ACOUSTIC SENSING: ROLES AND APPLICATIONS IN MONITORING AVIAN BIODIVERSITY.

Jason Wimmer

BComp (Monash University)
GCSc (University of Queensland)

A thesis by publication submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

June 2015

§

Principal Supervisor: Prof Paul Roe
Associate Supervisor: Dr Ian Williamson

Science and Engineering Faculty

Electrical Engineering, Computer Science

Queensland University of Technology

Brisbane, Queensland, Australia

Keywords

Acoustic Sensing, Avian Survey Techniques, Biodiversity Monitoring, Sampling

Abstract

Biodiversity monitoring at large spatial and temporal scales is becoming increasingly important as the effects of climate change and habitat loss threaten the natural environment. Environmental sensors such as acoustic sensors are becoming important for achieving this; they can remain deployed, passively collecting data over large areas for long periods of time, and they can detect species such as birds and frogs, which can be good indicators of overall environmental condition. However, acoustic sensors can generate large volumes of data which must be analysed to identify vocalisations of individual species. In addition acoustic sensor data can be complex and difficult to analyse. Many bird species exhibit considerable regional variation, and environmental noise such as rain and wind can make species identification difficult.

This thesis investigates some of the major challenges and opportunities presented by acoustic sensing for biodiversity monitoring. Tools for manually analysing large volumes of data are presented, along with the results of a detailed analysis of a typical acoustic sensor survey. A comparison of traditional survey methods and acoustic sensor surveys is presented, along with approaches for reducing manual analysis effort through the use of sampling techniques.

In the absence of automated analysis tools for a large number of species, acoustic sensor data must be analysed by experienced bird surveyors. This thesis presents a system for managing the manual analysis of large volumes of acoustic sensor data. The system generates spectrograms, plays audio and allows users to annotate spectrograms to identify individual species. The system was used to manually analyse acoustic sensor data, the results of which, form the basis of the research presented in this thesis.

Acoustic sensor data can provide unique insights into species behaviour which go beyond typical species richness or abundance estimates obtained from traditional surveys. A major component of this research was the analysis of five days of continuous acoustic sensor recordings from four sites. Calls were analysed by experienced bird surveyors and each species identified in each one minute segment annotated. In total, 28,800 one minute segments were analysed, 63,089 calls annotated and 96 bird species identified. From this data, detailed call frequency, diurnal variation, species accumulation, periods of high and low activity and the effects of weather on detectability were investigated. Additionally, a high resolution, fully annotated acoustic data set was created, which allowed for comparisons with traditional survey methods and testing of sampling methods to reduce manual analysis effort. To our knowledge this is the most comprehensively analysed acoustic data set of its kind, which will be of ongoing use for future research, including development and testing of automated species recognition tools.

Users of acoustic sensor technology require an objective assessment of the capabilities of acoustic sensors compared to traditional survey methods. Previous comparisons of traditional and acoustic sensor surveys have produced conflicting results. In this thesis, the results of detailed comparisons between traditional bird surveys and the manually analysed acoustic sensor data are presented. Acoustic sensor surveys consistently detected a higher number of species than traditional surveys, although the cost of analysis also increased significantly.

Analysis of acoustic sensor data is time consuming and costly. Automated analysis tools which can reliably detect a large number of bird species are yet to be developed. In the interim, users of acoustic sensor data technology require a means to efficiently manually analyse acoustic data. The final section of this thesis examined the use of sampling methods to reduce the cost of analysing large volumes of acoustic sensor data, while retaining high levels of species detection accuracy.

In this thesis, I present a series of original research publications which, when combined, make a significant and original contribution to our understanding of the appropriate application of acoustic sensing technology for large-scale biodiversity monitoring. This includes the demonstration of a system to manage and process large volumes of acoustic sensor data, examples of ecological insights which can be obtained from analysis of acoustic sensor data, a detailed comparison between acoustic sensor surveys and traditional surveys, and sampling strategies for analysing large volumes of data manually.

Table of Contents

List of Figures

List of Tables

List of Publications and Manuscripts

The following is a list of manuscripts accepted for publication as part of this thesis:

Wimmer, J., Towsey, M., Planitz, B., Williamson, I., Roe, P. (2012). Analysing environmental acoustic data through collaboration and automation. *Future Generation Computer Systems*, 29(2), 560-568. http://dx.doi.org/10.1016/j.future.2012.03.004

Wimmer, J., Michael Towsey, Paul Roe, and Ian Williamson. (2013). Sampling environmental acoustic recordings to determine bird species richness. *Ecological Applications* 23(6):1419–1428.http://dx.doi.org/10.1890/12-2088.1

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature:

Date: 10/6/2015

Acknowledgments

This work would not have been possible without the help, advice and support of many people. What began as a temporary break from corporate life has become a journey that has taken me to unexpected places and introduced me to interesting new people, many of whom have become close friends.

Firstly, thank you to my supervisors Professor Paul Roe and Dr Ian Williamson, who have been a constant and patient source of advice and guidance. They have provided the ideal balance of knowledge and experience required for cross-disciplinary research such as this. Without their support this would not have been possible, and the rewards from the time spent with both Paul and Ian go far beyond the conferring of a degree. Ian’s retirement from QUT will be a great loss to both teaching and stand-up comedy. Fortunately, he will be incapable of completely removing himself from both pursuits, but hopefully a short break will provide the opportunity to develop and test new material.

During the course of my research I have been fortunate to meet many talented and dedicated researchers, who have become friends and colleagues. In particular, thanks to Dr Bill Ellis and Dr Sean Fitzgibbon from the University of Queensland, who have provided support, guidance and endless entertainment. Over the course of this research and numerous field trips to remote islands and locations they have become good friends and I have been inspired by their dedication and professionalism.

Special thanks also to Dr Michael Towsey. Mike has been a continuous source of help and advice for not only me, but all research students in the bioacoustics lab over many years.

Finally, thanks to my wife Sarah and my two beautiful girls Juliette and Chloe. They are my long-suffering, patient and loving inspiration that make everything I do worthwhile.

Chapter 1: Introduction

The complex and interrelated environmental effects of climate change present scientists and policy makers with a challenging problem requiring innovative solutions. With estimates of extinction rates up to 1000 times the natural rate (IUCN 2010), monitoring the effects of climate change on the earth's biodiversity is becoming increasingly important.

Monitoring biodiversity allows us to take an inventory of the environment and to observe changes occurring over time, such as species composition, population size, range and habitat. Observing and understanding these changes allows us to account for the value of ecosystem services and to take steps to mitigate the risk of large-scale species extinctions. To do this however, we require efficient and effective means to collect and analyse environmental observations at large spatial and temporal scales. Historically, these observations have been made manually by scientists using traditional field survey methods. Environmental sensors are being used increasingly to augment and, in some cases even replace traditional methods.

Environmental sensors which can record detailed observations, consistently and repeatedly over long periods of time hold great promise for improving our capability to monitor the environment. These sensors can range from complex satellite-based systems which scan large geographic areas using multispectral imaging (Brumm 2004), to commodity meteorological sensors that can record basic temperature and relative humidity (Collins et al. 2006). Rapid advances in information and communication technology are making more sophisticated sensor devices available more quickly than ever before; however the vast amounts of data we are now able to collect, need to be analysed and interpreted.

Different sensor devices have different data analysis requirements. Simple data logging devices such as temperature sensors, record interval data (e.g. 32ºC) which can be directly understood, and have innate meaning. More complex sensors such as cameras or acoustic sensors generate data which requires a more sophisticated level of analysis. These data are rich in information, however also fundamentally opaque and cannot be interpreted until analyses have been performed to give the data meaning.

Take for example, an acoustic sensor recording of a rainforest habitat; many different species of birds, frogs or insects could be vocalising simultaneously in the recording. There may also be the sound of rain or wind, or there may be anthropogenic noise such as cars or planes. This single recording may contain a significant amount of information which could help to describe the condition of the rainforest, and the interpretation of this data may change through time, and in the context of larger spatial scales. Analysing the recording automatically to extract this information however, is highly challenging.

Capturing and understanding the scale and complexity of the natural environment using technology such as video or acoustic sensors, requires sophisticated analysis capabilities, or alternatively, methods to reduce the complexity or scale. Automated methods will continue to improve and become more sophisticated, but for the immediate future, methods which improve the ability of humans to manually analyse large volumes of sensor data are required. We also need to be able to describe and understand the limitations of sensor technology to ensure that it is used appropriately.

1.1 SIGNIFICANCE AND CONTRIBUTION

The core theme of this thesis is to critically evaluate the effectiveness of acoustic sensors as a means for monitoring biodiversity at large spatial and temporal scales. Acoustic sensors have the potential to play an important role in monitoring biodiversity. Although only a fraction of the earth's biodiversity have audible and consistent vocalisations, many species which do (i.e. birds, frogs and insects) are considered good surrogates of environmental condition (Slabbekoorn and Peet 2003). To be used effectively, we must understand the strengths and weaknesses of acoustic sensors and have the ability to process the large volumes of data associated with acoustic sensor deployments. The key contributions of this thesis are:

- Identifying the role of acoustic sensing in biodiversity monitoring, and the insights that acoustic sensing can provide over and above traditional survey methods.
- Evaluating the effectiveness of acoustic sensors as a means to monitor biodiversity, by comparing the results of acoustic sensors data with traditional field survey methods for bird species.
- Developing and testing sampling strategies to allow users of acoustic sensors to manually analyse sensor data efficiently.

