

An assessment of two types of sound recording device for avian field surveys in the monsoonal tropics

Sarah Fischer¹, Andrew C. Edwards¹, Timothy G. Whiteside², and Patrice Weber¹

¹College of Engineering, IT and Environment, Research Institute for the Environment and Livelihoods, Charles Darwin University, Darwin NT 0909. Corresponding author email: sarah.fischer@cdu.edu.au

²Environmental Research Institute of the Supervising Scientist, Darwin NT 0820

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High ambient temperatures and humidity for at least half the year in the Darwin, Northern Territory area of Australia make field surveying by established observational techniques onerous. Therefore, to explore possible aural detection and identification of birds during field surveys, the performance of two high-quality, low-cost sound recorders, the AudioMoth and Zoom H1n Handy (H1n) (with associated analytical software), was compared for (a) ground-based, point-count surveys, and (b) aerial surveys conducted with a remotely piloted aircraft (RPA). The performance of the audio-recorders in the point-count trials was also compared with that of a human observer. A set of pre-recorded, standardised vocalisations of seven bird species that occur naturally in the area was broadcast from a speaker to test for detectability and identification. In the point-count trials, the human observer was superior to both audio-recorders in detecting the broadcast signals but not in species recognition, and the AudioMoth facilitated better species recognition than the H1n recorder. In RPA trials, vertical distance from the speaker negatively affected detectability of vocalisations when the RPA was hovering in a stationary position. When the RPA was in flight, the H1n recordings facilitated detection of all broadcast vocalisations, whereas fewer than 50% of them could be detected from the AudioMoth's recordings due to its greater sensitivity to RPA noise. We concluded that in this environment the AudioMoth would be more effective for ground-based, stationary, point-count surveys and the H1n for RPA-assisted, mobile, aerial surveys.

Key words: sound-recording device; point-count survey; remotely piloted aircraft; bird vocalisation detectability; species recognition.

INTRODUCTION

Conventional methods of estimating species occurrence or relative abundance in bird communities usually involve either a) line-transect surveys, in which an observer moves along a pre-determined transect line and notes species' occurrence, or b) point-counts, in which the observer remains at a fixed location and records birds by sound and/or sight (Bibby *et al.* 2000; Buckland *et al.* 2000). Despite extensive analysis and standardisation of these two methods, they remain prone to both observer and habitat biases (Campbell and Francis 2011; Bird *et al.* 2014; Wilson *et al.* 2017), can be labour intensive, and can involve the challenges for surveyors in the tropics of high temperatures and humidity and seasonal flooding (Nalwanga *et al.* 2012).

Technology has revolutionised the way in which bird communities can potentially be assessed nowadays. Motion-sensor and/or thermal imaging camera traps are now often used to detect cryptic or nocturnal bird species (O'Brien and Kinnaird 2008; Benshemesh *et al.* 2014; Christiansen *et al.* 2014; Suwanrat *et al.* 2015), cellular sensor arrays and Light Detection and Ranging (LiDAR) techniques have been used to study migratory and nocturnal species (Brydegaard *et al.* 2010; Anthony *et al.* 2012), and DNA identification can be made from feather or faecal samples (Horváth *et al.* 2005; Jordan 2005; Joo and Park 2012).

The emergence of remotely piloted aircraft (RPA) as an observational platform has allowed researchers to access difficult and/or hazardous areas and approach target species that may be shy or potentially dangerous (Chabot and Bird 2015). A major advantage of using an RPA is the ability to cover a larger area than ground surveys permit in much less time. Additionally, there is a variety of sensors that can be mounted on RPAs to obtain high-resolution data, including standard digital still cameras, video cameras, GPS devices, VHF tracking devices and remote sensing equipment (Linchant *et al.* 2015). Furthermore, most RPAs are readily portable and able to collect up-to-the minute data in a repeatable manner (Anderson and Gaston 2013; Chabot and Bird 2015).

Sound recordings and soundscape ecology are potentially valuable in assessing avian communities in urban and peri-urban landscapes (Fukasawa *et al.* 2017; Ross *et al.* 2018; Alquezar *et al.* 2020). The simplest set-up requires only a microphone and a recording device, but the quality of recording depends on the type of microphone used (Brandes 2008; Farina *et al.* 2014). Commercial recorders designed specifically for recording wildlife are available but may cost several thousand dollars, and their high sensitivity level may make them inappropriate for use with noisy, movable surveying platforms such as RPAs. For citizen scientists, community groups and professional researchers with limited budgets, any reasonable quality, relatively low cost, digital sound recorder may be suitable for assessing bird communities through their vocal signals.

