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Short Communication

# Estimating Little Penguin population sizes using automated acoustic monitoring and citizen science

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While automated recorders are becoming a favourable tool to monitor birds, methods to analyse the large amount of data generated and their reliability for estimating population size are still limited. In this study, I compared Little Penguins *Eudyptula minor* call detection between a trained researcher, amateur volunteers and an automated software, assessed which environmental factors affect call variability and detectability and determined the feasibility of automated recorders to estimate population sizes. I found that (1) the number of calls detected by the trained researcher was significantly higher than those detected by the amateur volunteers and automated software, (2) neither wind speed nor moon illumination affected call variability and detectability, and (3) six automated recorders estimated between 3% (large colony) and 14–26% (small colony) of the population. This study contributes to our understanding of the efficacy of automated recorders for avian monitoring.

**Keywords:** acoustic monitoring, bioacoustics, citizen science, population trends, seabirds.

Seabirds are the sentinels of the marine ecosystem (Croxall *et al.* 2002, Lascelles *et al.* 2012) and the most threatened group of birds (reviewed in Dias *et al.* 2019). Therefore, accurate estimations of their population trends are needed (Croxall *et al.* 2012, Paleczny *et al.* 2015). Yet obtaining robust estimates can be challenging because many seabirds breed on remote islands or in deep burrows. In addition, the nocturnal and burrowing behaviours of some seabirds can make estimates difficult because they cannot be viewed from a distance and are only active on land at night. Population estimates are thus usually obtained by marking as many birds as possible (Sutherland & Dann 2012) or by estimating burrow occupancy (Pearson *et al.* 2013), both methods being labour-intensive.

Automated acoustic recorders are becoming a powerful and popular tool for monitoring birds (reviewed in Pérez-Granados & Traba 2021). Automated recorders can be deployed for several months and survey populations across time and space (Blumstein *et al.* 2011, Celis-Murillo *et al.* 2012, Brownlie *et al.* 2020), while minimizing costs and human disturbance (Buxton & Jones 2012, Borker *et al.* 2014, Oppel *et al.* 2014). Despite these advantages, the effectiveness of automated recorders remains unclear and estimating bird population size from sound recordings has proven difficult (reviewed in Pérez-Granados & Traba 2021; see also Arneill *et al.* 2020). There is thus a critical need for additional studies across species to determine the usefulness of automated recorders.

Another downside of automated recorders is that they generate substantial amounts of acoustic data that can be difficult and time consuming to analyse. While the recent development of automated software is advantageous in reducing the laborious task of manually scanning large datasets (e.g. Acevedo *et al.* 2009, Swiston & Mennill 2009, Bardeli *et al.* 2010), their success in identifying and classifying species calls vary between studies and species (reviewed in Priyadarshani *et al.* 2018). Often automated methods produce more false positives and miss more target sounds than a manual scanning method by a trained observer (Swiston & Mennill 2009, Bardeli *et al.* 2010). Therefore, it is still common for researchers to analyse recordings manually, which severely reduces the efficiency of automated recorders.

Citizen science may offer a potential solution to overcome the arduous task of manually scanning large datasets. Citizen science projects engage volunteers to collect and process large volumes of data (e.g. Dickinson *et al.* 2010, Sullivan *et al.* 2014), which reduces the time, resources and costs associated with manually analysing such data (McKinley *et al.* 2017). Citizen science can therefore expand research capacity and scientific knowledge, while offering exciting opportunities and skills development for volunteers (see Kobori *et al.* 2016, Ellwood *et al.* 2017). However, the use of amateur volunteers to detect calls in acoustic recordings may compromise accuracy; this was demonstrated by Wimmer *et al.* (2013), as volunteers only correctly identified 31% of bird calls from recordings and took longer to identify the calls compared with trained observers.