While some research has been conducted comparing acoustic sensing to traditional field survey (for bird species), the results have been contradictory with many non-standard comparisons made (Hobson et al. 2002; Hutto and Stutzman 2009; Rempel et al. 2005). There is therefore, no well-defined, clear guidance on the effectiveness of acoustic sensors which can facilitate their widespread use as a means of monitoring biodiversity.

To determine the effectiveness of acoustic sensors for monitoring biodiversity, a rigorous comparison of traditional manual bird surveys and manually analysed acoustic sensor data has been undertaken as part of this research. This provides clear and unambiguous guidance on the performance characteristics of acoustic sensors and makes it possible to quantify the difference in detection rates for traditional and acoustic sensor methods.

To compliment this, given that automated analysis techniques are not yet capable of detecting large numbers of species, a range of sampling strategies have been developed to reduce manual analysis effort. These sampling strategies have been tested systematically across a large manually analysed acoustic sensor data set, to determine optimal sampling times and sampling frequencies. This provides consumers of acoustic sensor data with the capacity to achieve higher rates of species detection than traditional methods, with effort comparable to traditional methods.

To achieve the goals of this research, a fully manually annotated dataset of five days replicated at four sites (28,800 one minute segments) of acoustic sensor data, with detailed species vocalisation data at one minute resolution has been analysed. This dataset has been the underlying foundation of all comparison work performed during this research, and will continue to be a valuable source of species vocalisation and detection data for future research. Work from this thesis has been presented at a number of national and international conferences and published in high quality, peer reviewed journals including *Future Generation Computer Systems* and *Ecological Applications*.

1.2 ACCOUNT OF RESEARCH PROGRESS LINKING THE RESEARCH PAPERS

The four research papers presented in this thesis are directly related, and present the outcomes of this research in a logical and coherent manner. Specifically, they focus on the use of acoustic sensors for monitoring biodiversity at large spatial and temporal scales for ecological research. Combined, these papers make a significant and original contribution to our understanding of the appropriate application of acoustic sensing technology for large-scale biodiversity monitoring. They address the following key questions:

- Chapter 3: Analysing Environmental Acoustic Data through Collaboration and Automation. How can we manage, visualise, play, annotate and summarise acoustic sensor data effectively and efficiently?
- Chapter 4: Assessing Bird Biodiversity with Acoustic Sensors – Insights from Avian Surveys in SE Queensland. What ecological insights, beyond estimates of species richness, can be derived from acoustic sensor surveys?
- Chapter 5: Do the eyes have it? – A comparison of traditional bird surveys and acoustic sensor surveys. How effective are acoustic sensor surveys (in terms of species detected and cost) compared to traditional biodiversity surveys?
- Chapter 6: Sampling environmental acoustic recordings to determine species richness. Can sampling approaches be applied to acoustic sensor data to reduce the amount of manual analysis required to produce high estimates of species richness?

Chapter 3 outlines a unique online acoustic data analysis workbench for identifying and annotating species vocalisations. The workbench provides tools to manage acoustic data, play audio, visualise spectrograms and annotate vocalisations. In addition, a number of semi-automated tools have been developed, which can assist in the correct identification of species. These include species call libraries (with prototypical spectrograms and audio of each species) and species specific automated recognisers. This workbench was central to the analysis of sensor data for this research. This chapter was accepted as an original research paper for publication in the *Future Generation Computing Systems Journal* in 2013 (Wimmer, Towsey, Planitz, et al. 2013).

Chapter 4 presents the results of full manual analysis of acoustic sensor data from four survey sites over a five day period, and demonstrates the insights that can be obtained from comprehensive analysis of acoustic sensor data. These insights include bird species richness, calling frequency, nocturnal and diurnal variations in calling and the effects of weather on calling behaviour and detectability. This chapter was submitted as an original research paper to *Austral Ecology* in 2013.

Having quantified the results of manually analysed acoustic sensor data in Chapter 4, Chapter 5 compares the results of manual analysis with traditional surveys. This chapter discusses the relative strengths and weaknesses of each method, in terms of both numbers of species detected overall and species detected solely by either method. It also demonstrates that while comprehensive manual analysis of acoustic data can yield valuable insights, the overall cost renders large scale manual analysis prohibitive. This chapter was submitted as an original research paper to the *Journal of Field Ornithology* in 2014. Demonstrating that manual sensor data analysis can detect a greater number of species than traditional survey provides the rationale for examining methods to reduce manual analysis effort (and therefore cost) in Chapter 6.

Chapter 6 presents an alternative to full manual data analysis which can reduce the analysis effort while maintaining high levels of species detectability. This includes sampling approaches ranging from random to biologically informed and systematic methods. This chapter was accepted as an original research paper for publication in *Ecological Applications* (Wimmer, Towsey, Roe, et al. 2013)

Chapter 7 concludes and summarises the research, highlighting areas of potential further work.

Chapter 2: Literature Review

2.1 BACKGROUND

Understanding and identifying anthropogenic effects on the environment is becoming increasingly important as the world recognises the impact of global climate change and loss of biological diversity. This impact, whether due to overutilisation of natural resources, agriculture, urbanisation, pollution or any number of other factors, is rapidly leading to habitat loss, and the resultant loss of species. It is in this context that it is critical to improve our capability to rapidly and accurately collect and analyse data to assess the ecological condition of a system at a given point in time.

Traditionally, ecologists have conducted field surveys to detect the presence or absence of particular species, or describe the biodiversity of a surveyed site. The data gathered provides valuable insights into the complex relationships between organisms and the environment and the effects of habitat degradation; however these surveys require trained ecologists to be present in the field gathering data and making observations. This work can be time consuming, expensive and limited in terms of scale. Achieving consistent observations across large temporal and spatial scales requires significant effort and resources. Often, because of cost constraints, these resources are not available which can limit the scope or applicability of field work. This comes at a time when climate change is threatening many species and mitigation strategies to prevent their loss require detailed species survey and population distribution data.

Acoustic sensors have been used by ecologists and marine biologists to monitor biodiversity for some time. Acoustic energy is a unique and potentially valuable tool for assisting ecologists to perform fauna surveys. Sound can transmit large amounts of information quickly and efficiently over relatively long distances. It provides many species such as birds, with the ability to communicate the presence of danger, to attract mates and defend territory (Catchpole and Slater 2008). These communications can be captured by acoustic sensors and analysed in the laboratory to monitor biodiversity. While acoustic sensors have an obvious bias towards species with regular and consistent vocalisations, many species with vocalisations (e.g. avian and amphibian species) are sensitive to changes in the environment and their presence or absence can monitored over time.

Both traditional survey methods and acoustic sensor surveys have a bias towards aural detections. Some research has been conducted into the effectiveness of acoustic sensing compared to traditional field survey techniques, however results have been conflicting and many comparisons have focused on single species or have not compared manual and audio recordings data directly. Additionally, research into acoustic sensor data analysis has focused primarily on automated methods for analysing large amounts of data. The inherent complexities in both the environment from which sensor data is derived and the species which are being monitored make complete automation of sensor data analysis an elusive goal.

In this section, a review of current literature is presented to demonstrate the current state of research in relation to the use of acoustic sensors for biodiversity monitoring and large scale analysis of acoustic sensor data. In this review I highlight potential knowledge gaps and identify areas in which this research makes a unique contribution. The aim of this section is to demonstrate that insufficient research has been carried out to provide environmental scientists with the knowledge and frameworks required to effectively apply acoustic sensing to large-scale biodiversity monitoring.

Ecological applications for acoustic sensing are numerous and varied however this research will focus primarily on terrestrial applications, and specifically on applications which assist ecologists in monitoring individual species and general biodiversity over large spatial and temporal scales. Additionally, this research will place particular emphasis on avian species due to their rich vocalisations, the unique structure of their calls and common use of vocalisations in communication (Catchpole and Slater 2008).

2.2 MONITORING BIODIVERSITY

Global climate change, irrespective of the cause, is having a detrimental impact on the earth's natural systems. Habitat loss and loss of biodiversity (genetic, species and ecosystem diversity) has dire consequences for all forms of life (Hunter and Gibbs 2007; Parmesan 2006; Thomas et al. 2004). Ecologists and conservation biologists study natural systems in an attempt to understand these changes and the associated impacts on biodiversity. Providing timely information to decision makers and developing strategies for conserving biodiversity is crucial to their efforts, and a core theme of this research (Bart 2005).

Ecologists face significant challenges in their efforts to monitor biodiversity, ranging from simple resource constraints to a fundamental lack of detailed species information. Putting aside very real considerations relating to taxonomic classification, consider that of the 2.75% of total described species evaluated by the IUCN Red List, 36% of these have been evaluated as ‘Threatened’ (IUCN 2010). Only a fraction of species identified have even been studied in sufficient detail to provide ecologists with an understanding of the effects of climate change on their survival (Begon, Townsend and Harper 2006). Additionally, sampling the environment over sufficient spatial and temporal scales to reliably infer disturbances in the environment or changes in species composition requires a significant amount of resources, which are often unavailable (Underwood 1994).