Whilst there has been a recent increase in avian studies utilising autonomous recording devices (Borker *et al.* 2014; Yip *et al.* 2017b; Pérez-Granados *et al.* 2019), there have been few published investigations that combined RPAs with sound recording devices. Significant work has been undertaken combining recording systems and balloon technology (Prevost 2016; Hockman 2018), but to date Wilson *et al.* (2017) is the only peer-reviewed study to be published that has used an RPA with sound recording equipment. To assess the suitability of using bioacoustic recording devices in avian surveys, our study compared standard point-count aural observations by a human observer with data gathered by two types of audio-recorder. Further, to determine whether RPA-mounted recording devices could be of assistance in avian surveys, we investigated bioacoustic detection using a recorder suspended from a hovering and, later, moving RPA (a DJI Phantom 2 quadcopter).

Wilson *et al.* (2017), using a sound recorder attached to a hovering RPA 50m above the sound source, showed that the number of species detected per point was generally comparable to that recorded in standard point-counts by a human observer; however, species recognition was slightly lower in the RPA counts. It was surmised that this was due to the noise of the RPA masking some low-frequency bird vocalisations. Broset (2017) assessed two different sound recording devices used with RPAs under controlled conditions. However, this research tested the devices independently on two different taxa (i.e. one device was used to detect recorded bird song, the other to detect ultrasonic signals made by bats) rather than comparing their performance on the same sounds. Both the above studies were undertaken in the northern hemisphere (Wilson *et al.* 2017 in North America; Broset 2017 in Belgium); there are no similar published studies for the southern hemisphere. Differing habitats, vegetation structure, climate and levels of human habitation are all known to affect bird vocalisation and sound transmission and attenuation (Nemeth and Brumm 2010; Nemeth *et al.* 2013; Darras *et al.* 2016; Yip *et al.* 2017a). It would therefore be unwise to assume that the results of the current study would necessarily replicate those from the northern hemisphere; replication is needed in various habitats and environments to assess the general potential of RPA-mounted recording devices to facilitate avian surveys.

This paper documents results from preliminary field trials undertaken for a study documenting the current bird assemblages of the region containing the city of Darwin, Northern Territory, Australia. The objective of the trials was to ascertain which of two types of cost-effective recording devices, differing in microphone sensitivity, would be most appropriate for use in the project. The recorders' performance in detecting and 'recognising' broadcast standardised bird vocalisations was compared to establish their likely utility in the field for 1) stationary point-count surveys, and 2) line-transect surveys conducted in conjunction with an RPA (DJI Phantom 4 Pro quadcopter). In the point-count trials, the recorders' performance was also compared with that of a ground-based, human observer. Although our study compared the performance of two particular audio-recorders, we believe that it has broader applicability because it is important to know in designing aural bird surveys to what extent using different devices can influence the quality of the surveying achieved.

We predicted for broadcast bird species' vocalisations that:

1. Due to the ability to listen numerous times to recordings, correct *identification* of species would be greater using recording devices than relying on human observation.
2. Human *detection* of broadcast bird vocalisations would be superior to that of recording devices owing to limitations in recorder sensitivity.
3. Use of an RPA would have a significant negative effect on *detectability* by both recording devices because of the noise generated by the drone.

METHODS

Study Area

Darwin (12.4634°S, 130.8456°E) is located on the tropical north coast of Australia and has a human population of approximately 140,000 (Australian Bureau of Statistics 2016). The climate is monsoon-affected, with distinct annual dry and wet seasons. Mean annual rainfall is approximately 1700mm, with more than 90% of the precipitation occurring in the wet season (November to April). Mean minimum and maximum ambient temperatures range from 19.3°C to 25.3°C and 30.6°C to 33.3°C, respectively (Bureau of Meteorology 2020). The urban/peri-urban environment of the city provides resources for birds that are not available elsewhere in the region in the dry season. The avian assemblage is unique, certainly in a national context but probably globally, as no feral bird species have become permanently established (Northern Territory Government 2018).

Recording devices

The vocalisations of birds overlap the range of human hearing of 20 – 20,000 Hz, with many in the 1,000 – 8,000 Hz frequency range (Greenewalt 1968; Nowicki and Marler 1988; Baptista and Trail 1992). Traditional microphone and speaker set-ups are perfectly suitable for recording and analysing avian sounds; however, in this project the weight and the portability of the recording devices were limiting factors. As well as using the devices in a free-standing capacity for point-count surveys, they were attached to an RPA, making weight a consideration. Although there is no official maximum payload capacity for the Phantom 4 Pro used in this study, anecdotal evidence suggests that more than 500g would cause detrimental strain on the device (Drones Etc 2017; Dronethusiast 2020). Therefore, with price and weight guidance from the literature in mind, the devices chosen were:

1. Zoom H1n Handy recorder

Both Wilson *et al.* (2017) and Broset (2017) used the earlier iteration of this recorder (the H1). The recorder is lightweight (82g including batteries), uses high quality X/Y stereo microphones within a protective enclosure, and is compact (50 × 137.5 × 32mm) and robust. It is relatively inexpensive (\$A200) for a good quality digital recorder.