The effectiveness of automated recorders can also be influenced by various environmental factors, such as wind speed (Buxton & Jones 2012, Arneill *et al.* 2020) and moon illumination (Bretagnolle *et al.* 2000, Mougeot & Bretagnolle 2000, Rubolini *et al.* 2015, Rodríguez

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*et al.* 2016, Brownlie *et al.* 2020), which are both known to impact seabird attendance and vocal activity. Strong winds may also mask bird vocalization, and thus increase false positives or negatives (Buxton & Jones 2012, Arneill *et al.* 2020). Therefore, the influence of environmental factors should be considered when assessing the usefulness of automated recorders.

In this study, I examined whether amateur volunteers or an automated software might provide useful alternatives to analyse a large quantity of acoustic data by comparing Little Penguins *Eudyptula minor* call detection between a researcher trained in acoustic analyses, 56 amateur volunteers and an automated sound analysis software. I then used automated recorders to determine whether wind speeds and/or moon illumination affected call variability and detectability. Finally, I tested whether Little Penguin call counts could provide an indication of their population size (see Buxton & Jones 2012, Borker *et al.* 2014, Oppel *et al.* 2014, Brownlie *et al.* 2020).

## METHODS

### Study sites and species

Little Penguin calls were recorded at two breeding colonies in South Australia: Granite Island (35°37′S, 138°36′E) – a rocky island (~ 24 ha) off the Fleurieu Peninsula; and Troubridge Island (35°06′S, 137°49′E) – a sandy island (~ 4 ha) off the Yorke Peninsula (Fig. 1). Troubridge Island is one of the largest Penguin colonies in South Australia with 450 adult Little Penguins at the time of the study, whereas Granite Island is one of the smallest with 28 adult Little Penguins (DEWNR 2016, Colombelli-Négrel 2018).

Little Penguins are burrow-nesting seabirds that breed any time between May and February, and moult between December and April (Colombelli-Négrel 2015, Johnson & Colombelli-Négrel 2021). While nationally categorized as 'Least Concern' (BirdLife International 2020), population declines of up to 80% have been recorded in South Australia since the 2000s (DEWNR 2016).

Little Penguins generally arrive at their colony at dusk and depart at dawn (Chiaradia & Kerry 1999), which are times of high vocal activity (D. Colombelli-Négrel pers. obs.), as found in other nocturnal seabirds (Landers *et al.* 2011, Buxton & Jones 2012, Brownlie *et al.* 2020). Brays and growls are their most common vocalizations (Miyazaki & Waas 2003, Colombelli-Négrel & Smale 2017) and hence are the focus of this study.

### Field data collection

#### *Automated recordings*

Six recorders were deployed on each island for 43 (Granite) and 52 (Troubridge) consecutive days between September and October in 2017 (the middle of the breeding season for this year, as this period provides the most robust population estimates). Three recorders were deployed on Granite Island between May 2019 and June 2020. All recorders were small (3 × 20 cm) waterproof cylinders developed by the New Zealand Department of Conservation. Each recorder was mounted to a tree trunk ~ 30 cm above ground, every 50 m (2017, both islands) or 100 m (2019–2020, Granite Island), along a single transect crossing the main breeding area (Fig. 1). These distances were chosen based on the results of the playback experiments (see below) to ensure independence of the recordings. Recorders were set to record as mono 16-bit .wav files (sample rate 16 kHz; 32 000 samples/s) continuously for 3 h every night immediately after sunset ('evening recordings'; 2017 and 2019–2020) and every morning immediately before sunrise ('morning recordings'; 2017).