It is in this context that information technology (IT) has the potential to provide scientists with the ability to scale field observations and associated analyses both spatially and temporally. Acoustic sensors have the potential to increase environmental observations by providing a cost effective, continuous, *in situ* recording capability across large areas and for extended periods of time (Penman, Lemckert and Mahony 2005; Gage, Napoletano and Cooper 2001; Porter et al. 2005). Collecting and analysing data at these scales can provide detailed information on the changes occurring in the environment and allow scientists and decision-makers to implement strategies to prevent large-scale loss of biodiversity. However, methods for efficiently analysing large volumes of data, and comparisons of the strengths and weaknesses of traditional and sensor survey methods, based on empirical research, are lacking.

2.3 ANIMAL COMMUNICATION AND SOUND

2.3.1 WHY DO ANIMALS COMMUNICATE?

The way in which animals communicate, the frequency of their communications, detectability and consistency in calling are all important considerations for both the use of acoustic sensors in monitoring biodiversity, and interpretation of acoustic sensor data. While this research will not attempt to study the nature of animal communication *per se*, this section provides an overview of various aspects of animal communication as it relates to the use of acoustic sensors for the monitoring of biodiversity.

Sound is used extensively for communication by a wide variety of species including insect species, terrestrial vertebrates and marine species (Endler 1993). Sound is used to alert animals to potential threats, defend territory and attract mates. Along with visual and chemical communication, acoustic communication is one of the principal methods of communication in the animal kingdom (Fletcher 1997). Communication between two individuals is considered to have occurred if the signal from the emitter (the vocalisation) has modified the behaviour of the receiver (Catchpole and Slater 2008). It is this communication, intended for the receiver that acoustic sensors can intercept and store for analysis.

Many species have evolved vocalisations that correspond to different niche frequencies to conserve energy while communicating over maximum distances, and some studies have observed a correlation between communication frequency and body mass (Fletcher 2004). Based on this correlation, detectability and range of detection information could potentially be derived for individual species.

The fundamental question as to *why* animals communicate is not fully understood. Some suggest that communication used solely for alerting others to the presence of danger would have an evolutionary result that calls would only be audible to the same species (as to not alert prey to their presence), however many passerine species (song birds) have loud and consistent calls to attract mates (Catchpole and Slater 2008). Irrespective of the evolutionary pressures which have shaped vocal communication between individuals, it is widely accepted that vocal communication transmits information to the receiver to communicate danger, defend territory, attract mates or to signal aggression (Krebs and Dawkins 1984).

2.3.2 WHEN DO ANIMALS COMMUNICATE?

Understanding the communication behaviour of the target species is critical to the success of any monitoring program. The temporal, environmental and behavioural aspects which govern when species communicate can inform traditional monitoring activities (Peterson and Dorcas 2001). As acoustic sensors remain *in situ* for extended periods of time, we can continuously monitor and record the environment, but calling behaviour of the species recorded need to be considered when analysing the data.

In avian species particularly, there is strong evidence to suggest that calling activity is related to breeding, and is therefore seasonal in nature (Catchpole and Slater 2008). Song activity is also highly correlated with the production of testosterone (also associated with breeding) which in some cases is triggered by an increase in sunlight beginning in Spring, while in Autumn song activity reverses as photoperiod decreases (Catchpole and Slater 2008). Unlike the complex exchanges of information in communication and diverse repertoire of many bird species, anuran species (frogs and toads) generally communicate solely to locate and attract mates. Micro-habitat however, may have an influence on variation and calling behaviour of some frog species (Bosch and De la Riva 2004). Temporal and environmental variations have also been demonstrated to have a significant impact on calling behaviour of anurans and acoustic sensors have been used to demonstrate this, and to inform monitoring activities (Bridges and Dorcas 2000).

Understanding the reasons for communication between species and factors affecting calling behaviour is an important consideration for the use of acoustic sensors in monitoring biodiversity. Fundamental issues such as location and habitat (e.g. does the location contain the appropriate habitat to support the species being observed?), individual calling behaviour, temporal influences and environmental aspects for each species must also be taken into consideration when applying acoustic sensors to biodiversity monitoring.

2.4 TRADITIONAL FIELD SURVEY METHODS

Traditional survey methods can be broadly categorised into methods to study species at the levels of individual organism, population and community (Begon, Townsend and Harper 2006). At the individual level, observations are concerned with the interaction between individuals and the environment. Population level observations are concerned with the presence or absence of species, and community level observations assess the composition and organisation of communities (Begon, Townsend and Harper 2006). Ultimately, these observations are taken to assess changes or fluctuations in species composition or relative abundance, and usually to assess the effects of human influence on the environment (Southwood and Henderson 2009). This section of the review focuses primarily on census techniques for estimating terrestrial species at the individual and population levels. These techniques typically aim to estimate species richness (number of different species) and relative species abundance (commonness or rarity of species relative to other species) – measures widely used to describe biodiversity (Magurran 2009). These are also measures which are increasingly being derived using information technology and sensing technology (Southwood and Henderson 2009).

2.4.1 SURVEY TYPES

Many methods exist to estimate species richness and relative abundance. Point count methods are commonly used to estimate avian populations (Bibby et al. 2000). These involve observers recording the occurrence of species and distance to individuals in a defined area for a fixed period of time, and are commonly used to estimate both species richness and abundance (Bibby et al. 2000; Southwood and Henderson 2009). Similarly, transect methods involve observers walking a fixed length transect and observing all species within a defined distance of the centre line (Southwood and Henderson 2009). Other area search methods which involve searching an unmarked fixed area (typically 2ha as used by Birdlife Australia) are common for estimating relative abundance (Loyn 1985). Capture/recapture is also a common method for estimating both species richness and relative abundance (Southwood and Henderson 2009). Capture/recapture methods involve capturing individuals (using mist nets, pitfall traps, Elliot traps etc), identifying and marking them before releasing them again. The subsequent proportion of recaptured marked individuals and captured unmarked individuals provides both an indication of species richness and relative abundance (Krebs 1999).

Point count, transect, area search and capture/recapture methods have many known biases, including the assumptions that all species have equal detectability, likelihood of capture and that observers have similar skill levels. These factors have been demonstrated to be significant sources of bias in both point count and capture/recapture methods (Boulinier et al. 1998; Sauer, Peterjohn and Link 1994; Alldredge et al. 2008). In addition, it is often assumed that the population is closed (i.e. no birth, death, emigration or immigration), which (depending on the species assemblages) may render species richness and relative abundance estimates invalid (Kendall 1999).

Significantly, the skill of observers has been demonstrated to play an important role in the accuracy of traditional survey methods, and aural identification can typically constitute over 50% and up to 94% of avian species observations depending on the habitat (Dobkin and Rich 1998; Sauer, Peterjohn and Link 1994; Dejong and Emlen 1985). In avian surveys, factors such as observer experience, choice of census method, effort and speed, levels of ambient noise, background bird calls, habitat and season may all have an effect on the accuracy of the survey (Bibby et al. 2000; Simons et al. 2007). Other factors such as the singing rate, distance and intra-observer differences may also significantly affect the results of avian point counts for songbirds (Alldredge, Simons and Pollock 2007b; Simons et al. 2009). The mere presence of observers in the field has also been demonstrated to have an effect on species richness (Gutzwiller and Marcum 1997; Riffell and Riffell 2002).

Finally, traditional species surveys require experienced observers whose skills are in demand, as greater importance is placed on collecting field data for analysis (Hobson et al. 2002). The lack of appropriately trained and skilled observers, the recognition that observer bias may negatively impact survey results and the ability of acoustic sensors to scale observations, has increased interest in acoustic sensor technology for field surveys.

2.4.2 SAMPLING

Due to the fact that it is often impossible to take a complete census of all individuals, the above survey methods for estimating either species richness, species composition or relative abundance rely on sampling. Sampling by definition uses a subset of the population to infer characteristics of the entire population, and therefore defining sampling effort is critical (Magurran 2009).

A number of techniques have been proposed to estimate species richness from samples (Southwood and Henderson 2009; Magurran 2009). Species accumulation curves plot the number of unique species detected against the sampling effort and this can be used to extrapolate species richness (Magurran 2009). In addition a number of parametric and non-parametric methods have been developed to derive the predicted increase in species richness based on increases in sampling, and to estimate species richness based on the number of observations of ‘rare’ species in relation to ‘abundant’ species (Magurran 2009). In all cases, there has been no definitive approach identified which can be used exclusively for any situation (Southwood and Henderson 2009).

2.5 SENSORS

Sensors are being increasingly utilised in ecological studies to allow scientists to extend the reach and scope of traditional research (Collins et al. 2006; Hu et al. 2009; Ellis et al. 2010; Ellis et al. 2011). Projects such as the Long Term Ecological Research network (LTER) and National Ecological Observatory Network (NEON) have been utilising sensors for some time to collect environmental data at large spatial and temporal scales to monitor the effects of humans and climate change on the environment (Hamilton et al. 2007). Sensors are unobtrusive, allow for continuous, intensive and extensive sampling and allow ecologists to respond in near real-time to changes or fluctuations in the environment (Frommolt, Tauchert and Koch 2008). They also maintain a permanent record of observations and allow for accurate comparisons over extended temporal and spatial scales (Porter et al. 2005; Suri, Iyengar and Cho 2006).