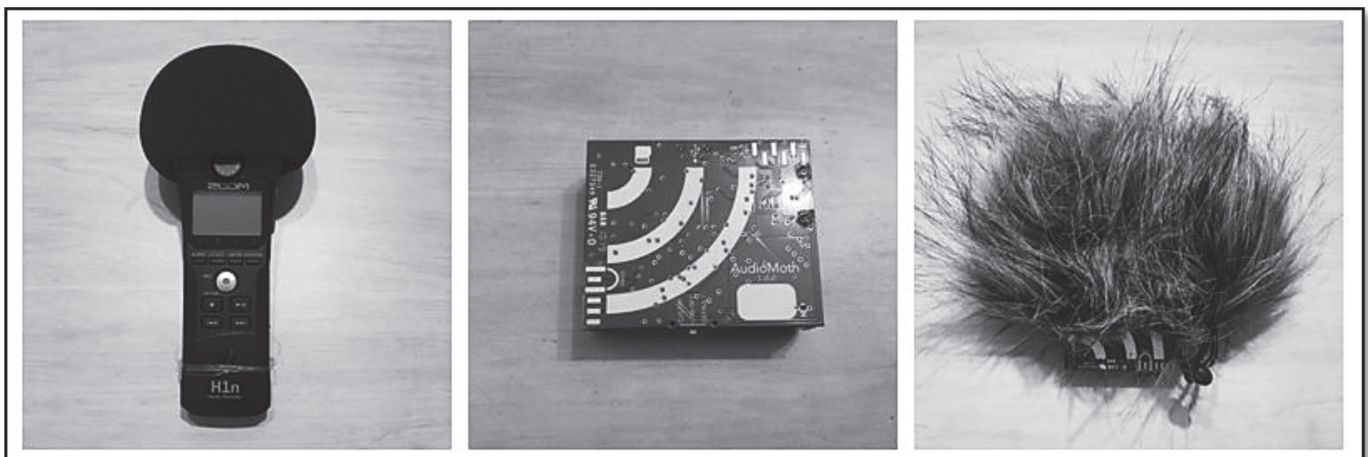
2. AudioMoth

Designed by the UK-based research organisation Open Acoustic Devices, AudioMoth is a compact, open-source recorder that was launched in 2017 (Hill *et al.* 2018). Based

Table 1

Habitat and calls of species whose vocalisations were broadcast in detectability and recognition trials.

Species	Preferred habitat	Call
Orange-footed Scrubfowl <i>Megapodius reinwardt</i>	Mangrove and monsoon forests; often in suburban gardens	Calls during day and night; noisy, deep ‘chuckles’ and ‘screams’
Whistling Kite <i>Haliastur sphenurus</i>	Variety of habitats, often seen over open woodland or wetlands; generally near water	Clear, loud, descending whistling call, followed by sharp, short, ‘upward’ notes
Peaceful Dove <i>Geopelia striata</i>	Natural habitat is open forest and lightly-timbered woodlands; common resident of suburban gardens	Far-carrying, staccato call; lilting ‘coo-wi-ook’
Bar-shouldered Dove <i>Geopelia humeralis</i>	Common in monsoon vineforests, tropical savanna woodland, also in mangroves; often breeds in suburban gardens	Loud, double-noted call, first part high, strong and clear, second part lower and diminishing
Pheasant Coucal <i>Centropus phasianinus</i>	Prefers dense groundcover and tall grass, but often seen along roadside verges and edges of mangrove habitats	Resonant deep, descending ‘oop-ooop-ooop’
Brown Honeyeater <i>Lichmera indistincta</i>	Woodlands and mangroves; common in suburban gardens	Loud, clear and melodious
Australasian Figbird <i>Sphecotheres vielloti</i>	Mangroves and <i>Eucalyptus</i> woodlands; also tropical gardens and orchards	Loud, rising and falling, musical notes

**Figure 1.** Recording devices with windscreens fitted for RPA trials (left: H1n; right: AudioMoth without and with windscreen).

on an EFM32 Gecko processor (Silicon Labs 2019) and a microelectromechanical systems (MEMS) microphone, it is a small (58 × 48 × 15mm) and lightweight (80g, including batteries) device that can detect sound well into the ultrasonic acoustic range. The AudioMoth we purchased cost less than \$A200.

