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An evaluation of acoustic field recorders paired with automated call recognition as a monitoring tool for the Mallee Emu-wren *Stipiturus mallee*

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Abstract. Advances in technology are changing the way that ecological monitoring is carried out, especially for those species with ecological characteristics that have traditionally made monitoring difficult. Autonomous acoustic recorders coupled with automated signal detection software is one such approach where technological advances are delivering rapid improvements in the passive monitoring of vocal fauna. Here we characterise the three common call types of the endangered Mallee Emu-wren *Stipiturus mallee* and present a signal detection template, or call recogniser, for the species. We evaluate the performance of this tool against an independent dataset of field recordings containing Mallee Emu-wren vocalisations. The recogniser performed well with mean precision and recall metrics ranging between 0.55–0.97 and 0.70–0.95, respectively, depending on user parameters. This tool is widely applicable in the ongoing conservation of the Mallee Emu-wren, particularly as a low-cost method for post-release monitoring following a future Mallee Emu-wren translocation.

Introduction

The Mallee Emu-wren *Stipiturus mallee* is a small, endangered passerine (*Environment Protection and Biodiversity Conservation Act 1999*; IUCN Red List of Threatened Species; Verdon *et al*. 2021a), specialised to live in habitat dominated by hummock grass *Triodia scariosa* (Brown *et al.* 2009; Verdon *et al.* 2020). Because Mallee Emu-wrens are shy, secretive and often occur at low density at the landscape scale, detection in the field may be challenging and is best achieved by listening for vocalisations (Higgins *et al.* 2001). Clearance of native vegetation, primarily in the early 20th century, has restricted the species to a fragmented network of large reserves, between 48,000 and 633,000 ha in size, located in the Murray Mallee region of north-western Victoria (Brown *et al.* 2009). Fire and drought are a natural part of the Australian landscape. However, change in land use since European settlement and a changing climate have led to longer droughts, and larger and more intense wildfires (Connell *et al.* 2017). By 2018, whole-reserve-scale wildfires had led to the local extinction of Mallee Emu-wrens from six of nine reserves previously occupied by the species, including all South Australian populations (Boulton & Lau 2015). In an attempt to mitigate these threats, a Mallee Emu-wren translocation from Murray–Sunset National Park, Hattah–Kulkyne National Park and Nowingi State Forest in Victoria to Ngarkat Conservation Park in South Australia was implemented in 2018 (Mitchell *et al.* 2021). This translocation provided an opportunity to assess autonomous acoustic recording units and automated acoustic detection software as a passive, long-term monitoring tool following translocation.

To demonstrate the long-term persistence of translocated populations, conservation managers require a detailed understanding of the dynamics of those populations. A failure to detect individuals when they are present (i.e. a false negative) can lead to considerable bias in population estimates (Tyre *et al.* 2003; Buckland *et al.* 2012). This problem is exacerbated when target species are cryptic and occur at low densities, as might be expected for the Mallee Emu-wren at a release site following translocation. Dynamic occupancy modelling is a method to estimate population size that explicitly accounts for bias associated with false negative survey error (MacKenzie *et al.* 2018). This method allows probability of detection, probability of occurrence, and other vital rates to be estimated by recording the presence or absence of a target species during repeated visits to survey sites (MacKenzie *et al.* 2018). Increasing the number of visits to each sampling site, whilst resulting in a demonstrated increase in accuracy of estimates of population parameters (MacKenzie *et al.* 2018), increases both the time and the resources that are necessary to carry out such surveys, which are already expensive and labour-intensive. Automating aspects of the data-collection process may increase efficiency, without sacrificing precision.

One method showing promise for vocal fauna, including songbirds, is autonomous acoustic recording units (ARU: Knight *et al.* 2017; Shonfield & Bayne 2017). Recordings that either contain or do not contain vocalisations of target species can be used to populate dynamic occupancy models (Campos-Cerqueira *et al.* 2016; Metcalf *et al.* 2019). An added advantage of this technique is that it is passive and minimises bias associated with observer avoidance or observer skill (Shonfield & Bayne 2017). Although initial investment in equipment may be greater than that of a typical observer-based survey, the cost of continued surveys becomes cheaper per unit effort, the longer that monitoring continues. Data-driven conservation management of threatened populations relies on monitoring that encompasses the natural variation that populations exhibit over time. However, such monitoring is not always implemented. A review by Taylor *et al.* (2017) concluded that translocation studies rarely incorporate long-term persistence into success criteria. Several factors have likely contributed to this trend (e.g. the cost of monitoring, funding cycles, periods of employment in

research positions, or difficulty in obtaining funding for monitoring in comparison with more active conservation initiatives). However, reducing the commitment to extended field times and the realisation of cost savings that can be achieved with automated data collection will enhance management capacity to maintain long-term monitoring post-translocation.

