

# Fledge or fail: Nest monitoring of endangered black-cockatoos using bioacoustics and open-source call recognition

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## Highlights

- Bioacoustic monitoring requires efficient and accessible call recognition methods.
- We examined open-source recognizers for nest monitoring in black-cockatoos.
- Recognizers correctly assigned nest activity in roughly 60% of survey days.
- Fledging was detected by the recognizers.
- Bioacoustics and semi-automated post-processing are useful for nest monitoring.

## Abstract

Ecologists are increasingly using bioacoustics in wildlife monitoring programs. Remote autonomous sound recorders provide new options for collecting data for species and in contexts that were previously difficult. However, post-processing of sound files to extract relevant data remains a significant challenge. Detection algorithms, or call recognizers, can aid automation of species detection but their performance and reliability has been mixed. Further, building recognizers typically requires either costly commercial software or expert programming skills, both of which reduces their accessibility to ecologists responsible for monitoring. In this study we investigated the performance of open-source call recognizers provided by the `monitoR` package in R, a language popular among ecologists. We tested recognizers on sound data collected under natural conditions at nests of two endangered subspecies of black-cockatoo, the Kangaroo Island glossy black-cockatoo *Calyptorhynchus lathami halmaturinus* ( $n = 23$  nests), and the south-eastern red-tailed black-cockatoo *Calyptorhynchus banksii graptogyne* ( $n = 20$  nests). Specifically, we tested the performance of binary point matching recognizers in confirming daily nest activity (active or inactive) and nesting outcome (fledge or fail). We tested recognizers on recordings from nests of known status using  $3 \times 3$ -h recordings per nest, from early, mid and late stages of the recording period. Daily nest activity was correctly assigned in 61.7% of survey days analysed ( $n = 60$  days) for the red-tailed black-cockatoo, and 62.3% of survey days ( $n = 69$  days) for the glossy black-cockatoo. Fledging was successfully detected in all cases. Precision (true positive / true positive + false positive) of individual detections was 70.2% for the south-eastern red-tailed black-cockatoo and 37.1% for the Kangaroo Island glossy black-cockatoo. Manual verification of outputs is still required, but it is not necessary to verify all detections to confirm an active nest (i.e., nest is deemed active

when true positives are identified). We conclude that bioacoustics combined with semi-automated post-processing can be an appropriate tool for nest monitoring in these endangered subspecies.

**Keywords:** Bioacoustics; Monitoring; Call recognizer; Breeding success; Black-cockatoo; *Calyptorhynchus*

## 1. Introduction

Acoustic technologies offer new ways to collect data on wildlife populations and ecosystems (Servick, 2014). Soundscapes and wildlife sounds can now be collected over spatial and temporal scales much greater than those historically possible (Shonfield and Bayne, 2017; Sugai et al., 2019; Towsey et al., 2014). For example, Australia's new, permanent continent-wide Acoustic Observatory (<https://acousticobservatory.org/>) is providing continuous soundscape recordings from 360 listening stations across representative ecoregions (Roe et al., 2021). Advances in recent decades have seen bioacoustic methods used to locate rare and cryptic species (Dema et al., 2018; Schroeder and McRae, 2020; Sebastián-González et al., 2015; Wrege et al., 2017), measure population density and abundance (Marques et al., 2013; Pérez-Granados and Traba, 2021), identify individual animals (Bailey et al., 2021; Ehnes and Foote, 2015), localize individuals (Frommolt and Tauchert, 2014), assess species occupancy (Campos-Cerqueira and Aide, 2016; Chambert et al., 2018; Furnas and Callas, 2015; Law et al., 2021), monitor breeding phenology (Larsen et al., 2021), and monitor invasive species (Brodie et al., 2021). However, bioacoustics faces several 'big data' problems, not the least of which concern processing large volumes of sound files to extract relevant ecological data (Kowarski and Moors-Murphy, 2021; Servick, 2014). These issues currently limit the utility of bioacoustic methods to ecologists and need to be addressed for the methods to be more widely adopted for wildlife monitoring and conservation.