Bird vocalisations used for field trials

To achieve consistency within and among field trials in the vocalisations to be detected and identified, recordings of seven species of birds common in the Darwin region were used (Australian Broadcasting Corporation and ABC Radio, Australia 2011; Morcombe and Stewart 2013). The species were selected to encompass a variety of avian families, habitat types occupied and diets (Table 1). Given the RPA battery life, each recording was cut to 30 seconds in duration. The maximum flight time for the Phantom 4 Pro battery is approximately 30 minutes; however, ambient temperature, altitude, wind conditions and take-off weight all affect flight times (DJI 2017). Limiting each broadcast bird vocalisation recording to 30 seconds allowed for trial repetition when required.

The recordings were broadcast via Bluetooth technology through a wireless speaker (BlueAnt X1, 14W peak, maximum volume level 100dB). The peak sound pressure level (SPL) of each bird vocalisation recording was measured using the NIOSH sound level meter application for iOS devices, version 1.2.1.39, developed by The National Institute for Occupational Safety and Health (EA LAB 2016). The format of sound files was Windows Media Audio (.wma) and the sample rate was 44,100Hz. One-way analysis of variance revealed no significant difference in peak SPL among recordings ($F_{6,14} = 2.39, P = 0.08$).

Point-count trials

To determine the maximum distance for vocalisation detection, ground trials were undertaken with two observers and the recorders placed at 10, 20, 40, 80 and 100m from the stationary speaker. To test the recorders in ‘real world’ conditions, trials were conducted out of doors during the dry season at the East Arm Rail Terminal (12.473546°S, 130.903854°E)

during weekends when there was little to no traffic. Trials were conducted between 14:00 and 16:00 hrs to cause the least impact on local bird communities (birds were absent or quiet, due to the heat of the day) and when wind speed was $< 2.8 \text{ m}\cdot\text{sec}^{-1}$ ($10 \text{ km}\cdot\text{hr}^{-1}$). However, each recorder was equipped with a windscreen to minimise wind interference (Fig. 1).

Recordings were played in a random sequence three times for each distance from the speaker, with Observer 1 standing at the measured distance from the speaker with the recorder and Observer 2 positioned at the speaker, noting the sequence of species' vocalisations broadcast. The speaker was mounted 1m from the ground and positioned facing upwards to minimise directional bias. For each distance of the recorder from the speaker, the species' identity and the sound level (rated as: 3=clearly audible, 2=audible, 1=just audible, or 0=inaudible) of broadcast signals were reported by Observer 1 and later assessed from listening to the recording. This allowed the detection and recognition of the broadcast signal at various distances from the speaker to be compared between the two recorders and between the recorders and Observer 1. Levels of detectability were also examined by grouping results into 'detected' or 'not-detected'. Observations rated '2' and '3' were considered 'detected' (clear enough for the species to be identified) and '0' and '1' not-detected (after Wilson *et al.* (2017) who maintained that at a rating of '1, just audible' the signal would not be easily identified if not already known).

Trials with recorders attached to an RPA

Wilson *et al.* (2017) and Broset (2017) undertook field trials using an RPA with an attached recorder hovering at altitudes of 20, 40 and 60m (recorder height); however, as the vegetation of the Darwin region rarely exceeds a height of 20m, it was more sensible in this study to trial altitudes of 5, 10 and 20m recorder height. Both the above studies determined that the best distance for the recorders below the RPA was 8m, so we decided against testing different distances and suspended each recording device below the RPA on an 8m length of 9.1kg 'Fireline' fishing line (NB. this meant that the altitude of the hovering RPA itself was 13, 18 and 28m, respectively).

RPA trials were conducted between 09:00 and 11:00 hrs during the dry season at a sports oval attached to the Charles Darwin University Palmerston campus ($12.475245^{\circ}\text{S}$, $130.976138^{\circ}\text{E}$). To minimise wind noise and its effect on the stability of the RPA, flying was restricted to wind speeds less than $2.8 \text{ m}\cdot\text{sec}^{-1}$ ($10 \text{ km}\cdot\text{hr}^{-1}$). Each recording device was fitted with a windscreen and the flight speed of the RPA was kept at or below $1.5 \text{ m}\cdot\text{sec}^{-1}$ ($5.4 \text{ km}\cdot\text{hr}^{-1}$). As in the point-count trials, the speaker was set up 1m from the ground with the device pointing upwards; however, the bird vocalisation sequence was played in the same order for all tests.

Three sets of trials were undertaken using the RPA:

1. Hovering directly above the speaker at different altitudes and recording the bird vocalisations broadcast. This trial investigated detectability of the broadcast signal as a function of vertical distance from the speaker.
2. Flying the RPA along a 50m transect line to determine a baseline level of sound caused by the RPA that is detected

by each of the recorders when the RPA is moving in flight. This trial determined whether the RPA motor noise would be unacceptably loud when attempting to detect broadcast bird vocalisations.

