into a distance matrix using the Jaccard similarity index to assess how the nocturnal bird species composition varied across surveys and other variables.

A metadata file was created based on several variables, specified to the gps coordinates of each audiomoth. These included the property itself, the month in which the majority of the recording was done, the season in which the majority of recording was done, the coordinates of the audiomoth, the average maximum and minimum temperatures throughout the period in which the recording was done, the regional ecosystem and broad vegetation group, the elevation and the distance to the nearest waterway. These two files were used for analysis 1.

A second file was created utilising the same variables as the metadata file as well as the number of days detected for each species and the number of days each survey went for. This file was used for analysis 2.

Statistical analysis

Analysis 1: What variables are driving total diversity?

The first analysis utilised PERMANOVA models to assess if various temporal, spatial and environmental variables (in the metadata) were strong predictors of nocturnal bird diversity. Once individual significant predictors were identified, they were combined with other predictors to see if in conjunction they could explain more of the variance in nocturnal bird diversity. The variance of the best PERMANOVA was partitioned using variance partitioning based on the Jaccard distance matrix. An RDA using spatial coordinates was used to see if differences in species diversity were spatially autocorrelated; whether two sites that were closer together would be more similar in diversity than those further apart. A principal coordinates analysis was also conducted to visually represent the differences in nocturnal bird diversity between surveys, sites and across seasons.

Analysis 2: What variables are driving species detection?

The second analysis utilised Integrated Nested Laplace Approximation (INLA) models to assess what the probability of detection for each species is. Several models were run using every combination of predictors for each species and compared using Log Pseudo-Marginal Likelihood (LPML) to find the best model. The best model for each species was then used to calculate the detection probability of that species. Species that were detected less were excluded as there was insufficient data to calculate detection probabilities.

Results and Discussion

Of the 32 surveys conducted, 18 surveys detected target nocturnal birds. No new species were detected that were not in the previous report. Species detected were the Powerful owl, Barn owl, Australian owlet nightjar, Southern boobook, White-throated nightjar and Tawny frogmouth.

Analysis 1: What variables are driving total diversity?

When used as individual predictors of nocturnal bird diversity, the only significant predictor was the property in which the audio moths were placed (see Table 1). This suggests that different properties have significant differences in nocturnal bird community composition. Unfortunately, other spatial and environmental variables were not found to be significant predictors, as such the underlying factor driving these differences in diversity is unknown.

Table 1. PERMANOVA output: Jaccard beta diversity using property and season as predictors.

	R^2	F	p-value
Model	0.74572	2.0528	**0.033**
Residual	0.25428		
Total	1		

When combined with other predictors, property and season were found to be significant (see Table 2). Partitioning the variance of these predictors found that the majority was explained by the property (~30%) and only a small amount was explained by season (4%). There was minimal shared variation between property and season suggesting that these two variables are separate effects. Approximately 60% of the variance remained unexplained.

Table 2. Variance Partitioning output: Jaccard beta diversity using property and season as predictors.

	Adjusted R^2
Property	**0.29580**
Season	**0.04392**
Combined	0.38246
Residual	**0.61754**

Audio moths that were closer to one another did not show any more similarity in nocturnal bird community composition than those that were further apart (not spatially autocorrelated).

The PCoA visually represents the findings of the PERMANOVA and the variance partitioning (see Figure 3). While property was a significant predictor and season was also significant in conjunction with property, most of the variance remains unexplained. The PCoA reflects this as while there is clustering appearing on the graph, it is not shown by season or property.