The use of ARUs has been demonstrated to reduce field labour by up to 97% (Digby *et al.* 2013). However, field recordings require a substantial investment in time for data processing to identify calls of targeted species (Shonfield & Bayne 2017). This process may be streamlined with the use of automated signal recognition software, hereafter referred to as 'recognisers' (e.g. de Oliveira *et al.* 2015; Katz *et al.* 2016; Priyadarshani *et al.* 2018; Marsland *et al.* 2019; Prince *et al.* 2019). Several methods exist but typically a user will 'train' the software to recognise the spectrogram signature of targeted species' vocalisations. The software then analyses field recordings using a moving window approach and any potential matches are given a similarity score (for the software used in this study, that score will fall between 0 and 1: Knight *et al.* 2017). Any similarity score that exceeds a threshold that has already been determined by the user is highlighted as a detection by the software. A detailed summary and comprehensive evaluation of popular recogniser software is presented in a review by Knight *et al.* (2017).

Here we characterise three common vocalisations of the Mallee Emu-wren and report on development and performance of an automated call recogniser for the species using spectrogram cross correlation with the *R* package *monitoR* (Katz *et al.* 2016).

Study area and method

Recogniser development

Mallee Emu-wren vocalisations are poorly described, though are generally considered to include three primary vocalisations: a short buzzing alarm call, a contact call comprising one to three high-pitched staccato notes, and a complex song (Higgins *et al.* 2001; Menkhorst *et al.* 2017). The first step in developing a Mallee Emu-wren call recogniser was to clearly define each of these vocalisations and assess their suitability as templates for a recogniser (Table 1). We produced spectrograms of each call using the *R* package *seewave* (Sueur *et al.* 2008) and visually assessed calls for two characteristics—intra-species consistency and inter-species uniqueness (Figures 1–2)—that would be favourable in automated call recognition. Of the three common vocalisations, we then identified the contact call as the best candidate for automated recognition. We chose 14 individual Mallee Emu-wren contact calls, each comprising two or three syllables as the basis for our recogniser (Table 1). We began with six three-syllable contact calls and then added an additional three two-syllable contact calls. We conducted unstructured tests of this preliminary recogniser and ultimately added an additional five vocalisations that the preliminary recogniser failed to detect. These calls were representative of the subtle variation that is typically found in Mallee Emu-wren calls, including intensity, pitch, ambient noise and recording quality.

To develop a recogniser for detection of Mallee Emu-wren calls in field recordings we used the package *monitoR* in the statistical environment *R* (Hafner & Katz 2018; R Core Team 2020). *MonitoR* includes two methods for signal detection: spectrogram cross-correlation and binary point matching (Katz *et al.* 2016). We used spectrogram cross-correlation using automatic point selection following Katz *et al.* (2016). We provide the resultant recogniser and additional code allowing batch-processing of field survey files as an annotated *R* script with associated *.wav* files as supplementary material (10.6084/m9.figshare.16915957). Our recogniser comprises 14 individual call templates, each consisting of a complete, two- or three-syllable Mallee Emu-wren contact call. *MonitoR* searches field recordings for matches with each call template individually and then provides a list of every detection associated with each template. We used a sample rate of 44,100 Hz as more than half of the files used to create this recogniser were provided at this frequency. Those recorded at different (higher) frequencies were resampled to 44,100 Hz using the function 'changeSampRate' in the *monitoR* package. To ensure that audio information is not lost, it is recommended that recording frequency be set to twice the maximum frequency of the targeted signal (i.e. the Nyquist frequency: Knight *et al.* 2017). Mallee Emu-wren calls typically fall in the range between 5000 and 12,000 Hz. To maximise recording time of ARUs per unit of memory without sacrificing quality, a sample rate of ~24,000 Hz may be used for future field recordings of Mallee Emu-wren calls.