3. Flying the RPA along a set path around the speaker to investigate the detection and audibility of bird vocalisations while the RPA was moving in flight. A diamond-shaped flight pattern was flown 18m above ground level (recorders at 10m) 25m away from the speaker with the RPA flight speed at or below $1.5 \text{ m}\cdot\text{sec}^{-1}$. The RPA was flown around the circuit for three repeat captures of the broadcast sound file by each recorder.

Resultant audio files were listened to a minimum of three times using the open-source software Audacity 2.1.3 (<https://www.audacityteam.org/>). Similarly to Wilson *et al.* (2017), we applied a high-pass filter of 575Hz and 6dB attenuation in Audacity to reduce the sound of the RPA.

Data analysis

All results were analysed using the R Stats Package in R version 3.6.1 (R Core Team 2019). Comparisons between the performance of Observer 1 and recording devices were analysed with paired *t*-tests, and analysis of general detectability was undertaken using chi-square tests of association and linear regression. Fisher's exact test was used to investigate the difference in overall signal detectability between devices attached to the RPA. Alpha in all tests was 0.05. Data analysed with parametric tests appeared to be normally distributed and were not transformed. We acknowledge that using multiple *t*-tests may inflate type 1 error rates.

RESULTS

Point-count trials

1. Species identification

There was no difference in the number of bird vocalisations correctly identified by the human observer and from the recordings of either of the two recording devices (observer \times H1n $t_{14} = 0.381$, $P = 0.709$; observer \times AudioMoth $t_{14} = -1.333$, $P = 0.204$). However, when comparing the recognition performance of the two recording devices, the AudioMoth was superior ($t_{14} = -2.358$, $P = 0.033$) (Table 2). On average, playback of audio files from the AudioMoth yielded more correct species identifications than achieved by either the human observer or the H1n. As expected, distance from the speaker and the total (observer and devices combined) number of correct species identifications were negatively correlated ($r^2_3 = 0.93$, $P = 0.008$).

2. Detectability

The difference in detection ability between Observer 1 and each of the recording devices was significant (observer \times H1n $t_{14} = 4.380$, $P = 0.001$; observer \times AudioMoth $t_{14} = 4.090$, $P = 0.001$), with the observer detecting a greater number of bird vocalisations at all distances except 10m, where the AudioMoth performed equally well (Fig. 2).

Table 2

Proportion of broadcast bird species' vocalisations *identified* by a human observer and from recordings by the two audio-recorders at various horizontal distances from the speaker.

Species	Distance from speaker (m)	Proportion identified		
		Human	H1n	Audio-Moth
Peaceful Dove	100	0.00	0.33	0.33
	80	0.33	0.33	0.67
	40	0.33	0.33	1.00
	20	1.00	1.00	1.00
	10	1.00	0.67	1.00
Pheasant Coucal	100	1.00	1.00	1.00
	80	0.00	1.00	1.00
	40	1.00	1.00	1.00
	20	1.00	1.00	1.00
	10	1.00	1.00	1.00
Brown Honeyeater	100	0.67	0.33	0.67
	80	0.00	0.00	0.00
	40	1.00	0.67	0.67
	20	1.00	1.00	1.00
	10	1.00	0.67	1.00
Bar-shouldered Dove	100	0.00	0.00	1.00
	80	0.00	0.67	0.67
	40	0.33	1.00	1.00
	20	1.00	1.00	1.00
	10	1.00	0.67	1.00
Orange-footed Scrubfowl	100	0.00	0.00	0.00
	80	0.00	0.00	0.00
	40	1.00	0.33	0.67
	20	1.00	1.00	1.00
	10	1.00	1.00	1.00
Whistling Kite	100	0.33	0.00	0.00
	80	0.00	0.00	0.00
	40	1.00	0.67	1.00
	20	1.00	1.00	1.00
	10	1.00	1.00	1.00
Australasian Figbird	100	0.33	0.00	0.00
	80	0.00	0.00	0.00
	40	1.00	0.33	1.00
	20	1.00	1.00	0.67
	10	1.00	1.00	1.00

As with species identification, distance from the speaker was negatively correlated with detectability of the signals ($\chi^2_2 = 159.159$, $P < 0.001$); proximity to the speaker enhanced detection for both recording devices and the human observer (Fig. 2). When using the AudioMoth, the species with the highest detection rates were the Peaceful Dove, *Geopelia striata*, Pheasant Coucal, *Centropus phasianinus* and Bar-shouldered Dove, *Geopelia humeralis*; these all had a detectability of 100% at 40, 20 and 10m. When using the H1n, only the Pheasant Coucal vocalisations had this overall level of detectability, with the next most detected species being the Bar-shouldered Dove (33% detectability at 40m and 100% at 20 and 10m). Table 3 shows the detection rates of each species' vocalisations by both recorders at the various distances tested.