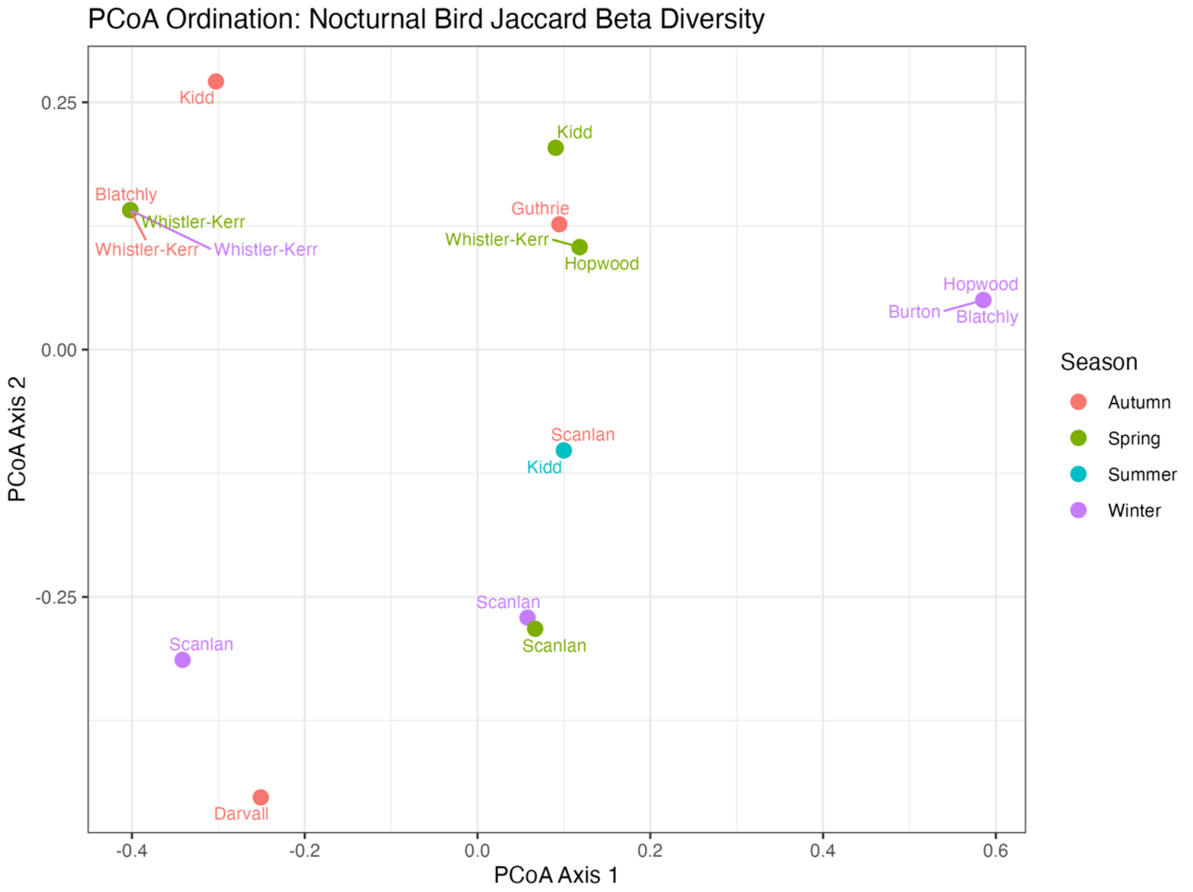


Figure 3. PCoA Plot showing differences in nocturnal bird community composition between surveys, based on Jaccard dissimilarities. Points represent individual surveys and distances between points represent the difference in species presence-absence.

Analysis 2: What variables are driving species detection?

Barn Owl

The best fitting model for barn owls used spatial coordinates as a random effect and the average maximum and minimum temperatures as fixed effects.

Both the average maximum and minimum temperatures were shown to have a significant effect on the detection probability of barn owls. Barn owls were shown to have an increased probability of detection when the average minimum temperature was higher, and the average maximum temperature was lower. With every 1°C increase in average maximum temperature detection probability was reduced by 46.5% and with every 1°C increase in average minimum temperature, detection probability increased by 81%. This suggests that barn owls prefer and are more active during milder temperatures in the western arc of the Lockyer Valley. A study on Australian owls found that maximum and minimum temperature did not have a significant effect on the detection of barn owls (Cooke et al., 2017). There are a few potential explanations as to why this discrepancy is occurring. This study was conducted in an urban study site in Melbourne, Victoria, while the nocturnal bird project was conducted on private properties that are composed of agricultural land, remnant and regenerated native landscapes (Cooke et al., 2017). These two areas vary in temperature and climate as well as habitat structure for barn owls which may alter detection probabilities, creating or masking relationships between species detection and temperature. Geographically separate populations of barn owls have also been shown to have morphological differences that allow them to be more suited to differences in temperature between these populations (Dreiss et al., 2016; Romano et al., 2019, 2020). As such, while temperature may have not had an impact on barn owls in Melbourne, they may have a more substantive effect on barn owls in the Lockyer Valley (Cooke et al., 2017). This study also utilised a different method of statistical analysis which may cause slight differences in the final outputs (Cooke et al., 2017).