A key issue in bioacoustic studies is detecting and classifying species' calls from sound recordings (Browning et al., 2017; Sugai et al., 2019). Manual processing involves examining spectrograms to detect calls visually and aurally; however, this approach is time-consuming and not typically feasible for anything other than short-term monitoring. For this reason, ecologists have increasingly used automated or semi-automated detection methods via call recognizers, a general term for various tools and algorithms that interrogate sound recordings to detect calls of interest (Sugai et al., 2019). The choice of recognizer and subsequent performance depend on many factors, including the characteristics of the calls to be detected, the presence of other species' calls and environmental noise (Brandes, 2008; Cragg et al., 2015; Crump and Houlahan, 2017; Knight et al., 2017; Priyadarshani et al., 2018; Salamon et al., 2016; Towsey et al., 2012). Recognizers have been used with varying levels of success (Priyadarshani et al., 2018; Sugai et al., 2019) but generally the field of recognizer development still faces difficulties and is not a panacea to bioacoustics' challenges. Reliable, fully-automated methods are rare. More often, semi-automated methods that combine automated recognition and manual verification are used to detect and classify species (Shonfield and Bayne, 2017; Sugai et al., 2019).

Although progress in recent years has been substantial, developing a high-performing call recognizer requires some expertise in programming and machine learning, which often limits accessibility to ecologists and managers responsible for on-ground monitoring (Priyadarshani et al., 2018; Sebastián-González et al., 2015; Sugai et al., 2019). Commercial software partly addresses this issue by providing a more user-friendly interface with which to train algorithms

and process sound files. These recognizers can perform well and improve monitoring. For example, Shonfield et al. (2018) found that Hidden Markov model recognizers built using Song Scope software (Wildlife Acoustics Inc., Maynard, MA, USA) allowed for many more detections to be acquired for three species of owl, *Strix varia*, *Aegolius funereus* and *Bubo virginianus* (c.f. manual listening and traditional field surveys). However, performance is not necessarily high, and results can be inconsistent among different software (Duan et al., 2013; Joshi et al., 2017; Knight et al., 2017; Lemen et al., 2015; Rocha et al., 2015; Russo and Voigt, 2016; Schroeder and McRae, 2020). For commercially-available bat detectors, which are often used by ecological consultants and others involved in monitoring, Russo and Voigt (2016) caution that their use has preceded proper testing and detections should not be accepted without scrutiny. The issue lies partly in that the underlying construction of the algorithms is not easily understood or altered by non-experts. An additional limitation of commercial software is their cost. Acoustic projects can be costly to setup (e.g., equipment) and operate, especially in terms of human hours needed for data analysis and processing (Browning et al., 2017). This may preclude conservation programs which often operate on small budgets from investing in commercial software. Together, these issues of programming skills, recognizer performance and cost may see traditional survey methods favoured over bioacoustics, despite the many benefits of acoustic methods for species monitoring.

In this study we examined the performance of call recognizers implemented in the `monitoR` package in R software (Katz et al., 2016b; R Core Team, 2019), an open-source statistical language popular among ecologists (Lai et al., 2019). Like most commercial options, `monitoR` recognizers are easily constructed from example training calls (templates) and allow the end-user to manipulate various parameters that alter the recognizer's performance. We tested the performance of recognizers in detecting daily nest activity (active or inactive) and nest outcome (fledge or fail) in two endangered subspecies of black-cockatoo endemic to south-eastern Australia. The Kangaroo Island glossy black-cockatoo *Calyptorhynchus lathami halmaturinus* and the south-eastern red-tailed black-cockatoo *Calyptorhynchus banksii graptogyne* comprise small and isolated populations whose recoveries are partly constrained by low reproductive output. While the Kangaroo Island glossy black-cockatoo has had some traditional nest monitoring (Berris et al., 2018), there has been no routine nest monitoring for the south-eastern red-tailed black-cockatoo. Both populations are remote and nesting occurs across large spatial areas, especially in the red-tailed black-cockatoo. As such, both would benefit from more efficient nest monitoring methods that reduce the requirement for in-field human observers.

To address these issues we applied the nest-associated vocalizations of both subspecies (Teixeira et al., 2020) to assess the utility of bioacoustics for nest monitoring. Their vocalizations are loud and distinct and are given at predictable times each day. These traits may make them potentially suited to automated or semi-automated methods of call detection. Using sound data collected under natural conditions at wild nests we aimed to (a) develop an open-source call recognizer using the `monitoR` package in R, and (b) for each nest, test the performance of the recognizer in detecting daily nest activity over the course of the nesting period, and (c) identify nesting outcome.