Table 1. Recordings used as templates for the development of a Mallee Emu-wren call recogniser. *Translocated birds were originally sourced from Hattah–Kulkyne and Murray–Sunset National Parks. CP = Conservation Park, NP = National Park.

Contact call templates	*Location*	*Date*	*Author*	*Notes*
1–7	*Ngarkat CP	03/05/2018	William Mitchell	Free-roaming translocated Mallee Emu-wrens in Ngarkat CP
8–11, 13, 14	*Ngarkat CP	20/04/2018	Luke Ireland	Mallee Emu-wrens calling from within transport boxes before release
12	Hattah–Kulkyne NP	17/01/2016	Andrew Spencer	Call sourced from Xeno-Canto (2020) https://www.xeno-canto.org/312210 (accessed 1 October 2020)

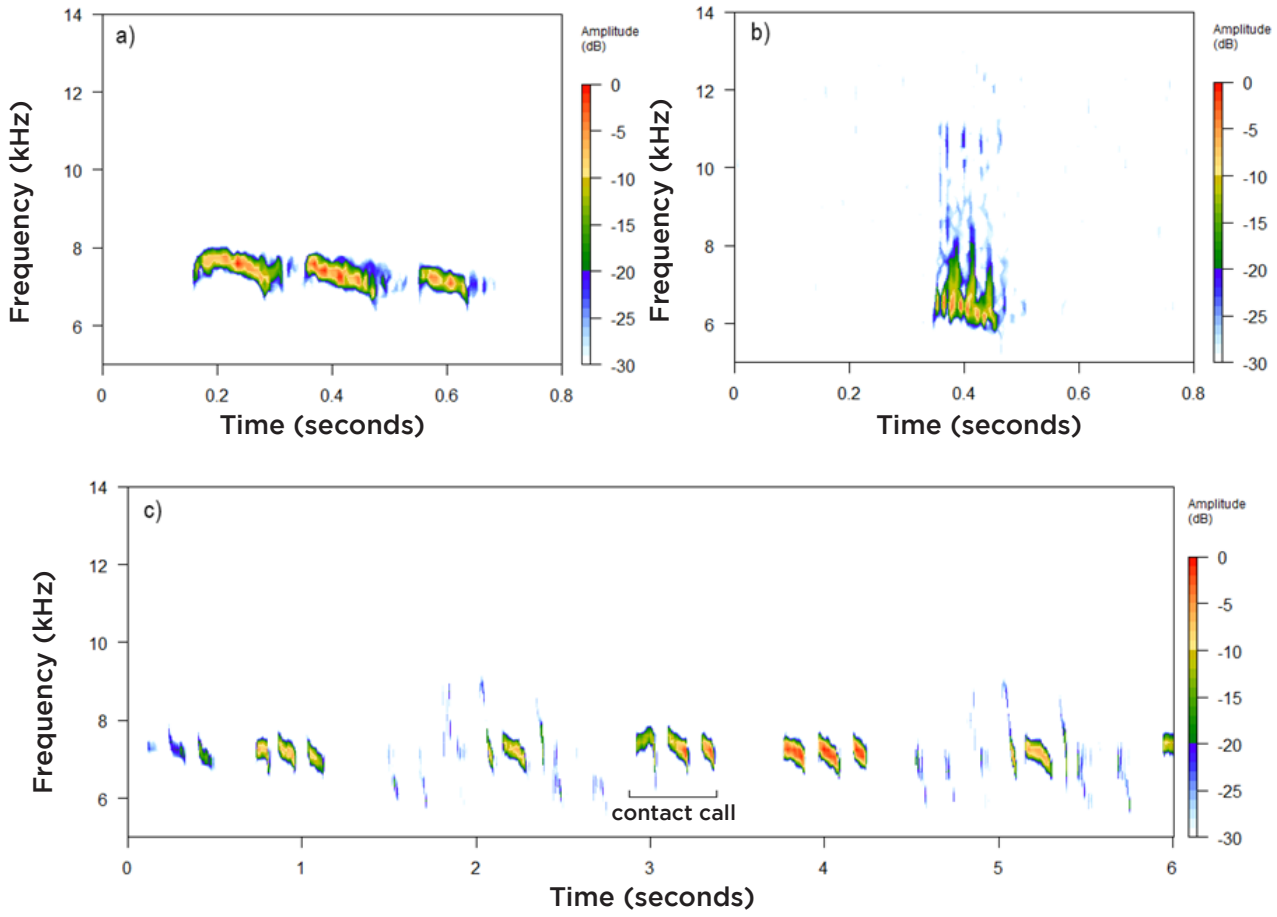