Playback experiments in September 2017 on both islands were used to assess at which distance Little Penguin calls could be distinguished clearly from the automated recordings using Raven Pro 1.5 (v.1.5.1; Cornell Lab of Ornithology, Ithaca, NY, USA). To determine this, brays and growls were broadcasted via an Apple iPod (Apple Inc., USA) connected to a Moshi Bass burger speaker (Moshi Corp., USA; sensitivity: > 80 dB; frequency response: 280–16 kHz) at natural volume (~ 65–85 db at 1 m; Mouterde *et al.* 2012, Schaefer & Colombelli-Négrel 2021) every 1 m until 50 m. Playback tracks were made from previous recordings (filtered < 1.5 kHz) and saved as 16-bit wav files in Amadeus Pro 2.2 (Hairersoft Inc., London, UK). Playbacks were performed during the day (to avoid overlapping natural Little Penguin calls) over 2 days (one on Granite Island and one on Troubridge Island) and showed that calls recorded up to 10 m from the recorders could be seen clearly on spectrograms. As the recorders are fitted with multidirectional microphones, recordings can be captured within a 10-m radius, and a minimum distance of 30–40 m between recorders is recommended.

#### *Little Penguin numbers*

Repeated censuses were conducted every 2 weeks between September and October 2017 within a 10-m radius of each recorder during the middle of the day to count active nests. A nest was recorded as active if it contained eggs, chicks or adults, or there was clear evidence of Little Penguin presence, such as fresh droppings, a strong penguin smell or recent excavation, or inactive if none of the above criteria were found or if it had cobwebs at the entrance indicating that no large animal was regularly entering/exiting the nest (Colombelli-Négrel 2015, 2018).

Between May 2019 and June 2020, the numbers of Little Penguins present on Granite Island (those arriving