2.5.1 SENSOR TECHNOLOGY

Sensor technology has advanced rapidly over recent years. The cost and availability of small and powerful, network-enabled electronic devices such as the Arduino (http://www.arduino.cc/) and Raspberry Pi (www.raspberrypi.org), has seen an increase in the application of sensor technology to environmental monitoring (Szewczyk et al. 2004; Wark et al. 2007). Many of these devices are modular and have the capability to monitor many aspects of the environment and communicate wirelessly. Not only have dedicated sensor platforms come into widespread use, commercially available electronic devices are being utilised as informal sensor devices. For example simple MP3 recording devices and smartphones can be utilised as acoustic sensors when enclosed in a water resistant container and powered by an external power source (Mason et al. 2008).

Dedicated acoustic sensor platforms are also becoming more widely available. Cane toad monitoring devices have been used extensively in the Northern Territory since 1996 (Hu et al. 2009) and the Wildlife Acoustics Song Meter SM2 (Wildlife Acoustics Inc.) device is capable of monitoring a range of terrestrial species including bats, with the addition of an optional bat detection daughter-board. Dedicated bat detection devices such as Anabat (Titley Scientific Inc., Missouri, USA) are also in widespread use (O'Farrell, Miller and Gannon 1999). Finally, the Cornell Lab of Ornithology has been involved in the development, testing and use of a wide range of recording devices and analysis software for many years (http://www.birds.cornell.edu/page.aspx?pid=1665#techHighlights=1).

2.5.2 CAMERAS

Visual sensors (cameras) have the capability to capture information not available to acoustic sensors, including detecting species with little or no vocalisations and monitoring specific areas for activity (Silveira, Jacomo and Diniz 2003). Cameras are being used increasingly to monitor a wide range of species where identification of individual species is important or in remote and extreme environments (McCarthy et al. 2010; Martinez, Hart and Ong 2004; Stein, Fuller and Marker 2008). While very effective for monitoring small areas and obtaining clear and unambiguous evidence of the presence of specific species (and even individuals), in the context of field surveys, the lack of range, directional nature and expense of visual sensors renders their use restrictive and targeted in nature.

Vegetation assessment is an important component of biodiversity monitoring, and preliminary assessments are often undertaken with the use of remote sensing (Cohen and Goward 2004). Remote sensing allows scientists to extend their ability to monitor vegetation condition and observe the effects of climate change on different vegetation types across large areas, using both passive (e.g. infrared) and active (e.g. radar) methods (Roerink et al. 2003).

2.5.3 ENVIRONMENTAL SENSORS

Environmental sensors have also come into widespread use for a multitude of monitoring purposes. From airborne meteorological sensors to water and air quality sensors, environmental sensors have become a critical environmental monitoring component enabling high resolution and continuous monitoring of the physical environment (Ho et al. 2005; Lieberzeit and Dickert 2007). Environmental sensors can provide a continuous, *in situ* monitoring capability however to maintain accuracy many of these sensors require regular (in some cases weekly) calibration (Ho et al. 2005).

2.5.4 ACOUSTIC SENSORS

Acoustic sensors have numerous roles in ecology, conservation biology and wildlife management research. These include:

- Localisation: detecting specific vocalisations/acoustic events and determining the spatial origin of the call (Ali et al. 2009; Freitag and Tyack 1993)
- Measures of species abundance: detecting and measuring the size populations of different species in a given area (Thompson, Schwager and Payne 2009; Riede 1993; Bart 2005)
- Measures of species richness: detecting and measuring the number of different species in a given area (Celis-Murillo, Deppe and Allen 2009; Penman, Lemckert and Mahony 2005; Haselmayer and Quinn 2000); and

- Measures of ecosystem health: generalised or relative measures of ecosystem health (Sueur et al. 2008; Gage, Napoletano and Cooper 2001)

Acoustic sensors have been used in both marine and terrestrial environments. Marine acoustic sensors are used extensively to monitor many aquatic species, the effects of climate change and the impact of human activities on natural aquatic systems (Akyildiz, Pompili and Melodia 2005b). They provide scientists with a rapid assessment capability, archival data for historical comparison and access to remote or extreme environments (such as the Polar Regions), where traditional survey and monitoring is limited to short durations in favourable conditions (Mellinger et al. 2007; Moore et al. 2006). Traditional surveys can also have the effect of disrupting the natural behaviour of species being observed. Once deployed, acoustic sensors do not interfere with the natural behaviour of species (Bridges and Dorcas 2000).

In the terrestrial environment, acoustic sensors have great potential to improve the scale and scope of traditional ecological survey methods by allowing ecologists to be virtually in many places at the same time, over longer periods (Parker 1991; Brandes 2008). This capability to remotely increase the sampling effort can improve the ability of ecologists to monitor small changes in biodiversity. Noss (1990), suggests a hierarchical characterisation of biodiversity, requiring tools to monitor and inventory species at the regional landscape, community-ecosystem, population-species, and genetic levels. Acoustic sensors have the ability to provide large-scale, high resolution monitoring at the levels of community-ecosystem and population-species, where the focus is on abundance, frequency, richness and evenness.

Rapid improvements in technology are quickly delivering the devices required to make large-scale, cost-effective acoustic sensing feasible (Liqian et al. 2007; Luo et al. 2009). Modern electronic recording devices are lightweight, robust, low cost and capable of storing large amounts of data over long periods of time. Deployment of sensors in the field does not require the same level of training or skill as traditional surveys, and large numbers of sensors can be deployed quickly and effectively in a short period of time (Brandes 2008).

Acoustic sensors have the potential to deliver far more information to ecologists, more rapidly than traditional methods (Parker 1991; Acevedo and Villanueva-Rivera 2006). There are limitations to the use of acoustic sensor technology however. Most obviously, acoustic sensors are typically confined to species with audible and predictable vocalisations such as amphibian, insect and avian species (with some notable exceptions, for example bat detection (Milne et al. 2004)). Analysis of acoustic sensor data is also complicated due to variations in species vocalisations and extraneous noise such as wind and rain, which can interfere with detection (Depraetere et al. 2011). Traditional surveys tend to avoid surveying in rain or wind to minimise variability in detectability across surveys.

While the restriction of acoustic sensors to vocalising species is clearly a limitation, studies have recognised the importance of amphibian and avian species (species with regular and predictable vocalisations) as general indicators of ecosystem health (Carignan and Villard 2002a). It is also widely recognised that identifying vocalisations is an effective way to survey avian and amphibian species (Riede 1993; Corn, Muths and Iko 2000; Penman, Lemckert and Mahony 2005; Swiston and Mennill 2009).

2.6 APPLICATIONS FOR ACOUSTIC SENSING IN BIODIVERSITY MONITORING

2.6.1 LOCALISATION

Localisation is the process of identifying the position or origin of an individual from its detected sound. Localisation has many practical benefits for monitoring biodiversity, including the ability to potentially improve the capability of monitoring abundance by isolating individuals from their vocalisations (Dawson and Efford 2009). Acoustic sensors have been used successfully to monitor several bird species in complex environments (e.g. humid, tropical rainforest environments) (Mennill et al. 2006; Collier, Kirschel and Taylor 2010). Much research continues into localisation, but the core requirement of highly time-synchronised arrays of devices limits the capabilities of many commodity devices. GPS time synchronisation is a commonly-used approach, however the lack of penetration of GPS signal (in underwater or dense canopy environments) and power consumption requirements of GPS-enabled devices continues to be a constraint (Patwari et al. 2005; Xiaohong and Yu-Hen 2005; Akyildiz, Pompili and Melodia 2005a).

2.6.2 SPECIES ABUNDANCE

Primarily due to the unique properties of acoustic energy in the marine environment (e.g. greater speed of sound and propagation properties), acoustic methods have been used extensively to study abundance of marine species (Barlow and Taylor 2005). Acoustic surveys of the abundance of some pelagic species have been undertaken regularly since 1972. One such case is the capelin (*Mallotus villosus*) which has been surveyed annually for nearly 40 years using this method to determine detailed abundance information (Toresen, Gjøsæter and de Barros 1998). Many other marine species are also regularly surveyed for abundance using acoustic methods, including sperm whales (*Physeter macrocephalus*) (Barlow and Taylor 2005) and herring (*Clupea harengus*) (Barlow and Taylor 2005; Huse and Korneliussen 2000). In the terrestrial environment, abundance indicators using acoustic sensors have been successfully developed for species such as the African Elephant (*Loxodonta africana cyclotis*) using distributed networks of acoustic sensors where species detection rates have already been established (Payne, Thompson and Kramer 2003; Thompson, Schwager and Payne 2009; Thompson et al. 2010).

2.6.3 SPECIES RICHNESS AND SINGLE SPECIES BEHAVIOURAL STUDIES

Acoustic sensors can overcome some of the limitations associated with traditional survey methods when measuring species richness (Celis-Murillo, Deppe and Allen 2009; Haselmayer and Quinn 2000; Bridges and Dorcas 2000). In addition, the ability to replay recordings to correctly identify species in areas of high species richness is a considerable advantage when using acoustic sensors (Haselmayer and Quinn 2000; Rempel et al. 2005).

Acoustic sensors have been used widely to monitor individual, rare, cryptic and even invasive species. In 1996, Grigg et al. (2006) monitored the pre and post effect of cane toads (*Bufo marinus*) on native frog species in the Northern Territory, Australia. Acoustic sensors have also been used to study vocalisations of koala (*Phascolarctos cinereus*) populations to understand calling behaviour (Ellis et al. 2011; Ellis et al. 2010), and to study the distribution of populations of the cryptic Lewin’s Rail (*Lewinia pectoralis*) in areas of South East Queensland at risk of habitat loss (Mason et al. 2008). However, contradictory results have been found when studies have been conducted monitoring species with rare vocalisations or temporal variation in calling behaviour (i.e. variable calling behaviour depending on the time of the year). Haselmayer and Quinn (2000) found traditional point count surveys to be more effective at monitoring avian species with rare vocalisations, while Bridges and Dorcas

(2000) found automated recording systems (acoustic sensors) more effective for monitoring anuran species with temporal variation in calling activity. Acoustic sensors have also been effective for monitoring koala populations which demonstrate temporal variation in calling (Ellis et al. 2010).

By virtue of their status, monitoring rare, elusive or secretive species presents some significant challenges to traditional biodiversity monitoring techniques. Rare species, species who have small numbers spread over a wide range or species that exhibit elusive or secretive behaviour may be more readily detected when techniques for increasing the probability of detection are found, or when the sampling effort is spread more effectively over the study area (Thompson 2004). Traditional sampling techniques suffer from their relative inability to scale to meet this requirement when monitoring rare or elusive species, compared to sensor-based methods, which allow ecologists to deploy sensors over wide areas, at appropriate resolutions, for extended periods of time (Porter et al. 2005). Additionally, interpreter variability has been demonstrated to increase for rare or uncommon species (Rempel et al. 2005). Acoustic sensor data collected in the field may be replayed repeatedly and validated in the laboratory to reduce interpreter variability when testing for the presence of rare species (Swiston and Mennill 2009).

2.6.4 ACOUSTIC SENSORS VS TRADITIONAL SURVEY METHODS

While the use of acoustic sensors in biodiversity and ecological research is not new, comparisons of sensor-based and traditional surveys have yielded contradictory results in several studies (Hobson et al. 2002; Rempel et al. 2005). Determining the accuracy and effectiveness (in both time and resources) of acoustic sensors compared to manual survey methods is crucial to understanding the appropriate application of this technology.

A number of measures have been applied to determine the effectiveness of acoustic sensors compared to traditional surveys. These include direct and indirect comparisons

Direct comparison methods provide an assessment of the performance of acoustic sensors relative to traditional survey methods. These methods involve conducting traditional surveys while recording at the same site over the same period of time (Celis-Murillo, Deppe and Allen 2009; Haselmayer and Quinn 2000; Penman, Lemckert and Mahony 2005). Acoustic data are subsequently analysed in the laboratory. The results of the analysis determine the comparative accuracy of either method, however different environments and conditions have been demonstrated to have an effect on the results. For example, Haselmayer and Quinn (2000) demonstrated that acoustic sensing yielded better results in areas with high species richness, due to the ability of observers conducting analysis to replay recordings and identify individual species amongst vocalisations of other species. In 2012, Campbell (2012) found that by analysing recordings once without spectrograms, listeners detected about the same number of species as point counts, but less than the total number of species actually on the recordings. They also found that recordings had the potential to improve detection of species and supplement point counts. Similarly, in 2009 Celis-Murillo et al. (Celis-Murillo, Deppe and Allen 2009) demonstrated that analysis of direct comparison acoustic sensor data required greater time and effort, however the analysis resulted in increased and faster rate-of-detection of species.

Conversely, when recordings conducted concurrently with traditional avian surveys were analysed, Hutto and Stutzman (2009) found that acoustic sensor data failed to detect a significant proportion of species that were detected in traditional surveys due to the effect of observer cues (visual etc) and lack of sensitivity in recording equipment.

Indirect methods compare different field survey techniques or make comparisons that do not directly correspond to traditional surveys (temporally or spatially). Acevedo and Villanueva-Rivera (Acevedo and Villanueva-Rivera 2006) compared manual point count surveys to acoustic sensor data collected from the same sites, using a seven minute sampling regime over 24 hours. The results indicated that the acoustic sensor data provided greater accuracy and a higher number of species detected, a permanent record of species detected and minimal disturbance to wildlife. There was however greater effort involved in analysing data, and difficulty in providing density estimates.

Thompson et al (2009) compared estimates of elephant abundance derived from dung analysis with elephant calls analysed from acoustic sensor data, and found that acoustic sensors were a valuable and effective tool for estimating elephant abundance (Hutto and Stutzman 2009).

2.7 SENSOR DATA ANALYSIS

2.7.1 MANUAL ANALYSIS

While acoustic sensors have the advantage of being able to remain remotely deployed across large areas for extended periods of time monitoring the sounds of the environment, manual analysis of large volumes of sensor data can be time consuming, costly and complicated (Swiston and Mennill 2009; Rempel et al. 2005).

Manual sensor data analysis typically involves the playback of recorded data for analysis by humans to identify individual species vocalising in the recordings. This can be augmented by the use of tools to visualise the audio, in the form of spectrograms, and by providing ‘reference calls’ which can be used to assist in identification of species (Wimmer et al. 2010).

While automated methods for scanning large volumes of data are maturing rapidly, manual methods have been found to be more accurate at identifying conspecifics, or species with rare vocalisations.

Manual analysis can be very accurate if experienced and skilled observers are involved. These observers can often overcome issues associated with regional variation in species vocalisation and complex acoustic environments (wind, rain, dawn chorus etc) (Swiston and Mennill 2009). Manual analysis can, however, be time consuming and expensive with a lack of trained and skilled resources. Ultimately, manual analysis fails to scale over the spatial and temporal frames required to effectively monitor loss of biodiversity (Rempel et al. 2005).

2.7.2 AUTOMATED ANALYSIS

Automated analysis involves the use of software to scan through acoustic data and either identify individual species, or generate acoustic indices. There is a substantial body of work associated with the automated analysis of acoustic sensor data (Acevedo and Villanueva-Rivera 2006; Corn, Muths and Iko 2000; Haselmayer and Quinn 2000; Brandes 2008; Mason et al. 2008; Collins et al. 2006; Towsey et al. 2014; Bardeli et al. 2010). These analyses fall broadly into two categories:

- Single species surveys: analysing acoustic recordings for vocalisation of a single species (many species have multiple vocalisations);
- Species richness surveys: analysing acoustic recordings and identifying all taxa to generate a measure of species richness.

These analysis types differ subtly in terms of the analysis methods and effort required to process large data sets. Single species analysis may sometimes be undertaken manually due to the smaller set of potential vocalisations the observer is required to identify - although, even with single species identification, this method does not scale effectively.

Species richness surveys require much greater time and effort in terms of analysing and annotating acoustic data, and ultimately manual analysis fails to scale effectively (Haselmayer and Quinn 2000). To take full advantage of the potential of acoustic sensors, the enormous amounts of data which accompany large scale deployments of sensors must be able to be analysed efficiently and effectively.

Perhaps due to the importance of birds as indicator species of environmental health, there is a significant amount of literature relating to the automated detection of bird vocalisations (Acevedo et al. 2009; Brandes 2008; Cai, Ee, Pham, et al. 2007; Chen and Maher 2006; Juang and Chen 2007; Kwan et al. 2004; McIlraith and Card 1997; Somervuo, Harma and Fagerlund 2006; Anderson, Dave and Margoliash 1996; Kasten, McKinley and Gage 2007; Bardeli et al. 2010; Wimmer et al. 2010; Sueur et al. 2008). These analysis methods can be broadly categorised into two types:

1. Single species detectors – analysis tools designed to detect specific species;
2. Bioacoustic Indices – analysis tools which generate indices which can act as surrogates for levels of species richness.

Single species detection methods focus on detecting specific species, generally through the application of modified automated speech recognition techniques. Several automated species recognition tools have been developed which produce varied detection results (Harma 2003; Somervuo, Harma and Fagerlund 2006; Bardeli et al. 2010; Agranat 2009; Brandes 2008; Kwan et al. 2004; Frommolt and Tauchert 2014).

Some approaches, focusing on limited numbers of migrating nocturnal species have exhibited promising results by extracting sets of specific features to classify calls (Schrama et al. 2008; Farnsworth, Gauthreaux and Blaricom 2004).

While some of these approaches have been successful for individual species, the problems of regional variation (Mundinger 1982) and noise (Baker and Logue 2003; Brandes 2008) mean that individual species recognition remains a challenging task.

Bioacoustic indices infer species richness or general environmental health through the generation of an index based on the features of the soundscape. These indices usually forego the complex task of individual species identification and instead generate a relative measure of species richness through similarity or dissimilarity indices (Depraetere et al. 2011; Sueur et al. 2008; Pieretti, Farina and Morri 2011).

Relative ecological health assessment methods, based on reference conditions are used widely in conservation biology as a means to compare similar ecosystems on a common scale (Parkes, Newell and Cheal 2003; Boer and Puigdefábregas 2003; Nielsen et al. 2007). The application of relative health assessment indices to acoustic sensing is an interesting and potentially important area of research. The development and implementation of relative acoustic indices, based on, and combined with relative vegetation assessment indices may provide an effective surrogate for large-scale manual environmental assessment activities.

Bioacoustic indices may offer an alternative method to processing large volumes of data. By selecting appropriate 'indicators' to provide an assessment of ecological health, the analysis process is potentially simplified. The challenge in applying relative measures to the assessment of ecological health using acoustic sensors is the selection of appropriate vocalisation indicators (Gage, Napoletano and Cooper 2001; Depraetere et al. 2011). Indicator selection remains highly contentious (Carignan and Villard

2002b), however this is a promising area of acoustic sensor research for biodiversity monitoring.

2.7.3 PARTICIPATORY ANALYSIS/CITIZEN SCIENCE

Participatory data analysis (citizen science) is another promising alternative approach for analysing large volumes of sensor data. Citizen science involves the use of individual volunteers and volunteer organisations to collect and analyse data over large spatial and temporal scales (Silvertown 2009; Greenwood 2007). These projects run the gamut of scientific investigations from identification of galaxy types (Galaxy Zoo), to long term monitoring of bird (eBird) and frog populations (iNaturalist Global Amphibian Blitz). On the surface, citizen science appears to be a win-win situation with large-scale scientific data collection and analysis being conducted by enthusiastic volunteers who are willing and able to be involved. There are a number of significant challenges that need to be overcome however with citizen science projects (Cooper et al. 2009) and critical success factors include:

- Training and development of participants;
- Development and testing of protocols for data collection and analysis;
- Develop and testing of tools, technology and education support materials to support participants;
- Analysis, visualisation, presentation and dissemination of results.

Galaxy Zoo (www.galaxyzoo.org) is a classic example of a successful citizen science project, with over 250,000 active users helping to manually classify galaxy types according to their shapes. Galaxy Zoo provides users with initial identification training and testing and then provides a web-based interface for classifying galaxies.

Tools and technology are used to train participants, control the identification process, determine final galaxy classification and provide visualisation and presentation tools.

eBird (www.ebird.com) is another excellent example whereby amateur bird watchers report bird observations via the eBird website. Species are then filtered according to geographic and temporal details, and a two-stage data verification process is undertaken to ensure the accuracy of data (Sullivan et al. 2009).

The rise of internet-enabled citizen science projects has led to masses of information being collected and analysed across numerous fields. While these projects are providing valuable information for their specific research topics, opportunities also exist to integrate and combine the many citizen science projects to develop a more holistic understanding of changes occurring in the environment (Havlik et al. 2011).

2.8 SUMMARY AND IMPLICATIONS

In this chapter I have discussed the current state of knowledge relating to acoustic sensing in ecology and the challenges which exist in adopting acoustic sensor technology to conduct large scale biodiversity monitoring.

To date, comparisons of acoustic sensor surveys and traditional surveys have yielded conflicting results. This may reflect the complex nature of environmental sensing (and the underlying environmental systems), or the nature of the comparisons which have been performed. This leaves some doubt as to the effectiveness of acoustic sensor surveys both in terms of detection of vocal species and of cost.

A large body of research exists on automated techniques for analysing acoustic sensor data, however little existing research has focussed on reducing the manual analysis burden. In addition, automated techniques for large numbers of bird or frog species are yet to be realised. In the absence of these techniques, efficient manual methods are required to analyse acoustic sensor data in the near-term. This is a key aim of this study.

Chapter 3: Analysing Environmental Acoustic Data through Collaboration and Automation

Title: Analysing Environmental Acoustic Data through Collaboration and Automation

Authors: Jason Wimmer[a], Michael Towsey[a], Birgit Planitz[a], Ian Williamson[a] and Paul Roe[a]

Affiliations: [a]Faculty of Science and Technology, Gardens Point Campus, Queensland University of Technology, Brisbane, Queensland, 4000, Australia

Email: (j.wimmer, m.towsey, b.planitz, i.williamson, p.roe)@qut.edu.au

Corresponding Author: Jason Wimmer

Corresponding Author Address: QUT, 126 Margaret St, Brisbane, Queensland, 4000, Australia. Ph: +61 7 3138 2000 Fax: +61 7 3138 9390

3.1 STATEMENT OF CONTRIBUTION OF CO-AUTHORS

The authors listed below have certified* that:

1. they meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the Australasian Research Online database consistent with any limitations set by publisher requirements.

In the case of this chapter: **Analysing Environmental Acoustic Data through Collaboration and Automation.**

Publication title and date of publication or status: Analysing Environmental Acoustic Data through Collaboration and Automation. (Published in the *Future Generations Computer Systems* Journal, 2013)

Contributor	Statement of Contribution*
Name: Jason Wimmer	Wrote manuscript, workbench system design, experimental design, analysis.
Signature:	
Date: 11/6/2013	
Co-author: Dr. M. Towsey	Automated analysis design. Manuscript review.
Co-author: Dr. B. Planitz	Automated analysis design. Manuscript review.
Co-author: Dr. I. Williamson	Experimental design. Manuscript review.
Co-author Prof. P. Roe	Experimental design. Manuscript review.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all Co-authors confirming their certifying authorship.

Professor Paul Roe		11/6/2013
Name	Signature	Date

3.2 ABSTRACT

Monitoring environmental health is becoming increasingly important as human activity and climate change place greater pressure on global biodiversity. Acoustic sensors provide the ability to collect data passively, objectively and continuously across large areas for extended periods of time. While these factors make acoustic sensors attractive as autonomous data collectors, there are significant issues associated with large-scale data manipulation and analysis. We present our current research into techniques for analysing large volumes of acoustic data efficiently. We provide an overview of a novel online acoustic environmental workbench and discuss a number of approaches to scaling analysis of acoustic data; online collaboration, manual, automatic and human-in-the loop analysis.

Keywords: sensors; acoustic sensing; data analysis; biodiversity

3.3 INTRODUCTION

Monitoring environmental health is becoming increasingly important as human activity and climate change place greater pressures on global biodiversity. Protecting biodiversity and developing effective conservation strategies requires a thorough understanding of natural systems, the relationship between organisms and environment and the effects of climate change (Stenseth et al. 2002). This understanding is traditionally derived from field observations using manual methods such as fauna and vegetation surveys (Sutherland 2006). While manual fauna survey methods can provide an accurate measure of species richness they are resource intensive and therefore limited in their ability to provide the large scale spatiotemporal observations required to monitor the effects of environmental change (Balmford and Gaston 1999; Penman, Lemckert and Mahony 2005). In this context there is a need to provide scientists with technology and tools to rapidly collect and analyse environmental data on a large scale (Nagy et al. 2009; Mason et al. 2008).

Acoustic sensors have the potential to increase the scale of ecological research by providing ecologists with acoustic environmental 'observations' from numerous sites over extended periods of time. This delivers far more information, more rapidly than traditional manual methods (Parker 1991; Acevedo and Villanueva-Rivera 2006). There are limitations to the use of acoustic sensor technology however. Most obviously, acoustic sensors are typically confined to species with audible and predictable vocalisations such as some amphibian species, insect and avian species (with some notable exceptions, for example bat species (Milne et al. 2004)). Acoustic sensors are subject to extraneous noise such as wind and rain (Depraetere et al. 2011). They also produce large volumes of complex data which must be analysed to derive detailed species information. It is the analysis of large volumes of acoustic sensor data which this research seeks to address, through the use of online collaboration and automation tools.

Analysis of acoustic sensor data is a complex task. Acoustic sensors generate large quantities of raw acoustic data which must be stored, analysed and summarised. For example, traditional avian point counts may involve ecologists making ten minute observations at dawn, noon and dusk over a period of five days at a single site. At 2.5 hours, the total observation time for a short term manual survey is a fraction of the potential 120 hours of a continuous automated acoustic sensor recording over the same period of time, at the same site. At long term scales, even scheduled recordings (e.g. five minute recordings every 30 minutes) provide ecologists with significantly more data than manually collected long term surveys. Detecting specific species in large volumes of acoustic data is a daunting task given factors such as varying levels of background noise, variation in species vocalisations and overlapping vocalisations. Because of this complexity, a 'one size fits all' automated approach to analysis of environmental acoustic sensor data is currently infeasible.

This paper describes a novel online Acoustic Environmental Workbench which addresses some of the challenges of manipulating and analysing large volumes of acoustic data through collaboration and human-in-the-loop semi-automation. The workbench is a web-based application which includes data upload, storage, management, playback, analysis and annotation tools all of which enable users to work collaboratively to scale acoustic analysis tasks.

In section 2 of this paper we outline the basic architecture of our system. In section 3 we describe our analysis techniques. Section 4 describes its implementation and section 6 discusses the results of our implementation and future work.

3.4 ONLINE ENVIRONMENTAL WORKBENCH

Part of our ongoing research has been to compare acoustic sensors with traditional manual fauna survey methods. This required us to work closely with ecologists to manually analyse large volumes of data (over 400 hours) to identify vocal species for comparison with tradition field survey results. Performing this analysis identified the need to provide ecologists with a framework which facilitates close interaction with acoustic data, and the ability to work collaboratively with other scientists. The result of this collaboration is an environmental acoustic workbench for the analysis of acoustic sensor data. The workbench is a collection of online tools which allow users to visualise and hear recordings to identify individual species and record their analysis results. The following is the core workbench functionality which has been implemented to achieve this:

- Acoustic data upload and storage.
- Acoustic data organisation and structure.
- Recording playback and visualisation.
- Recording analysis and annotation.
- Discussion and review facility.

We describe these core functions in turn.

3.4.1 ACOUSTIC DATA UPLOAD AND STORAGE

Acoustic recording devices are widespread and capable of recording in many different formats (e.g. MP3, WAV etc.). The acoustic workbench provides web-based access to recordings collected from a variety of sources including, but not limited to, networked sensors and standalone data loggers such as commercially available MP3 recorders. Acoustic data in either MP3 or WAV format may be uploaded from any device capable of generating files in these formats.

All acoustic sensor data is uploaded to a centralised, online repository. This centralised approach provides a number of advantages:

- Online access and collaboration: multiple users have access to the same data and same analysis tools, enabling users to collaborate on analysis tasks.
- Data retention: all raw data is retained to allow future analysis as techniques improve, to enable long term comparisons of historical data and to verify analyses.
- Data security and backup: all data is stored securely with regular backups and recovery facilities to prevent data loss.
- Data provenance and context retention (metadata): key experimental design details are retained to ensure accurate comparisons between datasets.

In this case however, there are a number of drawbacks to data centralisation. Most notably, accessing large volumes of acoustic data via the internet requires relatively high speed internet access and sufficient download quota. We have found that many of our users do not have access to high speed internet. We have therefore implemented a distributed system whereby raw acoustic data is installed to user's machines and accessed by our Silverlight audio player utilising Isolated Storage. Species annotation data is still stored in our centralised database, however data transfer is reduced by a factor of four.

3.4.2 ACOUSTIC DATA ORGANISATION AND STRUCTURE

The acoustic workbench allows users to browse and manipulate data in a logical, structured manner. Acoustic data are structured on a hierarchical model of Projects, Sites and Recordings. Projects are the top level. A project can represent any logical collection of experiments or studies and can be shared with other users. Each project consists of a collection of Sites. Sites are physical locations (identified by GPS coordinates), with sensors deployed at each site. Sensors are physical recording devices whose details are stored to ensure retention of experimental design details. Recordings are the raw acoustic data collected from sensor devices in the field and uploaded to the website. Figure 1 illustrates the workbench data organisation and structure.

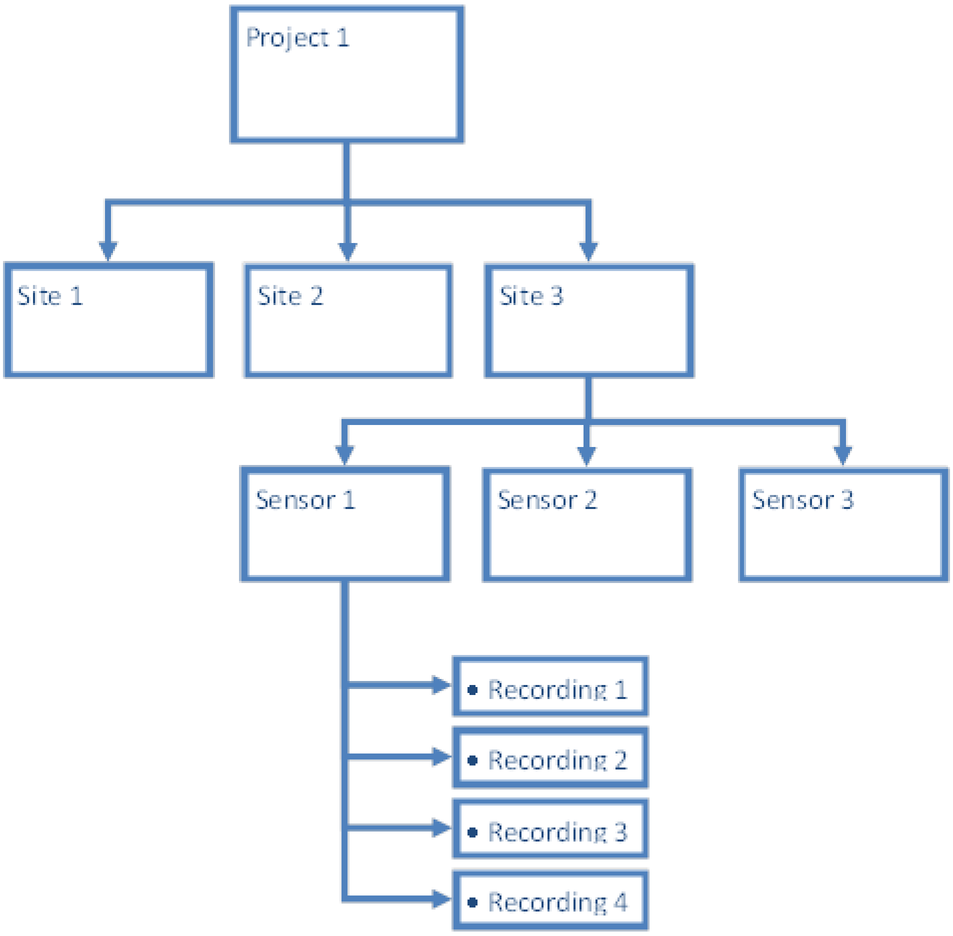

Figure 1. Workbench data organisation and structure.

Users are granted role-based permissions on a project by project basis. These control the level of access to data and analysis tasks. Access levels include:

- None (default): user has no access to any data or any function in the project.

- Read Only: user can view/play acoustic data, can annotate spectra, but cannot upload data and cannot perform analysis tasks.
- Full: user can view/play acoustic data, can annotate spectra, can upload data and can perform analysis tasks.

These access levels allow collaborative tagging, review and discussions of tagging as required for the semi-automated analyses of data.

3.4.3 RECORDING PLAYBACK AND VISUALISATION

Recordings can be played online using a custom-developed Microsoft Silverlight audio playback tool developed for the workbench. The playback tool plays audio and displays a spectrogram which allows the user to visualise and hear audio simultaneously. Long recordings are split into six-minute segments which are loaded dynamically as the player reaches the end of each segment. For example, a continuous 24 hour recording is divided into 240 six-minute segments. This allows the user to start listening without waiting for the entire 24 hour recording to download. A six minute segment length has been selected to reduce to time taken to download and access each segment, however providing a configurable segment size would improve the flexibility of the system. Figure 2 shows a screenshot of the workbench playback and visualisation tool with several annotated vocalisations.

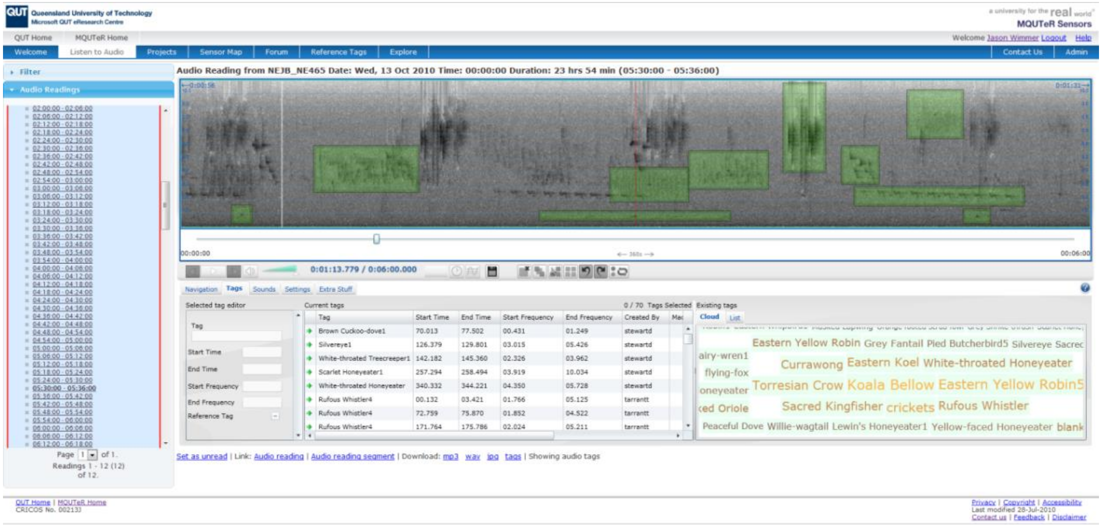

Figure 2. Workbench playback tool with annotated species vocalisations.

Users have sequential or random access to the contents of a recording using the player's navigation tools. This provides the ability to scan recordings rapidly or to locate specific times of interest, for example dawn and dusk. In addition, several recordings may be selected at once to create a 'playlist' of audio to play or to assign to analysis tasks. These playlists are generated using a filtering tool, which provides the capability to search recordings based on time and date, project, site and on tags which have been annotated in any recording.

3.4.4 RECORDING ANALYSIS AND ANNOTATION

One of the key goals of this research is to develop automated and collaborative analysis tools to scan acoustic data to identify distinct species. The purpose of the analysis is to determine ecological measures, such as species richness – a census of species with vocalisations in the recordings. Long term recordings to monitor species richness or changes in species composition can generate large volumes of data. As an indication of the volume of data produced by an acoustic sensor, recording in MP3 format at 44.1 kHz, 128 kbps for 24 hours generates 1.3GB of data. Our repository currently holds over 1TB of acoustic data.

To help ecologists to deal with these volumes, the workbench provides a flexible approach to data analysis. Users can work alone or in collaboration. They can annotate recordings manually with the assistance of call identification libraries, run a number of fully automated tools to find specific species, or interact with the system in a semi-automated fashion to reduce repetitive annotation tasks, while leveraging complex manual identification tasks. These tools combine to allow large volumes of data to be processed efficiently by a range of users. The goal is to allow users with a variety of species identification skills to contribute to the analysis of acoustic data. Analysis techniques and tools are discussed further in section 3.

Annotation of audio recordings involves users playing recordings online using the workbench playback tool and identifying species vocalisations both aurally and visually on a spectrogram. Once a vocalisation is identified, its visual component is annotated on the spectrogram by electronically 'drawing' a marquee around the call using a tagging tool. The upper and lower frequency bands and duration of call are captured in this process. To associate the marquee annotation on the spectrogram with a specific species, we have adopted a collaborative tagging approach as opposed to a controlled taxonomy. Collaborative tagging allows users to associate tags with content (in this case species names with audio data), and is particularly useful for sites with large amounts of content which require the contribution of many users to classify (Golder and Huberman 2006). The workbench allows users to tag acoustic content, and browse content tagged by others while a 'tag cloud' provides a visual representation of popular tags (both for tagging and searching).

3.4.5 DISCUSSION AND REVIEW FACILITY

The results of manual, automatic and human in-the-loop species analysis are necessarily subject to review and discussion. In some cases automated analyses or even expert users may incorrectly identify calls (false positives). We have found that even amongst expert listeners there may also be debate about particular calls due to the extensive repertoire of some species, regional variation or presence of environmental noise masking calls. These issues are managed in the system through two facilities:

- Tag (analysis) verification, and;
- Discussion forums where tagged calls may be discussed by users.

Tag verification enables the checking of analyses – automated, semi-automated and manual. Automated analyses provide a score (either in dB units or normalized in the interval [0,1]) which can be used to rank tagged calls. This score provides a confidence rating which indicates the likelihood that the recording segment contains a vocalisation of the target species. In a typical analysis, there are too many tagged calls for a single user to check manually. For example unique species calls tagged at one minute intervals can generate over 6000 tags per day. Hence a suitable score threshold must be found by the method of 'bracketing', that is, searching the ranked list at intervals for a threshold which optimizes the false positive, false negative trade-off. All tags having above threshold score are accepted. This method has the advantage of flexibility because the 'optimal' threshold is likely to vary according to location, background noise and other factors peculiar to the study.

For more involved analysis of tagging results, a discussion forum review system is used. The forum is linked to the tagged data and allows user to have threaded discussions around particular calls, analyses and tags. This is particularly important for expert users who may want to discuss unusual or novel calls and provides an audit trail for identification of species which are difficult to identify.

The discussion forum and tag browsing permit a degree of participatory analysis which allows many users to contribute to tagging and analysis. Users can manually tag raw acoustic sensor data, verify the accuracy of other manually tagged data or verify and confirm the accuracy of automated or semi-automated analyses. They can also engage in online discussions to assist in identifying cryptic or uncommon species. This provides a powerful mechanism for scaling the analysis of captured sound by volunteers or citizen scientists. To further enhance the accuracy of tagging, a structured review system could be implemented which provides independent tagging of the same vocalisation by a number of users – the consensus of the users would be accepted as the correct tag. This is similar to the approach adopted by citizen science projects such as Galaxy Zoo (www.galaxyzoo.org) and eBird (www.ebird.org).

3.5 ONLINE ANALYSIS TECHNIQUES

Recordings of the natural environment are subject to many effects including natural noise (such as wind and rain), man-made noise (such as cars and aeroplanes) and various other forms of interference. In addition, many animal species exhibit significant call variation and their call spectra vary depending on proximity to the microphone(Catchpole and Slater 2008). To deal with these challenges, our research has identified the need to provide ecologists with flexibility when analysing acoustic data. To this end, we provide the following techniques for analysing acoustic data:

- Manual analysis.
- Automated call recognition.
- Human-in-the-loop analysis.

3.5.1 MANUAL ANALYSIS

Given the volume of data associated with long term acoustic sensing, the time required to manually analyse recordings can be prohibitive. Additionally, manual analysis typically requires highly trained users who can discriminate between vocalisations and identify a large number of species. To help overcome some of these limitations, the workbench provides a number of tools:

- *Online collaboration*: enables users to scale manual analysis by allowing multiple users to collaborate on identification and annotation. The workbench incorporates a feedback and confidence rating system which provides the ability to rate the accuracy of collaborating users. Collaboration can also be used to focus the attention of 'expert' user's on difficult-to-identify calls.
- *Online species identification library*: assists in call identification. To reduce the time taken to identify vocalisations and to improve the productivity of novice users, the online species identification library can compare a call in a spectrogram with spectrograms of previously identified species vocalisation exemplars. To reduce the number of exemplar spectrograms to compare, the library can be filtered on features such a frequency band and call duration.
- *Removal of silence and noise*: removes sections of recordings with long periods of silence or periods with continuous noise pollution (e.g. caused by wind or rain). Automated removal of these sections of a recording reduces the volume of acoustic data to analyse, and focuses manual effort on those parts of a recording mostly amenable to analysis.

- *Rapid spectrogram scanning*: allows a user to visualise a recording in less time that it would take to listen. Many vocalisations have a characteristic spectral appearance that the human eye can recognise amongst other vocalisations even in complex acoustic environments e.g. dawn chorus. Rapid spectrogram scanning allows users to scan quickly through an entire recording for a specific species or vocalisation.

To establish the effectiveness of the manual analysis tools above, a small pilot study was conducted. A group of subjects inexperienced in bird identification (n = 6) were allocated 24 minutes of audio data to analyse using the online workbench collaboration tool and a standard MP3 audio player (Windows Media Player). The audio was split into two, 12 minute segments of audio. Each 12 minute segment of audio contained approximately the same number of unique species (20 species). Subjects were instructed to analyse the first 12 minute segment using the audio player only, without visualisation tools or the species reference library. Subjects were then instructed to analyse the second 12 minute segment using the online workbench visualisation and playback tools, with the assistance of the species identification library. Subjects were trained in the use of the website and tools and instructed to identify and annotate species in the recording. The time taken to annotate each 12 minute segment was recorded for each subject.

Subjects took between 14 and 25 minutes (mean = 17 minutes) to identify birds without the online workbench and achieved identification accuracy between 10% and 25% (mean = 16.7%). Using the online workbench with visualisation, playback and reference library tools, 5 out of 6 subjects took the allocated 60 minutes (mean = 55 minutes) and identified between 20% and 40% of species correctly (mean = 31%). The difference in the number of species correctly identified with and without the workbench tools was significant (paired t test: $t = 2.57$, $p = 0.003$). These results suggest that using the online workbench with the species identification library allows novice users to identify a greater number of species in acoustic sensor recordings than playing recordings alone. However the relative cost (time taken to analyse the 12 min segment) also increased.

3.5.2 AUTOMATED CALL RECOGNITION

Perhaps due to the importance of birds and amphibians as indicator species of environmental health, there is a considerable body of work published on the automatic detection of bird and frog vocalisations (Acevedo et al. 2009; Brandes 2008; Cai, Ee, Pham, et al. 2007; Chen and Maher 2006; Juang and Chen 2007; Kwan et al. 2004; McIlraith and Card 1997; Somervuo, Harma and Fagerlund 2006; Anderson, Dave and Margoliash 1996; Taylor et al. 1996). A common approach has been to adopt the well-developed tools of Automated Speech Recognition (ASR), which extract Mel-Frequency Cepstral Coefficients (MFCCs) as features and use Hidden Markov Models (HMMs) to model the vocalisations.

Unfortunately it is not so easy to translate ASR to the analysis of environmental recordings because there are far fewer constraints in the latter task. The two main issues are noise and variability. ASR tasks are typically restricted to environments where noise is tightly constrained, for example over the telephone. By contrast, environmental acoustics can contain a wide variety of non-biological noises having a great range of intensities and a variety of animal sounds which are affected by the physical environment (vegetation, geography etc.). Furthermore, the sources can be located any distance from the microphone. Secondly, despite its difficulty, ASR applied to the English language requires the recognition of about 50 phonemes (or 150 tri-phones). By contrast, bird calls offer endless variety; variety in call structure between species, variety between populations of the one species and variety within and between individuals of the one population. