# Sampling environmental acoustic recordings to determine bird species richness 

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#### Abstract

Acoustic sensors can be used to estimate species richness for vocal species such as birds. They can continuously and passively record large volumes of data over extended periods. This data must subsequently be analyzed to detect the presence of vocal species. Automated analysis of acoustic data for large numbers of species is complex and can be subject to high levels of false positive and false negative results. Manual analysis by experienced surveyors can produce accurate results, however the time and effort required to process even small volumes of data can make manual analysis prohibitive.

This study examined the use of sampling methods to reduce the cost of analyzing large volumes of acoustic sensor data, while retaining high levels of species detection accuracy. Utilizing five days of manually analyzed acoustic sensor data from four sites, we examined a range of sampling frequencies and methods including random, stratified and biologically informed.

We found that randomly selecting 120 one-minute samples from the three hours immediately following dawn over five days of recordings, detected the highest number of species. On average, this method detected $62 \%$ of total species from 120 one-minute samples, compared to $34 \%$ of total species detected from traditional area search methods. Our results demonstrate that targeted sampling methods can provide an effective means for analyzing large volumes of acoustic sensor data efficiently and accurately. Development of automated and semi-automated techniques is required to assist in analyzing large volumes of acoustic sensor data.


Key words: acoustic data analysis; acoustic sensing; biodiversity monitoring; sampling.

## Introduction

Acoustic sensors provide an effective means for monitoring biodiversity at large spatial and temporal scales (Haselmayer and Quinn 2000, Penman et al. 2005, Acevedo and Villanueva-Rivera 2006, Celis-Murillo et al. 2009, Thompson et al. 2009). They can record large volumes of acoustic data continuously and passively over extended periods. However, these recordings must be analyzed to detect the presence of vocal species. Acoustic recordings can be analyzed automatically by call-recognition software, or manually by humans to identify species-specific calls (Brandes 2008, Acevedo et al. 2009, Celis-Murillo et al. 2009, Wimmer et al. 2013).

Automated analysis of acoustic sensor data for large numbers of species is complex and can be subject to high levels of false positive and false negative results (Swiston and Mennill 2009, Towsey et al. 2012). Manual analysis can produce accurate results, however the time and effort required to process recordings can make manual analysis prohibitive (Rempel et al. 2005, Swiston and Mennill 2009). Continuous acoustic sensor deployments

[^0]are restricted practically only by data storage capacity, which continues to increase in size and decrease in price. Therefore, the volume of data that we are now able to collect far outweighs our present ability to process it efficiently and accurately. The result is that many scientists are employing acoustic sensors to monitor biodiversity and subsequently finding that it is difficult to analyze the data efficiently.

Many studies have identified the issues of efficiently analyzing large amounts of acoustic data collected in the field (Corn et al. 2000, Haselmayer and Quinn 2000, Acevedo and Villanueva-Rivera 2006, Collins et al. 2006, Brandes 2008, Mason et al. 2008). The amount of effort required to analyze acoustic data depends on the objective of the analysis. These objectives fall broadly into two categories: single-species surveys that analyze acoustic recordings of the vocalizations of a single species to assess aspects of that species' ecology or behavior and species richness surveys that analyze acoustic recordings and identifying all taxa to generate a measure of species richness for a study area.

These objectives differ subtly in terms of the analysis methods and effort required to process large data sets. Single species analyses may be undertaken manually (due to the smaller number of potential vocalizations), or automatically using custom developed software or existing tools such as Raven (Charif et al. 2006).

Automated detectors for species with distinctive vocalizations such as the koala (Phascolarctos cinereus) and cane toad (Bufo marinus) have been developed and used successfully for a number studies (Grigg et al. 2006, Ellis et al. 2010, 2011). Due to the larger number of species (and therefore range of vocalizations), species richness analyses typically require much greater time and effort. Irrespective of the objective, efficient analysis methods are required that can deal with the volumes of data that result from large-scale deployments of acoustic sensors.

Automated analysis tools use software development techniques borrowed from speech recognition to detect the vocalizations of individual species in recordings. Perhaps due to the importance of birds as indicator species of environmental health (Carignan and Villard 2002), there is a significant body of literature relating to the automated detection of bird vocalizations (Anderson et al. 1996, McIlraith and Card 1997, Kwan et al. 2004, Chen and Maher 2006, Somervuo et al. 2006, Cai et al. 2007, Juang and Chen 2007, Kasten et al. 2007, Brandes 2008, Sueur et al. 2008, Acevedo et al. 2009, Bardeli et al. 2010). Some approaches, focusing on limited numbers of species or single species surveys, have produced promising results by extracting sets of specific features to classify calls (Farnsworth et al. 2004, Schrama et al. 2008). Other approaches have focused on cataloguing and characterizations of acoustic diversity and disturbance (Kasten et al. 2012). Automated analysis techniques are evolving quickly, however, due to the inherent complexity of acoustic environmental data, it will be some time before automated methods are capable of detecting all species likely to be found at a location (Mundinger 1982, Baker and Logue 2003, Brandes 2008).

Manual analysis typically involves listening to recordings and identifying individual species vocalizing in the recordings. This can be assisted by the use of tools to visualize the audio in the form of spectrograms, and by providing "reference calls" of species, which can be used to assist in species identification (Wimmer et al. 2013). Manual analysis can be very accurate if experienced observers are involved, however it is time consuming, expensive and ultimately fails to scale over large spatial and temporal frames (Rempel et al. 2005).

To take advantage of the benefits of acoustic sensing in the near-term, users of this technology require effective methods to analyze large volumes of acoustic data to make estimates of species richness. It is rare that all species occupying an area are identified in any ecological survey. Temporal and spatial patterns of species abundance or diversity are often compared using relative measures that are based on surveys, where equivalent sampling effort has been applied at different times or locations. Given that sampling is a common and well-established method for estimating species richness for an area (Krebs 1999), the same approach can be applied to acoustic surveys.

The aims of this study were to determine if random sampling of acoustic sensor data could provide a reasonable estimate of species richness for birds found in woodland habitats of south east Queensland, Australia. We compared subsamples of acoustic data with a fully analyzed set of 480 hours of acoustic recording. We also compared subsamples of acoustic data with results of traditional surveys to assess if reasonable estimates of species richness could be obtained with effort comparable to traditional surveys.

## Materials and Methods

## Study site

Traditional avian area searches modified from (Loyn 1985) and acoustic sensor surveys were conducted simultaneously in four locations over five days at the 51-ha Queensland University of Technology (QUT) Samford Ecological Research Facility (SERF). SERF is located in the Samford valley in south east Queensland, Australia ( $27.388992^{\circ}$ S, $152.878103^{\circ} \mathrm{E}$ ).

The main vegetation at SERF is open-forest to woodland comprised primarily of Eucalyptus tereticornis, E. crebra (and sometimes E. siderophloia), and Melaleuca quinquenervia in moist drainage. There are also small areas of gallery rainforest with Waterhousea floribunda predominantly fringing the Samford Creek to the west of the property, and areas of open pasture along the southern border.

Sites were located in the eastern corner within open woodland, the northern corner in closed forest along a creek line, in the western corner within Melaleuca woodland, and in the southern corner where open woodland borders open pasture (Fig. 1).

Samford Valley has a sub-tropical climate and experiences approximately 1020 mm of rainfall per year. Maximum and minimum mean temperatures are $26^{\circ}$ and $13^{\circ} \mathrm{C}$, respectively (Australian Government Bureau of Meteorology 2012). During the month of the survey period (October 2010), the site experienced rainfall of 296 mm , compared to an average of 116 mm . During the actual survey period however (13-17 October), only 1 mm of rainfall was recorded.

## Acoustic sensors

Acoustic sensors were located at the center of each survey site and configured to record continuously for five consecutive days. There was at least 300 m between the center of each survey site, and therefore between any two sensors. Sensors used for this study were custom developed using commercially available, low-cost digital recording equipment: Olympus DM-420 digital recorders (Olympus, Center Valley, Pennsylvania, USA) and external omni-directional electret microphones. Data were stored internally in stereo MP3 format ( $128 \mathrm{Kbit} / \mathrm{s}$, 22.05 KHz ) on high-capacity 32GB Secure Digital memory cards (Sandisk Corporation, Milpitas, California, USA). The units were stored in weatherproof


Fig. 1. Samford Ecological Research Facility (SERF) with survey site positions.
enclosures and powered by four D cell batteries, providing up to 20 days of continuous recording.

## Acoustic sensor data analysis

At the completion of the survey, sensor recordings were analysed manually by two experienced bird surveyors to identify each unique species vocalising in each one-minute segment. Surveyors analysed five days from two sites each, processing one-minute segments sequentially starting from midnight on day one. To ensure calls were annotated consistently and accurately, a call library was compiled, which contained exemplar calls for each species identified. All calls in the library were agreed upon by surveyors and crosschecked with reference material (Morcombe 2004). In addition, surveyors were randomly allocated 1440 one-minute segments ( $10 \%$ of the data allocated to each surveyor) from each other's sites to audit. Results from the audit indicated that less than $5 \%$ of total annotations were incorrectly identified.

Calls were annotated using a custom online acoustic workbench designed to manage the process of acoustic data analysis (Wimmer et al. 2013). The workbench played audio and displayed spectrograms, which allowed the observers to visualize and hear audio simultaneously. Bird vocalizations were identified aurally and visually by listening to the recording with headphones and observing the corresponding spectrogram. To mark species vocalizations within recordings, the workbench provided the ability to annotate spectrograms. Annotation involved selecting the portion of the spectrogram image that contained the specific vocalization, using a rectangular marquee tool. A tag was then
assigned to the selection, which identified the species. The upper and lower frequency bounds, start time, end time, duration and species tag were associated with each selection.

To simplify data management and analysis, sensor recordings were split into one-minute segments. Each one-minute segment was played and assessed for species vocalizations, and a single vocalization from each species in that minute was tagged. To reduce overall effort, once a species had been identified in a one-minute segment, all further calls for that species in that minute were disregarded. Therefore, the data derived from the five days of recording at the four sites comprises the number of different species calling in each one-minute segment. Species richness measures are species calling per unit time (minute, hour, day). The information obtained from one-minute segments was considered an adequate compromise between the time-consuming task of identifying every call made over the five day period, and the need to have detailed information on the number of species calling at a particular time of the day. The amount of time taken to analyze each one-minute segment was also recorded for each observer.

Following manual analysis of the sensor data, species list reports were generated for each one-minute segment of recordings from the four sites over five days. These data were subsequently used to test the effectiveness of five sampling methods.

## Sampling methods

Five sampling methods were investigated to determine the method that returned the highest estimate of species richness for the least amount of manual analysis effort.

These sampling methods were: full day, one-minute samples selected randomly from the full 24-hour periods; dawn, one-minute samples selected randomly from 3 hours after dawn ( $05: 15-08: 14$ ); dusk, oneminute samples selected randomly from 3 hours before dusk (14:55-17:54); dawn + dusk, one-minute samples selected randomly from dawn + dusk periods; systematic, one minute every half hour on the half hour, from the full 24 -hour periods.

The full day sampling method included all data from all days for each site. In total, this constituted 7200 oneminute segments per site. The dawn sampling method included 900 one-minute segments over the five-day period per site. The dusk sampling method also included 900 one-minute segments over the five-day period per site. The dawn and dusk sampling method included both dawn and dusk periods, and hence comprised 1800 oneminute segments over the five-day period.

Many users of acoustic sensors have adopted a systematic sampling method as a means of reducing the data collected overall and hence the manual analysis effort (Ellis et al. 2010). The systematic sampling method selected one-minute every half-hour, on the hour and half-hour (total of two minutes every hour). This constituted 240 one-minute segments over the fiveday survey period for each site.

For each sampling method, the required numbers of one-minute samples were randomly selected from the pool of one-minute samples corresponding to the sampling method. For example, applying the full day sampling method to Site 1 involved taking $n$ random one-minute samples (without replacement) from 7200 one-minute recordings over five days, and counting the unique species detected in the $n$ samples. This sampling was repeated 1000 times for each sampling method and sampling frequency at each site to obtain a mean number of species detected for $n$ samples.

For each of these sampling strategies the mean number of species detected per 1000 samples was examined in relation to sampling effort (number of one minute segments examined). These data were compared with the number of species detected from full analysis (of all 7200 one minute samples from a site), and from traditional survey methods.

## Traditional area search surveys

Traditional bird surveys were conducted at each site using a modified area search survey method (Loyn 1985). A $200 \times 100 \mathrm{~m}$ plot was searched systematically over a 20 -minute period and all species detected were recorded as seen, heard, or seen and heard.