Figure 1. Primary vocalisations of the Mallee Emu-wren: (a) typical contact call, (b) alarm call and (c) song incorporating the typical contact call. All vocalisations were recorded by WFM in Nowingi State Forest, Victoria, in November 2020, using an AudioMoth autonomous acoustic recorder (Hill *et al*. 2019).

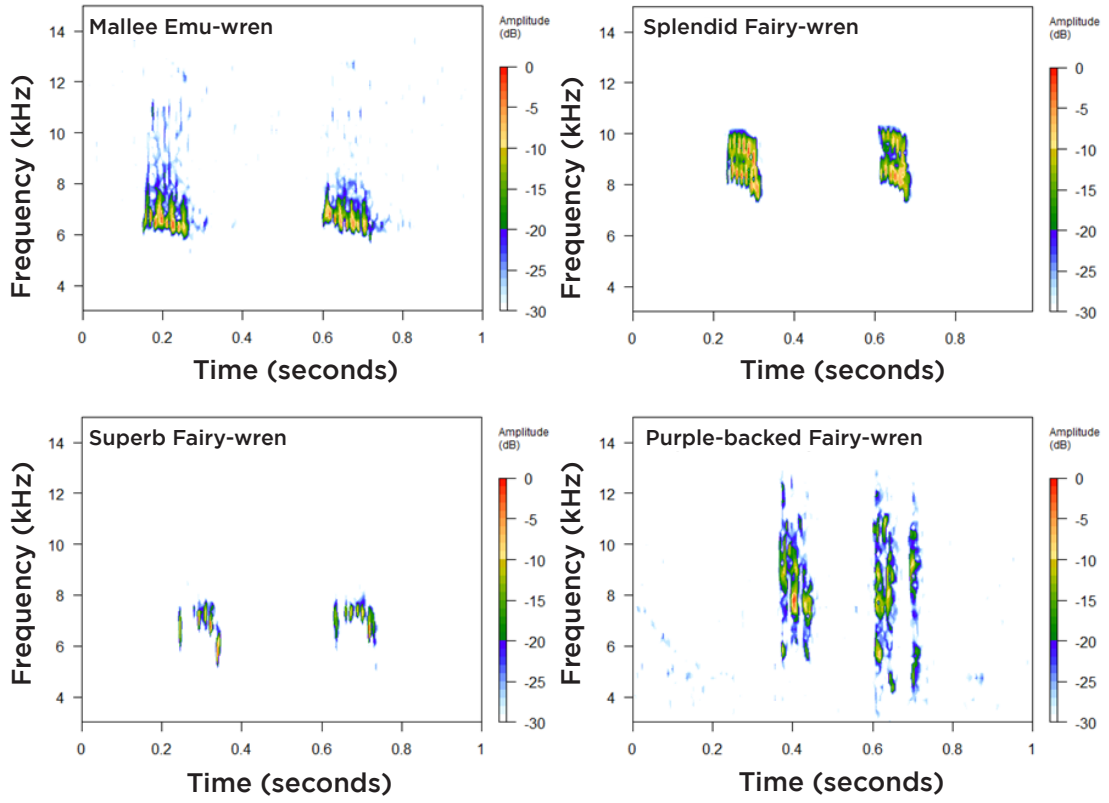

Figure 2. A series of spectrogram images displaying the alarm calls of the Mallee Emu-wren *Stipiturus mallee*, Splendid Fairy-wren *Malurus splendens*, Superb Fairy-wren *M. cyaneus* and Purple-backed Fairy-wren *M. assimils*. Mallee Emu-wren calls were recorded by WFM in Nowingi State Forest, Victoria, in November 2020. All fairy-wren calls were obtained from Xeno-Canto (2020) (accessed 17 August 2021)—Splendid Fairy-wren: https://www.xeno-canto.org/372259, Superb Fairy-wren: https://www.xeno-canto.org/370623 and Purple-backed Fairy-wren: https://www.xeno-canto.org/165132.