Table 3

Proportion of broadcast bird vocalisations *detected* by each recording device at varying horizontal distances from the speaker. Maximum detection distance determined by regression analysis.

Species	Distance from speaker (m)	Proportion detected		Maximum detection distance (m)	
		H1n	Audio-Moth	H1n	Audio-Moth
Peaceful Dove	100	0.00	0.00	43.02	26.86
	80	0.00	0.00		
	40	0.33	1.00		
	20	1.00	1.00		
	10	0.67	1.00		
Pheasant Coucal	100	0.00	0.00	26.86	26.86
	80	0.00	0.00		
	40	1.00	1.00		
	20	1.00	1.00		
	10	1.00	1.00		
Brown Honeyeater	100	0.00	0.00	43.02	33.30
	80	0.00	0.00		
	40	0.33	0.67		
	20	1.00	1.00		
	10	0.67	1.00		
Bar-shouldered Dove	100	0.00	0.00	39.36	26.86
	80	0.00	0.00		
	40	0.33	1.00		
	20	1.00	1.00		
	10	1.00	1.00		
Orange-footed Scrubfowl	100	0.00	0.00	44.75	44.75
	80	0.00	0.00		
	40	0.00	0.00		
	20	1.00	1.00		
	10	1.00	1.00		
Whistling Kite	100	0.00	0.00	44.75	39.36
	80	0.00	0.00		
	40	0.00	0.33		
	20	1.00	1.00		
	10	1.00	1.00		
Australasian Figbird	100	0.00	0.00	56.41	43.71
	80	0.00	0.00		
	40	0.00	0.33		
	20	0.33	0.67		
	10	1.00	1.00		

RPA-assisted trials

1. Trial 1 – RPA hovering at various altitudes

The altitude tests showed, as did the point-count trials for the horizontal plane, that distance from the speaker negatively affected detectability of the broadcast bird vocalisations ($\chi^2_4 = 135.710$, $P < 0.001$), signals of all species being detected 100% of the time by both recorders only at an altitude of 5m (Fig. 3). As with the point-count trials, the Pheasant Coucal and Bar-shouldered Dove vocalisations were most readily detected; the H1n detected their vocalisations at all trialled altitudes, whereas the AudioMoth only detected the Pheasant Coucal signal at 10 and 5m altitudes, with all other species' vocal signals only being detected at 5m (see Table 4).

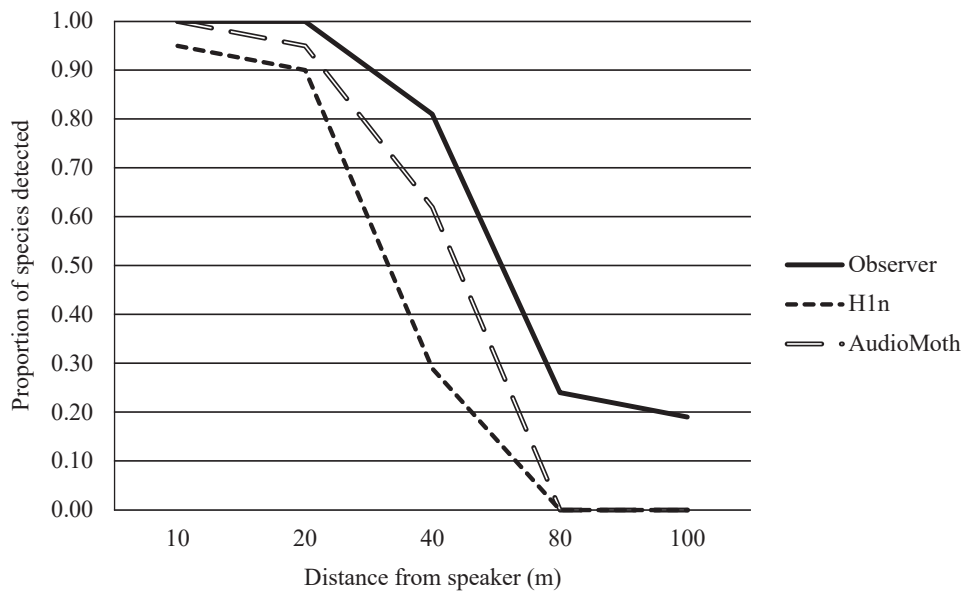


Figure 2. Proportion of species detected at various horizontal distances from the speaker in point-count trials.