During the study period, a total of 60 surveys were conducted at dawn, noon and dusk by two experienced bird surveyors with over 20 years of combined bird watching experience in the south east Queensland area. Observations for each survey were verified and agreed by both surveyors. In total, each survey constituted 40 minutes of effort (two surveyors $\times 20$ minutes) and each
day constituted 120 minutes of effort (two surveyors $\times$ 20 minutes $\times$ three surveys). Over the five-day period at each site, the traditional surveys constituted 10 person hours of effort.

## Statistical analysis

The main questions of interest were whether the number of species detected varied between different sampling methods, and how the number of species detected changed with increases in sampling effort (number of minutes sampled). The mean proportion of total species detected by each sampling method and number of samples were compared using a one-way ANOVA with sites as replicates. Because sites were used as replicates, the number of species detected with a given sampling approach was expressed as a proportion of the total number of species detected at that site. These proportions were arcsine transformed to satisfy assumptions of normality and minimize the risk of heteroscedasticity.

The EstimateS 8.2 package was used to calculate the Chao2 species richness estimate for each site (Chao 1987, Colwell 2009). Chao2 is a nonparametric richness estimator, which can estimate total species richness based on occurrence data. Chao2 species richness estimates were calculated to provide an estimate of species richness at each site for both survey methods and for comparison with estimates obtained from the different sampling methods.

Results

## Survey results

Acoustic data from the survey period were analysed in full to detect all species calling in each one-minute segment. Across the four sites and five days, a total of 28800 one-minute segments were manually analysed. Fifty-six percent (16019) of total segments contained calls, and from these, 63089 birdcalls were identified and annotated ( $\sim 2.2$ call types per minute).

Over the five-day survey period, across all sites, a total of 96 species were identified from the acoustic sensor survey and 66 species from the traditional survey. The total species detected through analysis of acoustic data at each site ranged from 75 to 80 species, while traditional surveys ranged from 34 to 49 species (Fig. 2). Chao2 species richness estimates from acoustic sensor data indicated that most detectable species were being identified at each site, with estimates ranging from 77 (Site 3) to 101 (Site 1; Fig. 2). Chao2 estimates from traditional surveys varied considerably, with estimates ranging from 41 (Site 3) to 110 (Site 2; Fig. 2)

The mean number of species recorded per site, per day across the five-day period from sensor surveys ranged from 57 to 59 , however there was some variation recorded between days, particularly at Site 1 (Fig. 3). The mean number of species recorded per site per day from traditional surveys across the five-day period ranged from 15 to 20 (Fig. 3).


Fig. 2. Total number of unique bird species detected and Chao2 species richness estimates for full acoustic sensor data analysis and traditional survey for each site over the five-day survey period.

Fig. 4 shows the mean number of species detected from sensor data analysis per hour across all sites for all hours of the day. The dawn period had the greatest number of species, with a lull around midday and a lesspronounced peak toward dusk. A smaller number of species were detected at night. On average, more than $80 \%$ of total species from each site were detected during the three-hour dawn period over five days. This compares with an average of $64 \%$ of all species at a site calling in the three-hour dusk period.

Although there was some day-to-day variation in the number of species detected, on average, acoustic sensor surveys detected $78 \%$ of total species in the first day. In addition, an average of $75 \%$ of species were detected by 07:00 on the first day. Traditional surveys detected an average of $50 \%$ of species in the first day, with $30 \%$ of
total species detected during the first dawn survey period.

Results from the sensor survey showed very little variation in species composition across the four sites, with $93 \%$ of species found at all sites. In contrast, $27 \%$ of species detected from traditional surveys were common to all sites.

Five species were detected only once over the five-day period at all sites: Pale-vented Bush-hen (Amaurornis moluccana), Glossy Black Cockatoo (Calyptorhynchus lathami), Forest Kingfisher (Todiramphus macleayii), Collared Sparrowhawk (Accipiter cirrhocephalus), and Azure Kingfisher (Alcedo azurea). Having vocalized in one out of 28800 one-minute segments, these species had a very low probability of detection. In contrast, the most frequently detected species was Rufous Whistler


FIG. 3. Number of bird species detected (species richness estimates; mean and $95 \% \mathrm{CI}$ ) daily from full acoustic sensor data analysis and traditional survey for each site over the five-day survey period.