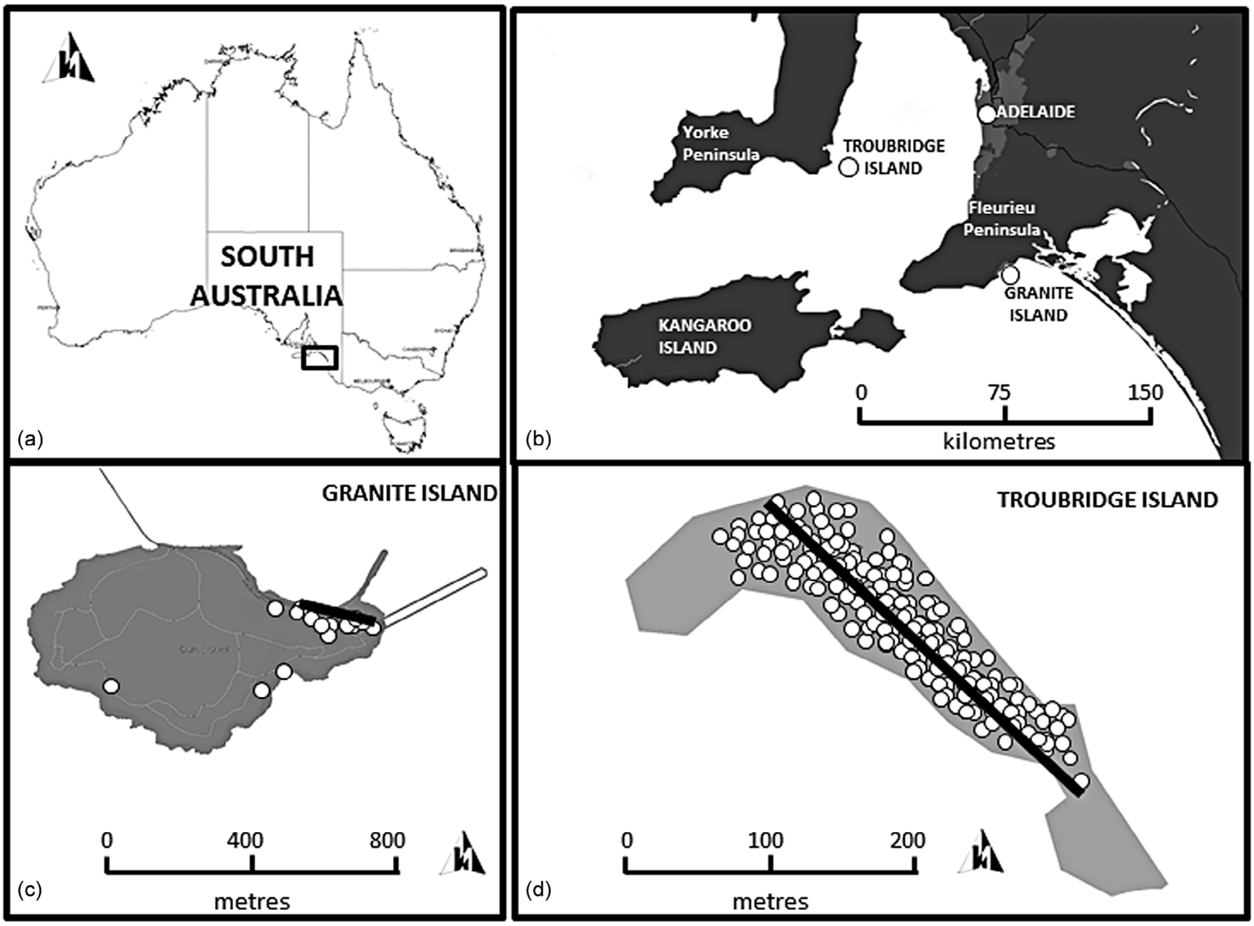


**Figure 1.** Map illustrating the location of (a) the study sites within Australia, (b) the two Little Penguin colonies, and active little penguin nests (white dots) as well as the transect along which the automated recorders were deployed on (c) Granite Island and (d) Troubridge Island.

from sea as well as those already in their nests during the day) along the transect of the recorders (Fig. 1) were obtained from daily night counts conducted by walking slowly and quietly back and forth along the transect while noting where Penguins were seen on a map to avoid double counting (see Colombelli-Négrel 2020).

## Call counts and detection

A randomly selected subset of recordings (169 h : 60 h on Granite Island and 109 h on Troubridge Island) was analysed using three methods: a manual scanning method using Raven Pro 1.5 by a researcher trained in acoustic analyses or 56 amateur volunteers, as well as an automated scanning method using Kaleidoscope Pro (v5.1.2; Wildlife Acoustics Inc., Maynard, MA, USA). All spectrograms in Raven Pro were in greyscale with the Hann algorithm and a discrete Fourier transform of 512 samples. The amateur volunteers were third-year university students tasked with analysing the recordings as part of their Animal Behaviour practical. Volunteers and the trained researcher were instructed to score the total number of Little Penguin calls for the first 2 h of the 3-h recordings using detailed information on how to use the software and various examples of Little Penguin brays and growls. Call counts were not influenced by volunteer bias (see Supporting Information Appendix S1 and Table S1).

All recordings obtained from the automated recorders were then scanned in Kaleidoscope Pro, which uses Hidden Markov Models (Makhoul & Schwartz 1995) to detect and classify vocalizations into clusters based on their spatio-temporal similarities and produces a .csv file of candidate vocalizations matching previously constructed recognizers. I constructed recognizers for Little Penguin calls using 4 h of independent recordings from both study sites with the following parameters: (1) frequency range 50–1500 Hz, (2) minimum and maximum length of detection 0.1 and 7.5 s respectively, and (3) maximum inter-syllable gap 0.1 s. For the 93 h obtained in 2017 (Granite Island: 56 h, Troubridge Island: 37 h), candidate vocalizations were examined manually by the experienced researcher to determine false positives (when a sound was incorrectly classified as a Little Penguin call by the software) and false negatives (when a Little Penguin call was not detected by the software).

### Statistical analysis

SPSS version 25.0 for Windows (SPSS Inc., Chicago, IL, USA) was used for all statistical analyses. Data are shown as means ± se. All models had a negative binomial distribution as dependent data were count data with high variance.

To assess call detection across methods, I analysed Little Penguin call counts obtained from the 169 h selected in 2017 using a Generalized Linear Mixed Model (GLMM) with 'methods' (trained, amateur, automated), 'time of recording' (morning vs. evening recordings) and 'colony' (island) as fixed factors, and 'recorder ID' (to account for variation in detection due to the location of the recorder) as a random effect (Model a). For the remaining analyses, I used the call counts obtained from the automated software (see Results).