Recogniser performance

The effectiveness of acoustic recognisers must be manually evaluated against a test dataset that is independent of any recordings used to build the recogniser (Knight *et al.* 2017). As a performance benchmark, we used 25 15-second audio recordings, each including 1–13 (mean = 6.7) known Mallee Emu-wren vocalisations. This test dataset contained 169 individual Mallee Emu-wren vocalisations that ranged in intensity from soft to loud. Vocalisations were manually verified by visual inspection of spectrograms and human listening. Recordings also included environmental noise and the calls of non-target species. Test audio was recorded in Nowingi State Forest, and Hattah–Kulkyne and Murray–Sunset National Parks in 2020 and 2021 by WFM. Mallee Emu-wren recordings were verified by direct observation of the calling bird at the time of recording.

We used the recogniser described above to search for Mallee Emu-wren recordings within the test audio files. To investigate the effect of similarity threshold on recogniser performance we repeated this process with threshold values of 0.15, 0.20, 0.25 and 0.30. Similarity threshold is a user-determined value that controls the sensitivity of the recogniser (Knight *et al.* 2017). Potential signal matches within an audio spectrogram are given a similarity score between 0 and 1. Any scores below the threshold value are dismissed, but signals with a similarity score above the threshold are retained as detections. For each test file at each threshold, we calculated three performance metrics advocated by Knight *et al.* (2017): (1) recall, the proportion of existing Mallee Emu-wren vocalisations in each field recording of the test dataset (verified manually) that were detected by the recogniser; (2) precision, the proportion of all detections that were true positives; and (3) *F*-score, a metric that combines precision and recall to aid users in identifying optimum threshold values based on the user's priorities (Knight *et al.* 2017). We calculated mean precision and mean recall across all field recordings in the test dataset at each threshold value and present the results as a box-and-whisker plot (Figure 3).

Recall is calculated as $$\frac{\text{true positives}}{\text{true positives + false negatives}}$$

precision as $$\frac{\text{true positives}}{\text{true positives + false positives}}$$

and *F*-score as $$\frac{(\beta^2 + 1) * \text{precision} * \text{recall}}{\beta^2 * \text{precision} + \text{recall}}$$

where β is a metric, defined by the user, that allows prioritisation of either precision or recall (Knight *et al.* 2017). Values of β>1 prioritise recall, <1 prioritise precision and when β=1 neither precision nor recall is favoured (Knight *et al.* 2017). We calculated *F*-scores with β set to 0.5 (precision twice as important as recall), 1 (precision and recall equally important) and 2 (precision half as important as recall) to compare optimum threshold choice under a range of priorities.

Results

The Mallee Emu-wren contact call is a good candidate for automated signal recognition for several reasons: few other species that share the same habitat have calls that overlap in frequency because of its high pitch (~6.5–7.5 KHz); it is simple and consistent; and because it is frequently incorporated into Mallee Emu-wren song, it makes up a high proportion of all Mallee Emu-wren vocalisations (Figure 1). Despite this call being described as thin, high-pitched and insect-like (Higgins *et al.* 2001), its spectrogram structure is distinct from that of insects (longer pulses and distinct frequency, Montealegre-Z & Mason 2005). By contrast, the alarm call is a poor candidate for recogniser development as it has many similarities with the alarm calls of other Maluridae species that overlap in range and habitat use with that of the Mallee Emu-wren (in particular Splendid Fairy-wren *Malurus splendens* and Striated Grasswren *Amytornis striatus*; fairy-wren and emu-wren calls are presented in Figures 1–2). Such similarities would increase the likelihood of false positive detections.

Table 2. *F*-scores for different threshold values and β values. *F*-score is a performance metric for automated signal detection that allows the user to prioritise precision and/or recall. β is a metric, defined by the user, that allows prioritisation of either precision or recall. Values of β >1 prioritise recall, β <1 prioritise precision, and when β = 1 neither precision nor recall is favoured (Knight *et al*. 2017).