FIG. 4. Number of species detected each hour (species richness estimates; mean and $95 \% \mathrm{CI}$ ) from full analysis of acoustic sensor data across all sites.
(Pachycephala rufiventris), which was detected in 6941 one-minute segments over the five-day period at all sites.

## Acoustic data sampling results

To compare the number of species detected by each of the sampling methods with the results from full analysis of all acoustic sensor data, the maximum number of species detectable in the time periods corresponding to each sampling method was calculated from the manually analysed acoustic data. This represents the maximum number of species detectable from the periods corresponding to each of the sampling methods (Table 1).

The minimum number of one-minute segments required (theoretically) to detect all species for each sampling method at each site, was calculated using a greedy optimization algorithm (Cormen et al. 2009) (Table 1). This algorithm first calculated and selected the one-minute segment from each site with the highest number of unique species. These species were then removed from analysis and the number of unique species per minute recalculated. The next one-minute segment with the highest number of unique species was then selected and the species removed from the analysis, and so on, until all species were recorded.

The results of the greedy algorithm analysis provide the theoretical minimum number of samples required to achieve the maximum number of species that were detected through full manual analysis for each of the sampling methods. This is theoretical because it assumes prior knowledge of the data set, from full analysis of the data. For example, for the dawn +3 hours sampling method for Site 1 (column 2, row 3 of Table 1), 66 species $(80 \%$ of total species detected at Site 1) were detected through full manual analysis, and a minimum of 28 one-minute samples are required to detect all 66 species. This represents the near-optimum result obtainable from sampling of the Site 1 data in the dawn +3
hours period. These data are included for comparison with actual sampling results, and provide the minimum number of samples that would theoretically be required to detect all species for each sampling method.

Fig. 5 shows the mean percentage of total species that were detected by each sampling method in relation to the number of one-minute samples examined. The relative difference in number of species detected by each sampling method changed in relation to sample size. This is because different numbers of species were detected calling during each sampling methods, and because the sampling methods reached their maximum after a different number of samples. For example, systematic sampling had a total of 240 one-minute samples ( 2 samples per hour $\times 24$ hours $\times 5$ days per site), whereas dawn sampling had 900 samples ( 180 minutes per day $\times 5$ days per site). Dawn plus dusk sampling had 1800 minutes of sampling available (combined dawn 180 minutes and dusk 180 minutes per day $\times 5$ days per site). Only sampling from the full day method did not reach its maximum in Fig. 5 as this did not occur until 7200 minutes were sampled ( 24 hours $\times 60$ minutes per hour $\times 5$ days).
Systematic sampling detected an average of $63 \%$ of species, and the dusk sampling period comprised $64 \%$ of species (Fig. 5). An average of $82 \%$ of species were detected at dawn, compared to $87 \%$ from the combined dawn and dusk sampling period (Table 1; i.e., an additional $5 \%$ of total species were detected by combining the dawn and dusk periods).

Sampling from the dawn period detected the highest mean proportion of species until 1080 samples were selected, at which point the dawn and dusk period took over, with an average of $83 \%$ of species. Detecting the remaining $4 \%$ of species present in the dawn and dusk period required a further 600 samples (one-third of the

Table 1. The maximum number (Max) and percentage (PS) of species detected for each sampling method from full manual analysis of sensor data, along with the minimum number (Min) of samples required to detect the maximum number of species (greedy algorithm).

| Sampling method | Site 1 |  |  | Site 2 |  |  | Site 3 |  |  | Site 4 |  |  | Mean |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Max | PS (\%) | Min | Max | PS (\%) | Min | Max | PS (\%) | Min | Max | PS (\%) | Min | Max | PS (\%) | Min |
| Full day | 83 | 100 | 43 | 82 | 100 | 39 | 77 | 100 | 30 | 81 | 100 | 38 | 81 | 100 | 38 |
| Dawn | 66 | 80 | 28 | 68 | 83 | 26 | 65 | 84 | 27 | 65 | 80 | 29 | 66 | 82 | 28 |
| Dusk | 51 | 61 | 26 | 50 | 61 | 26 | 54 | 70 | 25 | 51 | 63 | 26 | 52 | 64 | 26 |
| Dawn + dusk | 73 | 88 | 33 | 72 | 88 | 30 | 69 | 90 | 28 | 67 | 83 | 29 | 70 | 87 | 30 |
| Systematic | 48 | 58 | 48 | 50 | 61 | 48 | 55 | 71 | 48 | 50 | 62 | 48 | 51 | 63 | 48 |

Note: Results are presented for each site, and the mean of all sites.
total number of one-minute samples in the dawn and dusk period; Fig. 5).