Wind speeds were obtained via the Willy Weather website (https://www.willyweather.com.au) and classified as: light (< 11 km/h), moderate (< 29 km/h), strong (< 50 km/h) or gale force (< 75 km/h). Percentages of moon illumination were obtained via the Timeanddate website (https://www.timeanddate.com/moon) and classified as 0–25%, 26–50%, 51–75% or 76–100%. To assess factors affecting call variability and detectability, I analysed the number of false positives (Model b) and negatives (Model c) using GLMMs with 'colony' and 'wind speeds' as fixed factors, and 'recorder ID' as a random effect. I examined the relationship between call counts obtained in the evening vs. morning in 2017 using a General Linear Model (GLM; Model d). Evening call counts were used in all further analyses (see Results). I analysed the total evening call counts obtained per night in 2019–2020 using a GLM with 'wind speeds' and 'moon illumination' as fixed factors (Model e).

To assess Little Penguin numbers, I used two linear regressions to analyse the evening call counts obtained per recorder in 2017 in relation to the 'number of active nests' (found within a 10-m radius of each recorder), and the evening call counts obtained per night in 2019–2020 (sum of the three recorders) in relation to the 'number of Little Penguins' (i.e. number of adults counted during the Penguin tours). I then averaged the number of calls obtained per island for each of the recording periods and applied the fitted regression equations obtained from the above linear regressions to these averages to estimate population sizes (two adults/active nest following Sutherland & Dann 2012 and Colombelli-Négrel 2015, 2020).

## RESULTS

In 2017, I obtained 1343 and 1670 h of recordings on Granite and Troubridge islands, respectively. In 2019–2020, I obtained 3843 h over 427 nights on Granite Island. Results from all the models (Models a–d) used in this study are presented in Table 1.

### Call detection across methods

The number of calls detected by the trained researcher was significantly higher (~ 1.9× more calls) than those detected by the amateur volunteers and the automated software (GLMM: Table 1a; Fig. 2). Call detection correlated with recorder ID (Wald $Z = 2.10$; $P = 0.03$), and differed between islands and times of recording (Table 1a). The automated software accurately classified 77% (86% and 64% of calls on Granite and Troubridge islands, respectively) of Little Penguin calls (i.e. classified Little Penguin calls into the cluster 'Little Penguin calls'). Recall (the percentage of calls scored manually by the experienced researcher also found by the automated software) was 68%: 69% for Granite Island and 67% for Troubridge Island.

### Call variability and detectability

Using the call counts obtained from the automated software, the number of both false positives and false negatives was significantly lower on Granite Island (positives: 4.29 ± 0.43; negatives: 20.28 ± 1.31) than on Troubridge Island (positives: 36.63 ± 2.05; negatives: 89.15 ± 3.92) (GLMMs: Table 1b,c). Neither correlated with wind speed (Table 1b,c) or recorder ID (positives: Wald $Z = 1.66$; $P = 0.10$; negatives: Wald $Z = 1.90$; $P = 0.06$). Call counts obtained from the evening recordings positively correlated with those obtained from the morning recordings (GLM: Table 1d). The number of evening calls per night did not correlate with wind speed or moon illumination (GLM: Table 1e).

### Little Penguin numbers

Call counts (obtained from the automated software) significantly predicted both the number of active Little Penguin nests found in 2017 (linear regression: $R^2 = 0.56$, $t = 6.97$, $n = 39$, $P < 0.0001$; Fig. 3a) and the number of Little Penguins counted in 2019–2020 (linear regression: $R^2 = 0.12$, $t = 6.18$, $n = 278$, $P < 0.0001$).