Threshold	*F-score, β = 0.5*	*F-score, β = 1*	*F-score, β = 2*
0.15	0.601	0.696	0.829
0.2	0.756	0.790	0.827
0.25	0.876	0.831	0.790
0.3	0.897	0.811	0.739

The recogniser that we developed successfully identified Mallee Emu-wren vocalisations in the test dataset of field recordings (Table 2, Figure 3). Similarity threshold influenced both precision and recall performance, with lower threshold values associated with higher recall and lower precision, whereas higher threshold values led to lower recall and higher precision (Figure 3). When recall was prioritised, the optimum recogniser similarity threshold was 0.15; when precision was prioritised, it was 0.3; and when recall and precision were considered of equal priority, it was 0.25 (Table 2).

Discussion

We characterised the three common call types of the Mallee Emu-wren and successfully developed an acoustic recogniser utilising the contact call of the species. Our recogniser performed well on the test dataset in terms of both precision (0.55–0.97) and recall (0.70–0.95), indicating that passive acoustic recording represents a feasible monitoring tool for this species. Acoustic monitoring has the potential to reduce expense in any future translocation of this species by considerably reducing field labour requirements, and it may facilitate long-term passive monitoring of key populations within the current distribution (Mitchell *et al.* 2021).

Context is important when evaluating recogniser performance (Knight *et al.* 2017; Leseberg *et al.* 2020). Performance metrics should be considered reliable only under the environmental conditions in which they were

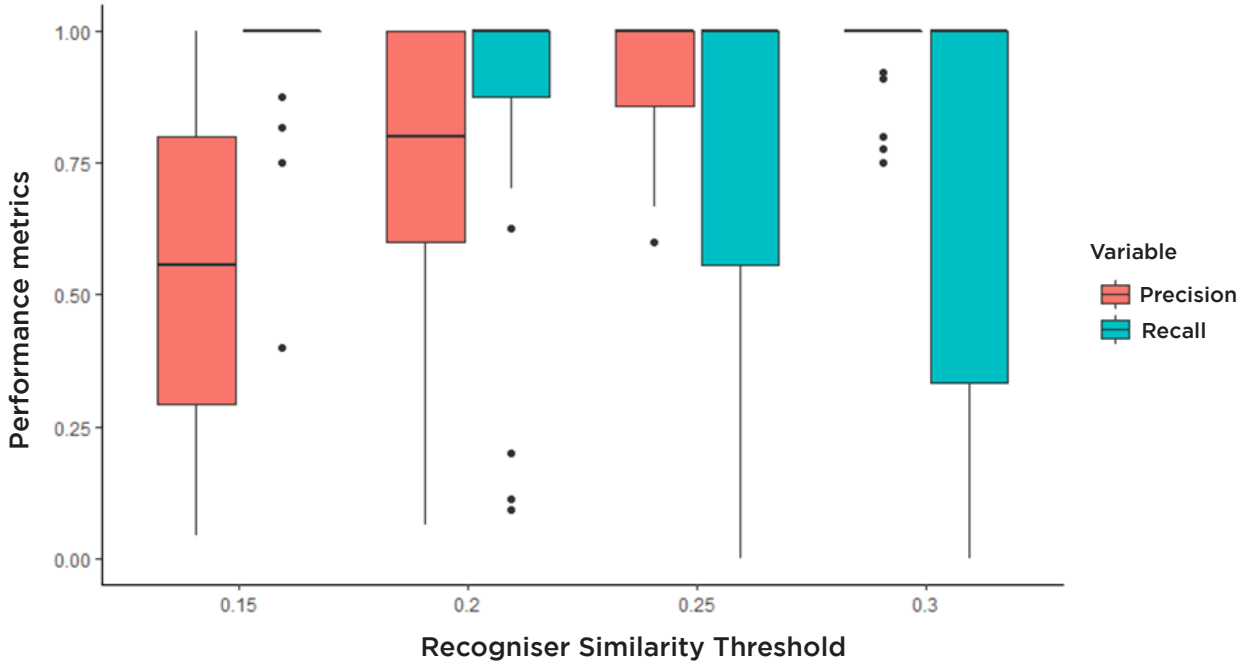

Figure 3. Performance metrics for an automated Mallee Emu-wren call recogniser, which was tested against a dataset of 25 independent 15-second field recordings containing vocalisations of Mallee Emu-wrens. Each detection made by the recogniser was manually verified to assess whether it was a true or false positive detection. Precision refers to the proportion of detections that were true positives. Recall refers to the proportion of vocalisations present in the recording (verified manually from spectrogram images) that were detected by the recogniser.