## Comparison with traditional surveys

To evaluate the relative effectiveness of acoustic sensor data sampling, results were compared with observations from traditional bird surveys, which were carried out concurrently over the same period as the acoustic sensor survey. A greater amount of effort was required to manually analyze acoustic sensor data than to conduct traditional bird surveys. For traditional surveys, every minute of survey effort yielded one minute of survey observations. For acoustic data analysis however, on average, it took approximately two minutes of effort to analyze one-minute of acoustic data ( $2: 1$ ratio). This is because there was a tendency for analysts to replay recordings to distinguish individual species, and because of the time taken to load and annotate vocalizations. Hence, one minute of effort to analyze observations from acoustic sensor data is equivalent to two minutes of traditional survey observation effort.

For traditional surveys, each site had 120 personminutes of effort per day (three 20-minute surveys $\times$ two surveyors), and 600 person-minutes of effort in total over the duration of the 5 -day survey period. Based on the $2: 1$ ratio of effort, the equivalent sensor data analysis effort is therefore 60 one-minute samples per day (half of 120 person-minutes of traditional survey effort), and 300 minutes over the duration of the survey (half of 600 person-minutes of traditional survey effort).

Fig. 6 shows the average per cent of species detected using different levels of sampling (from 60 to 300 minutes), and for traditional surveys that had equivalent effort (e.g., 60 one-minute samples $=$ one day of traditional survey [120 person-minutes]). At all levels of sampling effort there was a significant difference in the number of species detected in relation to the sampling method ( 60 minutes $F_{5,18}=21.32, P<0.001$; 120 minutes $F_{5,18}=16.145, P<0.001 ; 180$ minutes $F_{5,18}$ $=12.783, P=0.000 ; 240$ minutes $F_{5,18}=9.956, P=$ 0.000 ); 300 minutes $F_{5,18}=10.461, P<0.001$ ). Post hoc tests (Tukey; $P<0.05$ ) indicated that traditional surveys detected significantly lower numbers of species


Fig. 5. Percentage of total species detected for each sampling method (species richness estimates; means) for the associated number of minutes sampled (Data combined over sites).


Fig. 6. Percentage of total species detected by each sampling method (species richness estimates; mean and $95 \%$ CI) for the associated number of minutes sampled. Error bars for each group of samples have been offset for clarity.
than all acoustic sampling methods at 60 minutes sampling effort, and all sampling methods/sampling effort with the exception of dusk (Table 2).

## Discussion

Acoustic sensors are being used increasingly to augment traditional field survey methods. They can increase the spatial and temporal scales of observations (Parker 1991, Brandes 2008), however, analysis of acoustic sensor data is complex and time consuming (Rempel et al. 2005, Swiston and Mennill 2009). Methods for the analysis of acoustic sensor data will continue to mature and improve, but there is currently a significant gap in analysis capability. Manual analysis, which is expensive and time consuming, contrasts with fully automated analysis, which though potentially cheaper, cannot currently cater for large numbers of species and lacks verifiable high detection accuracy.

Our results demonstrate that reasonable estimates of bird species richness can be obtained through targeted
sampling combined with manual analysis of acoustic sensor data. Specifically, randomly selecting 120 oneminute segments from dawn over a five-day period can detect up to $62 \%$ of total species, compared to $34 \%$ of species from the equivalent amount of traditional survey effort. Similarly, systematic sampling (i.e., recording one minute every half hour) can detect over $50 \%$ of species from 120 recordings while reducing the volume of data collected.