## **2. Materials and methods**

### **2.1. Sound data collection**

We collected sound data over two breeding seasons from 24 nests of the glossy black-cockatoo on Kangaroo Island in South Australia, and 22 nests of the red-tailed black-cockatoo in the Casterton region of Victoria. Each nest tree was fitted with an autonomous sound recorder (Frontier Labs Bioacoustic Audio Recorder, <https://frontierlabs.com.au/>) for the duration of the nesting period (i.e., until fledging or confirmed failure). If a female cockatoo was incubating an egg or brooding a nestling, we installed the recorder on a nearby tree within 10 m of the nest tree, to minimise disturbance during this sensitive period. A distance of up to 10 m was considered appropriate for the amplitude of most nest-associated vocalizations, most importantly those that are loud and clear in sound recordings (i.e., not in-nest vocalizations) (Teixeira et al., 2020). Although we did not directly measure detection space, we observed clipping in spectrograms from some nests, which indicates that the amplitude of vocalizations was too high for the microphone at short distance. As such, we considered a distance of several metres (<5) to be ideal.

Each sound recorder was programmed to record for three hours per day, concluding at 30 min after sunset (sunset-based schedule), as this is when the birds are most active at nests (DT, pers. obs.). Additionally, one day per week, recording commenced at 30 min before sunrise and concluded at 30 min after sunset (full-day schedule). Technical issues in the first breeding season resulted in some recorders losing their sunset-based schedules, and therefore recorded only during morning schedules. To increase the chances of recording the fledging event, some recorders were updated to record every day at the full-day schedule if a large nestling was observed at the nest hollow entrance during field inspections.

All recordings were made using an omnidirectional microphone, with a fixed gain of 20 dB and a sample rate of 44.1 kHz and a bit depth of 16 bits. Microphones had an 80 Hz high-pass filter to reduce the effects of low frequency noise (e.g., wind and traffic). All recordings were made in uncompressed wave (.wav) format. The major costs associated with the field recording and analysis were the Bioacoustic Audio Recorders (approx. \$1000.00 AUD per unit including microphones and batteries), external hard drives (approx. \$150.00 AUD per 4 TB unit) and Raven Pro 1.6 software (\$100.00 USD per year). Recordings were backed up to the Ecosounds repository ([www.ecosounds.org](http://www.ecosounds.org)) for permanent, cost-free storage.

### **2.2. Recognizer development**

We used binary point matching, implemented using the *monitoR* package in R version 1.0.7, as the recognition algorithm for this study (Hafner and Katz, 2018; Katz et al., 2016b). We chose *monitoR* because it is open source, easily shared among end-users and, once scripted, does not require expert programming skills. These are important considerations for making automation accessible to conservation stakeholders. Binary point matching is a template matching algorithm, that compares reference calls (hereafter ‘templates’) to spectrograms of sound recordings (‘surveys’). The method of binary point matching used in *monitoR* is a variation of that described in Towsey et al. (2012) (Katz et al., 2016b). *MonitoR* also provides spectrogram cross correlation, but in preliminary trials we found this method returned many more false positive detections than binary point matching, and therefore we did not pursue it further. Binary point matching delimits ‘on’ and ‘off’ regions (call and non-call) of the template, which are based on a user-set amplitude cut-off, and ignores all others. Each template

is ‘stepped’ across survey files and each time bin is scored for similarity between surveys and templates as the difference in mean amplitude between on and off regions. A higher score indicates greater similarity between signals in a survey file and a template. For each template *monitoR* allows the user to set a score cut-off (or detection threshold) which is the minimum score that will return a positive detection. As such, score cut-off determines the relative proportions of true and false positives, as well as true and false negatives (Brauer et al., 2016; Katz et al., 2016a; Knight and Bayne, 2019). Projects seeking to locate cryptic species, for instance, will require a lower detection threshold (i.e., greater sensitivity) to detect rare or faint calls, with the likely trade-off of increased false positive detections (i.e., poorer specificity).

The choice of templates and their specified amplitude and score cut-offs is crucial in recognizer development. To quantitatively assess these parameters, we performed a pilot study on a sample of surveys using a range of call templates of varying amplitude and score cut-offs. The results from this pilot study informed final recognizer construction and performance testing (see section 2.3). To select sample calls as templates, we randomly selected three nests at which nestling calls were recorded for each subspecies. For each nest, we selected three adult flight calls, three adult perch calls, three adult female nest calls and three nestling calls as call templates (see Teixeira et al., 2020 for details on call types). Selected calls were not masked by other sounds and they clearly showed the structure of the call. Using a custom function in R, we created three copies of each call template, which differed in their amplitude cut-off. To determine these cut-off values, we first manually viewed each call template in *monitoR* and chose the amplitude cut-off until that appeared to best show the call's structure. The R function used this value as a mid-point, creating two additional copies of the template at  $\pm 2$  dB. As such, for each subspecies, a sample of 108 call templates was used in the pilot study.