tested (Knight *et al.* 2017). Many bird species may exhibit regional variation in vocalisations (e.g. Valderrama *et al.* 2013; Goretskaia *et al.* 2018), potentially leading to reduced performance. Similarly, the potential for false positive detections may vary as a response to the soundscape in which ARUs are deployed (Knight *et al.* 2017). The contextual information associated with field recordings may also provide an opportunity for improved performance. A recent study by Leseberg *et al.* (2020) could increase recogniser precision and recall by modelling the influence of contextual and intrinsic variables on the likelihood that each detection was either a true or false positive. Although performance metrics described in the present study are informative, potential users should consider them as a guide only and make context-specific evaluations of recogniser performance in line with their research goals.

Research goals must be carefully considered when choosing recogniser parameters (Shonfield & Bayne 2017). A high call similarity threshold will lead to high precision and low recall, whereas a low threshold will have the opposite effect. Precision is paramount when there is limited time available for manual verification of detections (Knight *et al.* 2017). False negatives as a result of emphasis on precision may be accounted for using statistical approaches such as dynamic occupancy modelling (Metcalf *et al.* 2019). When trying to detect sparsely distributed species of conservation concern, where a single detection has high value, low threshold values should be considered.

Many of the locations highlighted as potential release sites for future Mallee Emu-wren translocations have environmental characteristics that favour passive acoustic monitoring. Mallee Emu-wrens have a strong association with hummock grass (Verdon *et al.* 2020). Most extant Mallee Emu-wren populations in north-western Victoria inhabit '*Triodia* mallee' vegetation characterised by relatively large areas of mallee eucalypt trees with partial ground-cover of hummock grass. Home range size in this vegetation type has been estimated at ~5 ha (Brown 2011). To adequately cover such an area, multiple ARUs would be required. By comparison, potential translocation release sites, including parts of Ngarkat Conservation Park in South Australia, are composed of 'mallee heath' vegetation: mostly treeless shrubland with dense pockets of hummock grass forming at drainage points, such as at the base of dunes (Mitchell *et al.* 2021). Mallee Emu-wrens move throughout this matrix of vegetation, but home ranges are typically anchored to those pockets of dense hummock grass. In this system, ARUs would have the greatest likelihood of capturing vocalisations of this species if placed within these pockets of hummock grass. For this reason, a single ARU may effectively cover a single home range. With this ARU placement, researchers may expect a territorial group of Mallee Emu-wrens to spend a high proportion of time in the audible vicinity of an ARU. Thus, recogniser parameters that prioritise precision over recall would allow efficient monitoring of changing occupancy at release sites following translocation.

Autonomous acoustic recorders provide a low-cost and efficient tool for the long-term monitoring of any translocated Mallee Emu-wren population. Acoustic monitoring may also be applied to conservation management of translocation source populations. The 2018 translocation program was not successful in establishing a viable population in Ngarkat Conservation Park (see Mitchell *et al.* 2021). Nevertheless, this program framed primarily around trialling and optimising translocation methods generated considerable new knowledge that will inform a future larger-scale translocation (Hunt *et al*. 2019; Mitchell *et al.* 2021). Mallee Emu-wren populations experience fluctuations in size in response to prevailing climatic conditions (Connell 2019). In the context of harvesting of Mallee Emu-wrens

for the purpose of future translocations, impact on source populations has been predicted to be lowest during periods of population growth associated with favourable climatic conditions (Verdon *et al.* 2021b). It is critical that conservation benefits from translocating birds are not outweighed by the negative impacts of harvesting for translocation (Mitchell *et al.* 2022). ARUs may be deployed to monitor Mallee Emu-wren occupancy at proposed translocation source sites, providing quantitative evidence that occupancy is increasing before any harvesting event. For such an approach to be efficient, recogniser parameters must prioritise precision over recall.

The acoustic recogniser presented here (https://doi.org/10.6084/m9.figshare.16915957.v1) has potential to be applied widely in conservation management of the endangered Mallee Emu-wren. ARUs in tandem with automated signal detection have surged in popularity over the last decade (Towsey *et al.* 2012; Shonfield & Bayne 2017; Priyadarshani *et al.* 2018) and as this field develops it is likely that cost and efficiency will further improve.

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