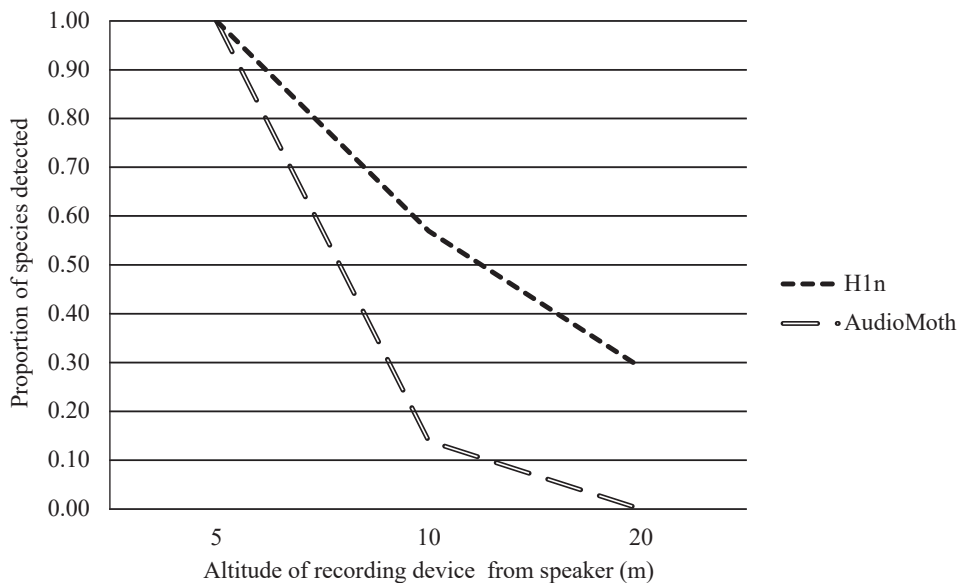


Figure 3. Proportion of species detected at varying altitudes from the speaker when using the RPA in Trial 1.

2. Trials 2 and 3 – RPA in flight

Trial 2 found that the difference in the mean level of noise generated by the flying RPA detected by the two recorders was less than 1dB (AudioMoth RMS 24.17dB; H1n stereo RMS 25.15dB); the baseline sound levels measured were considered to be within acceptable limits (Safe Work Australia 2020). Trial 3 indicated that all bird species’ vocalisations were detected by the H1n, whereas fewer than half were detected by the AudioMoth due to sound interference from the RPA, even though this was less than 1dB louder than that detected by the H1n. This difference in detectability of the broadcast vocalisations was significant (Fisher’s exact test $P = 0.00005$).

DISCUSSION

As noted in several studies comparing autonomous sound recording with direct observer surveys of bird communities, observer accuracy will obviously be affected by the level of observer expertise and both methods can be somewhat habitat dependent (Venier *et al.* 2012; Leach *et al.* 2016; Kułaga and Budka 2019). More research is required examining the efficacy of autonomous recording for assessing avian communities in many different habitat types. Our study provides further evidence that these autonomous technologies are valuable in bird surveying and describes the accuracy of two such devices compared with that of an *in situ* observer in point-

Table 4

Proportion of broadcast bird vocalisations detected by each trialled recording device suspended at varying altitudes below an RPA. Maximum detection distance determined as in Table 3.

Species	Recorder altitude (m)	Proportion detected		Maximum detection distance (m)	
		H1n	Audio-Moth	H1n	Audio-Moth
Peaceful Dove	20	0.00	0.00	16.38	11.62
	10	1.00	0.00		
	5	1.00	1.00		
Pheasant Coucal	20	1.00	0.00	20.00	16.38
	10	1.00	1.00		
	5	1.00	1.00		
Brown Honeyeater	20	0.00	0.00	16.38	11.62
	10	1.00	0.00		
	5	1.00	1.00		
Bar-shouldered Dove	20	1.00	0.00	20.00	11.62
	10	1.00	0.00		
	5	1.00	1.00		
Orange-footed Scrubfowl	20	0.00	0.00	11.62	11.62
	10	0.00	0.00		
	5	1.00	1.00		
Whistling Kite	20	0.00	0.00	11.62	11.62
	10	0.00	0.00		
	5	1.00	1.00		
Australasian Figbird	20	0.00	0.00	11.62	11.62
	10	0.00	0.00		
	5	1.00	1.00		

count surveying. In addition to the economic and feasibility benefits of autonomous recording, a specific advantage is that the recordings can be further analysed by a greater range and number of experts and archived for data quality control and further future assessment.