Call templates were tested on a balanced sample of presence-absence sound files from every nest monitored, except for one nest of the south-eastern red-tailed black-cockatoo where only absences (true negatives) were recorded. For all other nests, we selected one 5-min sound clip where the birds were present (true positive) and one where the birds were absent (true negative). We ensured that true negative sound clips included other species' calls, as these may be a source of false positive detections. The sample used in the pilot study comprised  $39 \times 5$ -min sound files for the south-eastern red-tailed black-cockatoo and  $46 \times 5$ -min sound files for the Kangaroo Island glossy black-cockatoo.

Pilot sound files (pilot surveys) were processed using the pilot call templates with a low score cut-off of five. Each template was summarised for the number of true positive, false positive and true negative detections returned at score cut-off increments of 0.2 from a minimum of five to a maximum of 25. The minimum cut-off value was arbitrary, but a low value was necessary to quantify the performance at a range of values from higher sensitivity/lower specificity (low cut-off value) through to lower sensitivity/higher specificity (high cut-off value). Preliminary trials showed most true positive detections scored above 15 and, as such, a minimum of five was deemed suitably low. A true positive (TP) detection was taken to be any detection in a sound file where the birds were present, and a false positive (FP) detection was any detection in a file where the birds were absent. True negatives (TN) were the absence of detections in files where the birds were absent. The performance of each template was calculated as  $TP + TN / n$ . From this, we selected the two best-performing templates across all call types, and their optimal score cut-offs, for each subspecies' final recognizer (i.e., two templates per species). For the Kangaroo Island glossy black-cockatoo, six templates performed equally well and two of these were copies of the same original template which differed in their amplitude cut-off value (see above). As such, for this subspecies, we randomly selected two templates to form

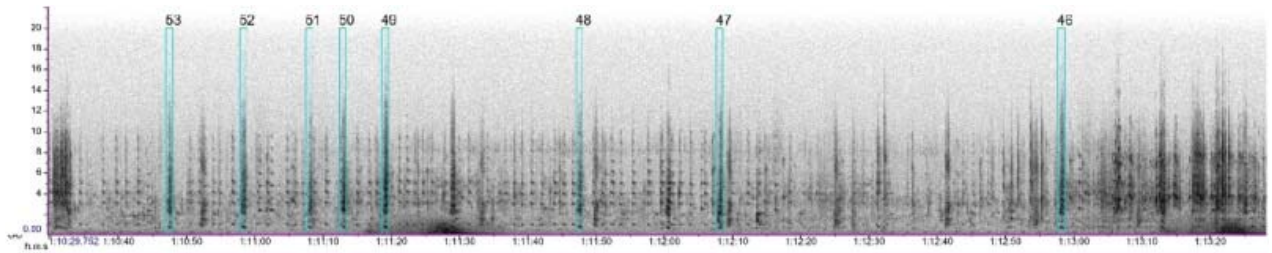
the final recognizer, but ensured these were not copies of the same original template (Table S2). The selected templates were nestling calls from two nests. For the south-eastern red-tailed black-cockatoo, the three best templates were copies of the same original template that differed in their amplitude cut-off value. We selected one of these and the next highest-scoring template, both of which were adult flight calls from two nests, to form the final recognizer (Table S1). The performance of each template at its optimal score cut-off is provided in the Supplementary Material (Table S1 and Table S2). Nests from which final templates were selected were excluded from subsequent recognizer testing (see Section 2.3). One of these nests of the Kangaroo Island glossy black-cockatoo was monitored as trial only and was not intended to be included in the final dataset.

### 2.3. Recognizer performance

A total of 46 nests (excluding trial nests) were monitored in this study ( $n = 24$  for the Kangaroo Island glossy black-cockatoo;  $n = 22$  for the south-eastern red-tailed black-cockatoo). We quantitatively measured the performance of the recognizer on recordings from every nest except those from which the templates were constructed. For most nests, we recorded  $3 \times 3$  h in the late afternoons, finishing at 30 mins after sunset. In some cases, technical problems caused recordings to fail, in which case we used recordings collected earlier in the day (e.g. 3 h commencing 30 min before sunrise). Recordings to be tested were chosen randomly from three defined time periods in each nest's recording schedule: early, mid and late recording stages, which we categorised as time 1, time 2 and time 3. For nests that fledged, we randomly selected one recording before fledging (time 1) and one recording after fledging (time 3), as well as the recording on the day of fledging (time 2). Fledging is vocally indicated in these subspecies (Teixeira et al., 2021) and this knowledge was used to confirm fledging date from sound recordings. In short, fledging is associated with loud calling by all three birds (fledgling and parent birds) and calls decrease rapidly in amplitude as the distance from the sound recorder increases with flight (Teixeira et al., 2021). As the birds do not return to the nest after fledging, no further nest-associated vocalizations are recorded. For nests deemed successful but where the fledging event was not recorded (e.g., batteries lost power before fledging), we randomly chose three recording days from early, mid and late stages to represent times 1, 2 and 3. The same was done for unsuccessful nests, noting that the recording period was often shorter for failed nests because sound recorders were removed if nesting failure was confirmed through in-field inspections. The recording period per nest ranged from 6 to 153 days. For nests that were monitored over several months, the test recordings were often separated by weeks or months. For nests monitored for shorter periods, test recordings were temporally closer (sometimes consecutive days). We did not exclude any recording days due to poor conditions (e.g., rain) as this is an unavoidable factor in bioacoustic monitoring of these subspecies.