**Table 1.** Outputs from the GLMMs and GMM testing whether (1) Little Penguin calls detection differed across methods (trained researcher, amateur volunteers, automated) (Model a, residual deviance/df = 0.9), (2) the number of false positives (Model b, residual deviance/df = 1.3) and (3) the number of false negatives (Model c, residual deviance/df = 1.0) differed between colony or wind speed categories, (4) evening call counts correlated with morning call counts (Model d, residual deviance/df = 0.9), and (5) the number of Little Penguin calls differed between wind speed and moon illuminations categories (Model e, residual deviance/df = 0.7).

| Fixed effects | Estimate | se | *t* | *P* |
|---|---|---|---|---|
| Model a – call counts (GLMM) | | | | |
| *Intercept* | 4.49 | 0.13 | 33.18 | **<0.0001** |
| Methods (trained–automated) | 0.11 | 0.05 | 2.24 | **0.02** |
| Methods (trained–amateur) | 0.53 | 0.05 | 10.99 | **<0.0001** |
| Time of recording (evening–morning recordings) | −0.05 | 0.05 | −0.98 | 0.32 |
| Island (Granite – Troubridge) | −1.14 | 0.18 | −6.09 | **<0.001** |
| Model b – false positives (GLMM) | | | | |
| *Intercept* | 3.52 | 0.29 | 12.11 | **<0.0001** |
| Island | −2.27 | 0.26 | −8.73 | **<0.0001** |
| Wind speeds (light–moderate) | 0.09 | 0.27 | 0.34 | 0.74 |
| Wind speeds (moderate–strong) | 0.13 | 0.22 | 0.59 | 0.56 |
| Model c – false negatives (GLMM) | | | | |
| *Intercept* | 4.32 | 0.25 | 16.98 | **<0.0001** |
| Island | −1.47 | 0.26 | −5.69 | **<0.0001** |
| Wind speeds (light–moderate) | 0.26 | 0.21 | 1.22 | 0.22 |
| Wind speeds (moderate–strong) | 0.02 | 0.17 | 0.11 | 0.91 |
| Model d – evening vs. morning counts (GLM) | | | | |
| *Intercept* | 45.82 | 36.54 | 1.25 | 0.21 |
| Morning call counts | 0.91 | 0.04 | 24.91 | **<0.0001** |
| Model e – number of Penguin calls (GLM) | | | | |
| *Intercept* | 6.14 | 0.18 | 33.55 | **<0.0001** |
| Wind speeds (light–moderate) | 0.36 | 0.18 | 1.98 | 0.05 |
| Wind speeds (moderate–strong) | 0.13 | 0.18 | 0.74 | 0.46 |
| Wind speeds (strong–gale force) | −0.27 | 0.19 | −1.40 | 0.16 |
| Moon illumination (0–25%) – (26–50%) | −0.01 | 0.08 | −0.14 | 0.89 |
| Moon illumination (26–50%) – (51–75%) | −0.11 | 0.10 | −1.07 | 0.28 |
| Moon illumination (51–75%) – (76–100%) | −0.10 | 0.10 | −1.01 | 0.31 |

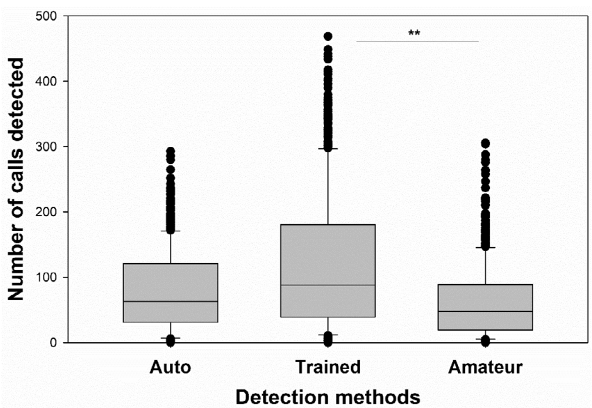


**Figure 2.** Number of calls detected by each method (auto: automated software, trained: trained researcher, amateur: amateur volunteers) for 676 recordings collected on Troubridge and Granite Islands. Horizontal lines within the boxes represent the means. The upper and lower limits of the boxes show the 75th and 25th percentiles, respectively. Black circles indicate outliers.