The spatial random effect also found spatial clustering in the detection probability of barn owls, with an average radius of approximately 600 metres. This spatial clustering may be driven by environmental variables not utilised in the analysis. Barn owls have been shown to prefer open grasslands and farmlands for hunting (Séchaud et al., 2021). The availability of hollows and increased distance from roads has also been shown to increase occupancy of barn owls (Martínez & Zuberogoitia, 2004; Séchaud et al., 2021). It is important to note however, that this is an estimation. Most sites where audio moths were placed were greater than 600 metres apart. As such, this metric should be taken with a grain of salt.

The average detection probability ranged between 50% and 65% between surveys and when plotted was shown to have a positive relationship with average minimum temperature (see Figure 4)

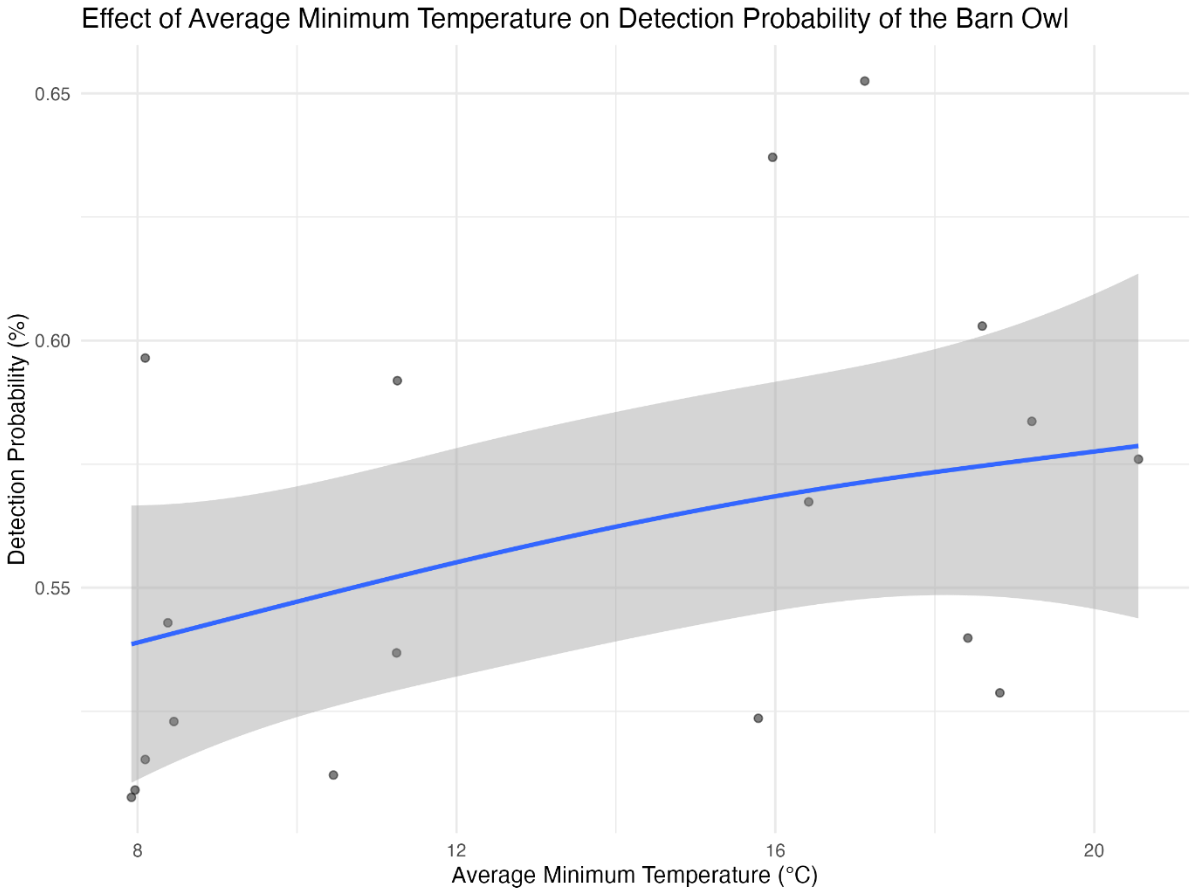


Figure 4. A plot showing the relationship between barn owl detection probability and average minimum temperature.

Australian Owlet Nightjar

The best fitting model for Australian owlet nightjars used elevation and average maximum temperature as fixed effects.

Both elevation and average maximum temperature were shown to have a significant effect on the detection probability of Australian owlet nightjars. Elevation had the stronger effect with a 1.9% increase in detection probability with every one metre increase in elevation. When visualised, there was also a strong increase in detection probability above 400m above sea level (see Figure 5). Average maximum temperature had a smaller effect with 19% increase in detection probability with every 1°C increase in temperature. This effect may be because Australian owlet nightjars enter a state of torpor when temperatures drop below a threshold, which thereby reduces their activity and detection (Brigham et al., 2000). This may explain why the strength of the relationship between average maximum temperature and Australian owlet nightjar detection was not very strong. Perhaps with a greater sample size, the model may find that average minimum temperature has a stronger effect, suggesting that the birds are entering a state of torpor (Brigham et al., 2000).

The average detection probability ranged between 50% and 62% between surveys.