Detections were verified using Raven Pro 1.6 (spectrogram parameters: Hann window; window size = 512 samples; hop size = 512 samples; 50% overlap) (K. Lisa Yang Center for Conservation Bioacoustics, 2022, Ithaca, New York). We verified detections at two levels: individual detections and survey day. First, detections were categorised as 'yes' if they were a call of a glossy or red-tailed black-cockatoo (true positive), and 'no' in all other cases (false positive) (Fig. 1). Judgements of true positive detections were informed by in-field observations where possible, but for some nests this information was extracted exclusively from the sound recordings. We did not differentiate call types (e.g., adult flight calls versus nestling calls). However, adult calls from birds other than the nesting pair were flagged as false positives. This was based on in-field observations of nest activity (i.e., we noted if and where other nests were located) and expert judgement by the lead researcher (DT) based on the

amplitude of the calls. Calls were deemed to be false positive detections from other nesting pairs if most calls within a given calling bout were low in amplitude and if there was no indication of those birds flying towards to the nest of interest (progressive increases in call amplitude).



**Fig. 1.** Example spectrogram showing true positive recognizer detections (blue boxes; numbers denote detection number in the sound file) of Kangaroo Island glossy black-cockatoo nestling calls. The soundscape also contains the female begging call (repetitive calling until approx. 1:12:20) and male perch calls (1:11:05, 1:11:51), and non-target species including galah, red wattlebird, and little corella. Airplane noise is also present (approx. 1:11:25 and 1:13:20). Spectrogram created using Raven Pro 1.6 (Cornell Lab of Ornithology; Hann Window; window size = 1024 samples; hop size = 512 samples; 50% overlap).

Precision of individual detections was calculated as  $TP / TP + FP$ . We then categorised each survey day as: (a) Correctly assigned nest activity (true positive: nest active and true positive detections verified; or true negative: nest inactive and no detections returned), (b) Missed nesting activity (false negative: nest active but no true positive detections returned), or (c) Incorrect detection of nesting activity (nest inactive but false positive detections returned).

Finally, for each nest where fledging was recorded ( $n = 6$  for the Kangaroo Island glossy black-cockatoo and  $n = 2$  for the south-eastern red-tailed black-cockatoo; excluding nests from which the templates were constructed), we noted whether the recognizer successfully detected the fledging event. We considered a successful detection to be detections of calls given at the moment of a nestling's take-off or immediately preceding this event (see Teixeira et al., 2021 for a description of fledging vocalizations). Fledging was recorded at seven nests of the glossy black-cockatoo, but one of these was used for template calls and therefore was not tested here. Fledging was recorded at three nests of the red-tailed black-cockatoo and two were tested here. Verifications were summarised using the dplyr package (Wickham et al., 2019) in R statistical language (R Core Team, 2019).

### 3. Results

#### 3.1. Pilot study

The two best-performing templates that formed the recognizer for the south-eastern red-tailed black-cockatoo had performance scores ( $TP + TP / n$ ) of 0.8205 and 0.7945, respectively, at their optimal score cut-offs (Table S1). The worst-performing template at its optimal score cut-off had a performance score of 0.5128. For the Kangaroo Island glossy black-cockatoo, the two best-performing templates that formed the recognizer both had performance scores of 0.8261 and the worst-performing template had a score of 0.6087 (Table S2).