All sampling methods investigated, with the exception of the dusk method, detected a higher number of species on average than traditional survey methods, when compared using the equivalent amount of analysis/ traditional survey effort. This supports other research comparing traditional survey methods and acoustic sensors (Haselmayer and Quinn 2000, Penman et al. 2005, Acevedo and Villanueva-Rivera 2006, CelisMurillo et al. 2009, Swiston and Mennill 2009), however there are issues relating to the detection range of acoustic sensors that should be considered. When conducting traditional surveys, surveyors disregard species seen or heard outside the survey area, whereas with acoustic sensor analysis, all species heard (regardless of potential distance from the sensor) are included. Given the close proximity of sites (approximately 300 m ), species with loud calls may have also been detected by more than one sensor.

Ignoring the travel time to and from sites (which were deemed to be approximately equivalent for both traditional and acoustic sensor survey methods), the ratio of two traditional survey minutes to one acoustic data analysis minute is possibly higher than necessary. This ratio was initially observed when each species was annotated once per minute over the duration of the survey period. For species richness studies, one annotation per species over the duration of the survey period would be sufficient to establish presence. This would therefore reduce the time taken to analyze data considerably. In addition, improvements in the graphical user interface design of annotation systems could reduce repetitive tasks, assist in rapid identification of species and automate manual documentation tasks.

These results are promising, but they fall considerably short of the maximum number of species detectable from full manual acoustic data analysis. Theoretically,

Table 2. Tukey post hoc test results for traditional survey against each sensor survey sampling method, and sampling effort up to 300 samples.

|  | Number of samples |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Sampling method | 60 | 120 | 180 | 240 | 300 |
| Full day | 0.001 | 0.002 | 0.005 | 0.011 | 0.012 |
| Dawn | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Dusk | 0.008 | 0.093 | 0.032 | 0.545 | 0.846 |
| Dawn + dusk | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 |
| Systematic | 0.000 | 0.001 | 0.002 | 0.005 | 0.029 |

Notes: Results are significant ( $P \leq 0.05$ ) for all sampling methods and sampling effort with the exception of dusk at 120 samples and higher.
all species at each site could be detected in less than 50 samples (see greedy algorithm results; Table 1). This represents the optimum result obtainable with the highest return for effort. Even at 720 samples, the best-performing random sampling method (dawn) detected a maximum of $80 \%$ of species. In practice, manually analyzing more than 240 minutes is prohibitively expensive and impractical in most cases.

To take full advantage of the capability of acoustic sensors, automated methods are required that can assist in reducing manual analysis by selecting samples most likely to contain vocalizations. This also means finding cryptic species, which call very infrequently or not at all during targeted periods, such as dawn. Here automated analysis does not attempt to identify individual species; rather it attempts to identify segments of recordings with potential calls, or removes from analysis, segments that contain "noise," such as rain or wind. Segments containing potential calls can then be analysed manually to identify individual species. Considering approximately $18 \%$ of species were detected only 10 times or less across the five-day period, the probability of detecting a significant proportion of species by random sampling alone is very low ( 0.0014 ). By using automated methods to target periods that contain potentially unique species vocalizations, and removing extraneous noise, we can significantly reduce the amount of manual analysis required to process large volumes of data, and improve the chance of detecting cryptic or rare species.

Ultimately, analysis of large volumes of acoustic sensor data is a trade-off between analysis cost and detection accuracy. At one extreme, manual analysis of acoustic data is costly with high levels of detection accuracy. At the other, automated analysis can be less costly, but with less certainty in the confidence of detection accuracy. Methods that combine the strengths of both approaches may help to make acoustic sensing for monitoring biodiversity feasible at larger spatial and temporal scales.

## Acknowledgments

This research was conducted with the support of the QUT Institute of Sustainable Resources and the QUT Samford Ecological Research Facility. Thanks to Tom Tarrant, Julie Sarna, and Rebecca Ryan for assistance conducting surveys and analyzing acoustic sensor data. Special thanks to William Ellis and Lucas Bluff for their insightful comments and suggestions. Special thanks also to Peter Grace and Michelle Gane (QUT Institute for Future Environments) for their assistance and support conducting this research.

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Queries for ecap-23-06-10
This manuscript/text has been typeset from the submitted material. Please check this proof carefully to make sure there have been no font conversion errors or inadvertent formatting errors. Allen Press.


[^0]:    Manuscript received 31 December 2012; revised 26 March 2013; accepted 28 March 2013. Corresponding Editor: D. Brunton.
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