Prediction 1:

Our first prediction, that in ground-based point-count trials correct *identification* of broadcast species' vocalisations would be better when using recording devices (and associated analytical software) than when employing human *in situ* observation, was incorrect. The devices permitted species identification that was as accurate as that of the human observer. However, AudioMoth recording playback analysis resulted in 10% better species identification than H1n playback and was perceived to be more sensitive overall.

Prediction 2:

Our second prediction, that in point-count trials human *detection* of the broadcast signals would be superior to that of either of the recording devices, was upheld. The observer detected a significantly greater number of broadcast vocalisations at all distances from the speaker except the shortest one. These findings are comparable with those of Yip *et al.* (2017b). A

possible explanation for this finding is the phenomenon of auditory selective attention i.e. the ability of humans to focus attention on a specific sound source and block out extraneous noise in their surroundings (Woldorff *et al.* 1993; Pugh *et al.* 1996; Koch *et al.* 2011). Indeed, when listening to the playback of audio files recorded by the devices, we noted that there was considerable background sound (wild bird song, traffic noise, sound created by other animals etc.) that had not been noticed by the observer when conducting the trials. This was also apparent when reviewing recordings from the RPA trials.

Prediction 3:

Our third prediction, that use of an RPA would have a significant negative effect on *detection* of the broadcast signals by both recording devices because of the noise generated by the drone, was partly supported. The baseline RPA noise measured in Trial 2 had an average volume below that of 'normal conversation' (Safe Work Australia 2020) but was noticeable when listening to recordings. However, despite the sound of the RPA, many of the broadcast signals were captured and could be heard clearly. The H1n recorder performed much better than the AudioMoth in this respect. This can be explained by the fact that the AudioMoth has a MEMS microphone. Although such microphones work on the same principles as the condenser microphones in the H1n, they are considered to have higher levels of sensitivity, and consequently the AudioMoth can detect sound frequencies ranging from audible to ultrasonic (Open Acoustic Devices 2017; Hill *et al.* 2018). This can be considered advantageous for point-count surveying, but we concluded that the slightly lower sensitivity of the H1n recorder's condenser microphones, combined with the device's omnidirectional, downward pointing stereo microphone arrangement, would allow for better environmental sound recording when used with the RPA because the noise of the RPA would be less dominant. Thus, in the environment in which we worked, the AudioMoth is likely to be superior to the H1n for point-count data collection where the only noise would be from the surrounding landscape, and the H1n superior for use with the RPA in line-transect surveying.

Our results may be specific to the particular equipment set-up that we used, geographic location and specific vocalisations broadcast. Other studies may yield considerably different outcomes with respect to RPA interference and bird vocalisation detectability, as noted by Wilson *et al.* (2017). Furthermore, as this study was conducted under semi-controlled conditions, we did not consider the need for altitude variations during RPA flight that might be required to avoid obstacles (such as tree canopies or powerlines), the effects of sudden changes in weather, or the RPA attracting the attention of birds of prey or other highly territorial species. Using an RPA in surveying birds may cause changes in bird behaviour and vocal output (Weston *et al.* 2020), although during this study wild birds seemed more curious about the recordings broadcast from the speaker than about the RPA. In urban environments, due to the level and proximity of human activities, we might expect birds to be more habituated to 'unnatural' noises and devices than are nonurban birds.

It was not the aim of this study to compare many sound recording devices for wildlife surveying, as in the research of Rempel *et al.* (2013) and Yip *et al.* (2017b); time and financial

constraints simply did not permit such broad-scale studies. The choice of recorders came down to convenience and cost, as might be the situation for a non-profit organisation or citizen scientist. Both devices filled the brief of the broader study being planned in being easy to use, relatively inexpensive, light and portable. This was important, as a component of the broader study to which this investigation was a prelude was to cost-analyse how feasible such methods may be in 'real-world' situations. Although considerable time is required to analyse recorded data, there are now many free or low-cost bird-call identification apps that can greatly aid in data analysis. This audio-technology is a boon for researchers with constrained budgets, as the cost of using specialised observers and wildlife monitoring equipment in the field can inhibit the ability of land managers, conservation groups and researchers to gather sufficient data on natural systems (Hill et al. 2018), which in turn may prevent the execution of many appropriate management strategies.

This study assessed the suitability of two low-cost, high-quality recording devices and an associated RPA to aid long-established methods of surveying bird communities in the monsoonal tropics. That the two recorders differed in their suitability for specific components of the survey methods further emphasises the need to tailor study design and methods to best suit the location and wildlife to be investigated. The fact that a human observer performed more effectively than either of the recording devices in point-count trials with respect to *detecting but not identifying* the broadcast vocalisations has relevance for the design of other bird surveying projects in which the use of autonomous sound recording is being considered.

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