### 3.2. Recognizer performance

At the level of the survey day, nest activity was correctly identified in 61.7% of recording days analysed (nest active and true positive detections verified, or nest inactive and no detections returned) for the south-eastern red-tailed black-cockatoo ( $n = 60$  survey days) (Table 1). Nest activity was missed in 10.0% of recording days (nest active and no detections returned), and in 28.3% of recording days nest activity was incorrectly detected (nest inactive and detections returned). For the Kangaroo Island glossy black-cockatoo ( $n = 69$  survey days), nest activity was correctly assigned in 62.3% of recording days. Nest activity was missed in 21.7% of days, and incorrectly detected in 15.9% of days. The recognizers successfully detected the fledging event in all cases for both subspecies.

**Table 1.** Recognizer performance evaluated at the level of the survey day for the south-eastern red-tailed black-cockatoo (RTBC), *Calyptorhynchus banksii graptogyne*, and the Kangaroo Island glossy black-cockatoo (GBC), *Calyptorhynchus lathami halmaturinus*. (a) Nest activity correctly assigned as active (true positive detections verified) or inactive (no detections returned); (b) Nest active but no true positive detections returned; (c) Nest inactive but false positive detections returned.

	Day-level verification	n days	% days
<b>RTBC</b>	(a) Correctly assigned nest activity (active or inactive)	37	61.7%
	(b) Missed active nesting	6	10.0%
	(c) Incorrectly detected active nesting	17	28.3%
<b>GBC</b>	(a) Correctly assigned nest activity (active or inactive)	43	62.3%
	(b) Missed active nesting	15	21.7%
	(c) Incorrectly detected active nesting	11	15.9%

At the level of individual detections, precision was moderate and many false positives were returned (Table 2). In total, the recognizers returned a total of 1388 detections for the Kangaroo Island glossy black-cockatoo and 1136 detections for the south-eastern red-tailed black-cockatoo. Calls were correctly assigned (i.e., nesting adults or nestlings) in 70.2% of detections for the south-eastern red-tailed black-cockatoo and 39.2% of detections for the Kangaroo Island glossy black-cockatoo. For both subspecies, fledged nests had the greatest precision in all time periods, but false positive detections were returned for every nest type (fledged, failed and unsure) and every time period (Table 2). The relative proportion of true positive detections was generally highest mid-stage in the recording periods (time 2).



**Table 2.** Precision (% TP) of binary point matching call recognizer for detecting nesting calls of the south-eastern red-tailed black-cockatoo (RTBC), *Calyptorhynchus banksii graptogyne*, and the Kangaroo Island glossy black-cockatoo (GBC), *Calyptorhynchus lathami halmaturinus*. Total detections (n total), number of nests for which detections were returned (n nests), and mean number of detections per nest (mean n per nest) are shown. Times 1, 2 and 3 represent early, mid and late stages of the recording periods. Precision = true positives / (true positives + false positives).

		Time 1					Time 2					Time 3				
		n nests	n detections (total)	n nests (detections returned)	n detections (mean/nest)	% TP	n detections (total)	n nests (detections returned)	n detections (mean/nest)	% TP	n detections (total)	n nests (detections returned)	n detections (mean/nest)	% TP		
<b>RTBC</b>	Fledged	4	76	4	19.0	85.5%	295	4	73.8	96.9%	49	3	16.3	49.0%		
	Failed	9	128	8	16.0	68.0%	87	6	14.5	28.7%	70	7	10.0	4.3%		
	Unsure	7	166	6	27.7	68.7%	220	7	31.4	78.2%	45	4	11.3	46.7%		
	Total	20	370	18	20.6	71.9%	602	17	35.4	80.2%	164	14	11.7	29.3%		
<b>GBC</b>	Fledged	11	355	7	50.7	41.4%	419	11	38.1	55.6%	216	7	30.9	19.4%		
	Failed	9	45	5	9.0	35.6%	14	6	2.3	35.7%	56	6	9.3	8.9%		
	Unsure	3	95	3	31.7	1.1%	136	3	45.3	34.6%	52	2	26.0	36.5%		
	Total	23	495	15	33.0	33.1%	569	20	28.5	50.1%	324	15	21.6	20.4%		

#### 4. Discussion

In this study we examined the utility of open-source call recognizers in a bioacoustic nest monitoring program for two endangered subspecies of black-cockatoo. We aimed to test the utility of a bioacoustic program, including post-processing of the acoustic data with *monitoR*, in a regime appropriate for a monitoring program of these subspecies. Specifically, for each nest, we tested the call recognizer on three recording days representing early, mid and late stages of the recording period (named time 1, time 2 and time 3). In practice, this approach would help to, in the first instance, confirm nest activity (nesting active or inactive) across the duration of the recording period, which can be up to four months if recorders are deployed soon after egg laying. This information can then inform additional recording days to be interrogated, if any. This is more efficient than using the call recognizer on all survey days. With this approach, we were able to determine daily nest activity with a moderate level of success. At the level of the survey day, recognizer performance was similar for both subspecies. Nest activity was correctly assigned in 61.7% of recording days for the red-tailed black-cockatoo and 62.3% of recording days for the glossy black-cockatoo. Most errors were incorrect detections of nest activity, where the nest was inactive but false positive detections were returned. As such, manual verification is required, and the recognizers' outputs should not be accepted without inspection. This concurs with many previous studies that show semi-automated methods to be most reliable (Sugai et al., 2019).