Little Penguin numbers were estimated as 12 adults on Troubridge Island (3% of the total population) and four (2017; 14%) and seven (2019; 26%) on Granite Island. Figure 3b demonstrates how Little Penguin vocal activity (total number of calls recorded per night by the automated recorders) aligned with Little Penguin numbers counted at night as well as their variation over time.

## DISCUSSION

Obtaining accurate indexes of seabird population size is critical to develop appropriate conservation measures. Here, I report on the first application of automated recorders to assess Little Penguin population sizes and demonstrated that an automated software can be used to score Little Penguin vocal activity (with an average call detection of 77% and recall of 68%), thereby significantly reducing analysis time. While I acknowledge the small sample (trained researcher = 1) and the disadvantages of using a single trained researcher (i.e. time-consuming and

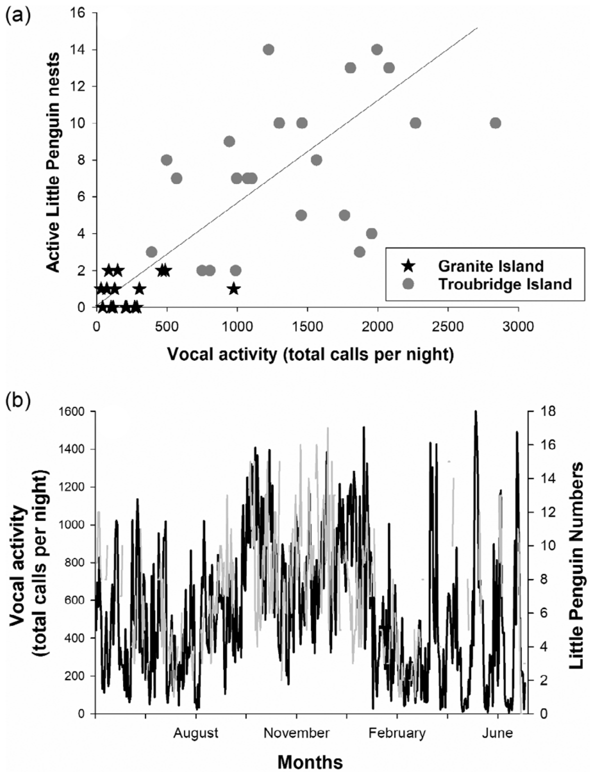


**Figure 3.** (a) Relationship between Little Penguin vocal activity (total number of calls per night) and the number of active Little Penguin nests within 10 m of the automated acoustic recorders deployed on Granite Island (black stars) and Troubridge Island (grey circles). (b) Little Penguin vocal activity (black line; total number of calls per night) and numbers of Little Penguins counted at night (grey line) recorded on Granite Island between May 2019 and June 2020.

being unable to cross-check analyses), this study still contributes to our understanding of the application and efficacy of automated recorders and sound analyses software for monitoring of seabirds (Buxton & Jones 2012, Borker *et al.* 2014, Oppel *et al.* 2014, Brownlie *et al.* 2020).

Analysing significant acoustic datasets is a time-demanding and complex task. In recent years, there has been a growing interest in involving large numbers of amateur volunteers in bird surveys (see Greenwood 2007). While this study did not assess whether amateur volunteers scored false positives or negatives, it did confirm previous results (Wimmer *et al.* 2013) that amateur volunteers underestimate call counts, therefore supporting the idea that citizen science may not be useful in analysing large acoustic datasets, even when volunteers receive clear and detailed instructions, as done in this study (see also Kosmala *et al.* 2016). Future research should investigate whether intensive training of call analyses prior to analysing datasets would improve volunteer call count estimates. In addition, further developments in the field of sound analyses software (e.g. Priyadarshani *et al.* 2018, Juodakis *et al.* 2021) may help improve the time-demanding task of analysing complex acoustic datasets.