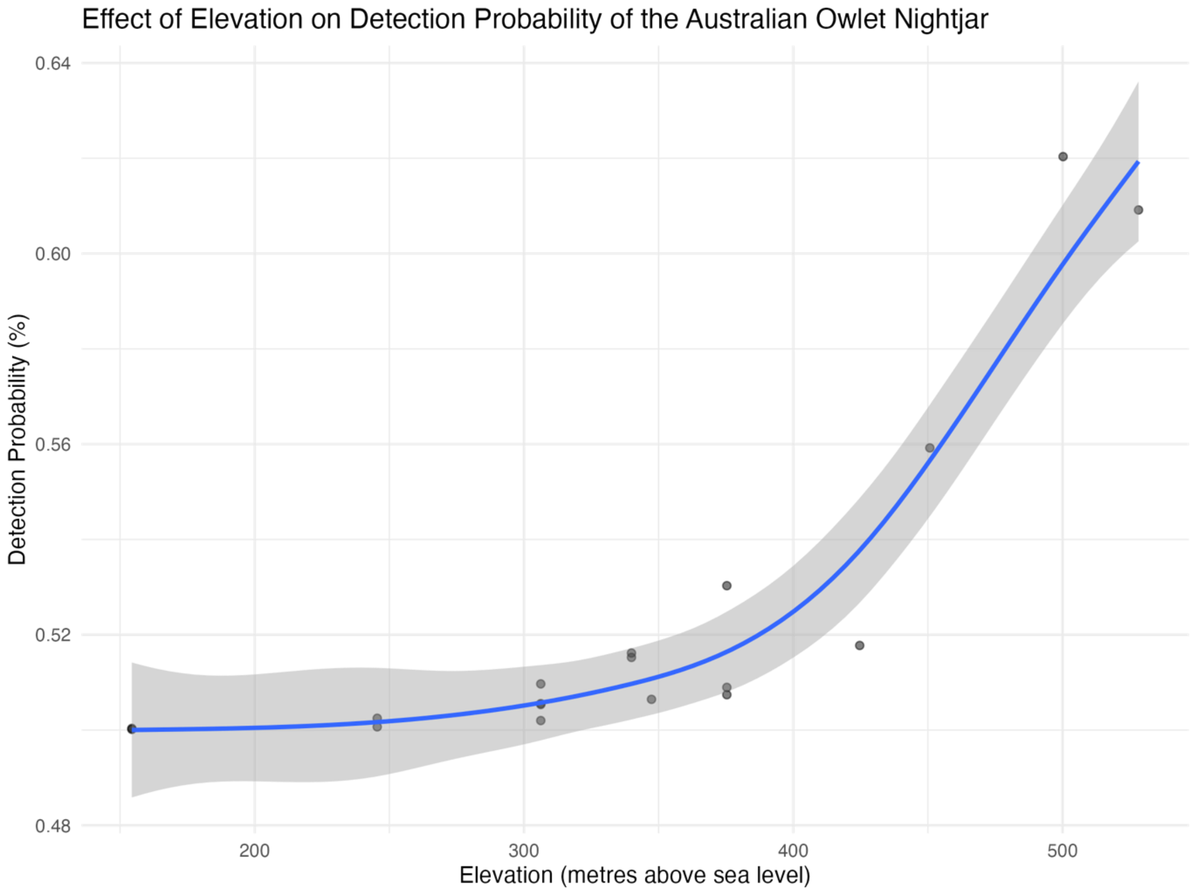


Figure 5. A plot showing the relationship between Australian owlet nightjar detection probability and elevation.

Other species

Detection probability of both the powerful owl and southern boobook were found to not be influenced by any of the covariates when modelled. This may be due to a few reasons. Firstly, both species were rarely detected. This in conjunction with a limited number of surveys may have resulted in too small a sample size for a significant effect to be detected. Secondly, it may also be possible that the predictors used simply do not influence the detection probability of these two species. As a result of this, detection probability of these species was not calculated.

Detection probability of both the tawny frogmouth and white throated nightjar were found to be influenced by a spatial random effect. However, the model hyperparameters for both the tawny frogmouth and white throated nightjar suggest that the spatial effect is both weak and likely being overfit into the model. This is also most likely a result of both species being rare and a limited sample size. However, the inability of other predictors to improve model fit may also suggest that, like the powerful owl and southern boobook, the detection probability of the tawny frogmouth and white throated nightjar are not influenced by them.

Conclusion and Recommendations

The nocturnal bird project successfully identified two variables that are driving the diversity of nocturnal bird diversity and found variables that influenced the detectability of two of these species: the barn owl and Australian owlet nightjar. However, most of the variance in nocturnal bird diversity remains unknown, suggesting that there are other variables that are still driving differences in diversity. Future work should utilise a greater set of environmental, spatial and temporal variables to understand what drives these differences in nocturnal bird community composition.

Due to the limited number of surveys conducted and some species being rare, it was difficult to acquire meaningful results regarding the variables that influenced their detection. The greatest strength of technologies such as bioacoustics and camera traps is the ability to collect large amounts of data. In conjunction with machine learning algorithms such as BirdNET, it is then possible to sort through and interpret this data with little active work. This was largely inhibited for the nocturnal bird project due to technical issues with the audio moths.

This issue resulted in abrupt endings to recording periods and several surveys that failed to record however, it has now been remedied. This issue arose from a combination of improper clearing of storage (SD cards) as well as low voltage and faulty batteries, resulting in the device being unable to write audio files into the storage. With these issues rectified, it should be possible to increase the amount of data collected using the audio moths.

This report utilised detection probability modelling in analysis 2. The issue with detection probability modelling is that it assumes that the species is present at each site and during each survey, when this is unlikely to be true, especially for rarer species such as the powerful owl. Occupancy models can be a solution to this as they consider the detectability of the species as well as whether the species is/is not present. However, they were not utilised in this report as they have a greater sample size requirement and require several audio moths per site. With the remediation of the technical issues that were limiting the amount of data collected, future work may be able to utilise occupancy models with larger sample sizes to calculate both detection probability as well as the occupancy of species at certain sites.

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