For these subspecies, a direct measure of nest success is the presence of vocal behaviors that characterize the fledging event (Teixeira et al., 2021). Where a fledging event was recorded ( $n = 6$  nests for the glossy black-cockatoo;  $n = 2$  nests for the red-tailed black-cockatoo), the recognizer successfully detected fledging in all cases. This direct measure of fledging greatly improves our ability to measure breeding success, since monitoring fledging has not been viable with human observers; breeding success is estimated from in-field observations at nests (e.g., large nestlings are assumed to fledge) for the glossy black-cockatoo, or post-breeding flocks for the red-tailed black-cockatoo (Berris et al., 2018; Russell et al., 2018). One benefit of bioacoustics over traditional methods is that it allows for more direct measures of some behaviors that are otherwise difficult to record (Teixeira et al., 2019). For example, vocalizations can indicate copulation in elephants (Payne, 2003; Poole, 2011), the birth of a calf in killer whales (Weiß et al., 2006), mother-pup reunions in Weddell seals (Collins et al., 2011) and foraging in sperm whales (McDonald et al., 2017). For glossy and red-tailed black-cockatoos, there are at least six behavioral contexts vocally indicated at nests (Teixeira et al., 2020). Some changes in calling behavior and nestling call structure can be seen through nestling development (Teixeira et al., 2021). For cockatoos and other species with a wide vocal repertoire, this vocal complexity offers a range of data that can be collected in bioacoustic monitoring programs. Fledging vocalizations are among the most useful signals for bioacoustic monitoring as it relates to breeding. For conservation, understanding how nest outcome varies by spatial location and resource availability can help prioritize management actions that seek to maximise reproductive success.

Most studies investigating recognizer performance have done so at the level of the individual call or detection, albeit inconsistently (Knight et al., 2017). For comparison, we also quantified performance at this level by manually verifying all detections returned. Relative to the survey day, recognizer performance was good for the red-tailed black-cockatoo but moderate for the glossy black-cockatoo when considering each detection individually. Of the 1388 detections returned by the recognizer for the glossy black-cockatoo, only 39.2% were correct. For the red-tailed black-cockatoo, 70.2% of 1136 recognizer detections were correct. False positives (i.e.,

lower precision) are often generated by calls of other species (Cragg et al., 2015). The better precision for the south-eastern red-tailed black-cockatoo reflects the unusually quiet environment in which this subspecies nests. All nests occurred as paddock trees, and most were isolated from other nest trees and vegetation by hundreds of metres. Common sources of biological noise were livestock, little ravens *Corvus mellori*, yellow-tailed black-cockatoos *Calyptrorhynchus funereus*, and sulphur-crested cockatoos *Cacatua galerita* (a common source of false positives), but the soundscape was quiet relative to more natural habitats. As such, calls from the nesting birds were usually the loudest vocalizations which would have improved precision. On Kangaroo Island, glossy black-cockatoo nests occur in close proximity to other nests and vegetation, and the soundscape can be very noisy. The recognizer did incorrectly detect vocalizations from other glossy black-cockatoos, but the major source of false positive detections, albeit unquantified, appeared to be galahs *Eolophus roseicapilla*, which were very common at the study sites. Poor precision can greatly increase the burden of post-processing if every call requires verification, such as in studies seeking to detect rare or cryptic species (Dema et al., 2018; Frommolt and Tauchert, 2014; Schroeder and McRae, 2020) or to obtain population metrics from call rate (Borker et al., 2014). While this does not apply to nest monitoring in black-cockatoos, which operates at the level of the survey day, improving precision would reduce the number of days at which nests are incorrectly deemed to be active. This would improve the method overall and options to achieve this should continue to be investigated.