Contrary to previous studies (Bretagnolle *et al.* 2000, Mougeot & Bretagnolle 2000, Rubolini *et al.* 2015, Arneill *et al.* 2020, Brownlie *et al.* 2020), vocal activity in Little Penguins did not correlate with moonlight or wind speed. Similarly, this study showed that wind speed did not affect call detection (but see Buxton & Jones 2012, Arneill *et al.* 2020), which is surprising as the low frequencies of Little Penguin brays and growls often overlapped with wind noises. This may be due to the small population size on Granite Island (and thus small numbers of birds vocalizing), but this remains to be tested further. The number of false positives and false negatives was, however, higher on Troubridge Island than on Granite Island, perhaps due to the large breeding colony of Silver Gulls *Chroicocephalus novaehollandiae* on Troubridge Island often calling at the same time as Little Penguins. One might improve call detection by only analysing optimal recordings without overlapping sounds, but this would limit the usage of automated recorders, as seabirds rarely breed in isolation from other species.

Burrow occupancy and seabird population size can vary both spatially and temporally (Weerheim *et al.* 2003, Whitehead *et al.* 2014, Colombelli-Négrel 2018). Accounting for temporal variation is important when populations are surveyed infrequently (Parker & Rexer-Huber 2016) or exhibit asynchronous breeding (Sutherland & Dann 2012). The number of Little Penguin calls in this study started to increase from August onwards (Fig. 3b), which is when the first nest was observed on Granite Island (Colombelli-Négrel 2020), highlighting that automated recorders can be useful in obtaining information on the timing of breeding (Brownlie *et al.* 2020; this study). Similarly, the peak of vocal activity occurred after sunset and before sunrise, as found for other nocturnal seabirds (Landers *et al.* 2011, Buxton & Jones 2012, Brownlie *et al.* 2020), and evening recordings were sufficient to assess Little Penguin numbers. Determining recording windows is critical to ensure accurate estimations of population sizes as well as extending the recording capacity of the recorders and saving analysis time.

The significant relationships between vocal activity and the number of active nests (2017) or adult Little Penguins (2019–2020) confirm that automated recorders can provide a valuable tool for assessing population size for nocturnal burrow-nesting seabirds (Buxton & Jones 2012, Oppel *et al.* 2014, Brownlie *et al.* 2020). However, the small detection range of the recorders is a limiting factor, as only 3–26% of the total populations were estimated in this study, implying that 200 recorders would be needed fully to assess the larger colony (Troubridge Island), which would imply that automated recorders are not a cost-effective alternative. However, the 10-m threshold was selected based on clear spectrograms only, and thus the true detection range of the recorders may be higher than reported. Additional playback experiments could test this further. In addition, with some knowledge of Penguin distribution within their colony, information on population sizes and trends in larger colonies could be obtained by installing fewer recorders in selected areas with different Penguin densities and extrapolating to the whole colony, as often done with manual surveys (Sutherland & Dann 2012, Colombelli-Négrel 2017, 2020). Therefore, conducting rapid spatial surveys before installing automated recorders is highly recommended to provide accurate information on population trends. Future studies should also test the utility of automated recorders using colonies of various population sizes (small, moderate, large) and thus soundscapes.

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## ETHICAL NOTE

This project was approved by the Flinders University Ethics Committee (E388-E449) and supported by a scientific permit (Y26040).

## CONFLICT OF INTEREST STATEMENT

None.

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## Data Availability Statement

Data are available on the Flinders University data repository at DOI: 10.25451/flinders.22114628.

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## SUPPORTING INFORMATION

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

**Table S1** Post hoc pairwise comparisons from the ANOVA comparing call count estimates between the 56 volunteers. Statistically significant (< 0.05) values are marked in bold and highlited in blue.

**Appendix S1** Results of the ANOVAs showing that call count was not influenced by volunteer bias.