Our findings align with many studies that have tested call recognizers under natural conditions; recognition can be helpful, but it is not yet a perfect solution (Sugai et al., 2019). Difficulties arise from extraneous source of noise and vocalizations of sympatric species, as well as the varying quality of the vocalizations for the species of interest (e.g., with distance from the sound recorder) (Cragg et al., 2015; Heinicke et al., 2015; Sebastián-González et al., 2015; Zwart et al., 2014). More sophisticated methods may improve performance but, even if they exist, they are often not easily available to the people responsible for on-ground monitoring. Currently, options for ecologists are more limited unless they collaborate with computer scientists. Nonetheless, ecologists using call recognizers, whether commercial or open-source, should carefully consider the choice of algorithm and its construction, particularly the quality of training data used.

Recognizer construction should ideally be an adaptive process whereby training data are tested and refined to improve performance. In our case, we chose call templates following a large pilot study of 108 candidate calls (per subspecies), which were tested on verified sound clips where the target species were present or absent. We included both adult and nestling calls in our pilot study. Since nestling calls are most indicative of active nesting (Teixeira et al., 2020), we expected these to be included in the final recognizers. While this was true for the Kangaroo Island glossy black-cockatoo, pilot testing for the south-eastern red-tailed black-cockatoo showed that templates of adult flight calls were better at confirming nesting activity. This result, in addition to large variations in performance between templates (Tables S1 and S2), highlights the importance of rigorously testing template calls, as well as construction parameters (e.g. here, score cut-off and amplitude cut-off) prior to recognizer construction, whenever possible. Lastly, in addition to recognizer performance, the design of a bioacoustic program, including its recording schedule, is critically important. While bioacoustics is appealing in its ability to collect more data than other methods, appropriately reducing recording times (e.g., targeting optimal times of day) can lessen the burden of post-processing (Law et al., 2015; Wimmer et al., 2013). For species such as black-cockatoos that typically

only provision their nestlings mid-morning and late afternoon to early evening (Higgins, 1999), this is an important consideration.

## 5. Conclusion

Black-cockatoo nesting is well suited to monitoring using bioacoustic methods. The birds vocalize loudly, at predictable times each day, and have call repertoires that indicate various nesting behaviors (Teixeira et al., 2020). In this study, we used simple open-source call recognizers, in combination with manual verification, to detect daily nest activity and nest outcome (fledging or failure) at 43 known nests of the Kangaroo Island glossy black-cockatoo and the south-eastern red-tailed black-cockatoo. We conclude that the non-intrusive approach suggested in this study can be an appropriate tool for ecologists to monitor nest outcomes in these endangered subspecies.

Despite many false positive detections, acoustic visualization software (such as Raven Pro 1.6 used here) makes detection verification a relatively streamlined process. As bioacoustic technology continues to advance and become more affordable, it is foreseeable that large numbers of sound recorders could be deployed at both known and potential nests. Indeed, by providing reliable daily data on nesting from more nests than could reasonably be monitored by human observers, the ability to scale-up monitoring would likely offset the effort of verifying detections. The method could also be applied to other less-studied populations of glossy black-cockatoo and red-tailed black-cockatoo. This would allow, for the first time, a comprehensive understanding of nest use across large spatial areas for these species. Lastly, this work demonstrates the utility of a different approach to call recognizer testing, whereby the species' behaviors and research questions directly inform the level at which performance is measured. Applying this approach to other species and issues will allow for more practical discussions of bioacoustics' utility to wildlife monitoring.

## Ethics

This work was conducted under animal ethics approval number SBS/076/17/VIC and SBS/DEWNR/219/17 issued by The University of Queensland Animal Ethics Committee.

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## CRedit authorship contribution statement

**Daniella Teixeira:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Simon Linke:** Formal analysis, Writing – review & editing. **Richard Hill:** Conceptualization, Data curation, Writing – review & editing. **Martine Maron:** Conceptualization, Supervision, Writing – review & editing. **Berndt J. van Rensburg:** Conceptualization, Project administration, Supervision, Funding acquisition, Writing – review & editing.

## Declaration of Competing Interest

The authors 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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## Appendix A. Supplementary data

Results of pilot study for the south-eastern red-tailed black-cockatoo, *Calyptorhynchus banksii graptogyne* and the Kangaroo Island glossy black-cockatoo, *Calyptorhynchus lathami halmaturinus*. The performance of each template at its optimal score cut-off is shown. Performance was calculated as  $TP + TN / n$  where TP is the number of true positive survey files, TN is the number of true negative survey files and n is the total number of survey files tested. Template names state the associated amplitude cut-off (prefix), the call type, and the unique ID (suffix) of the nest from which the call was recorded. Templates with an asterisk (\*) are those that were selected to form the final recognizer.

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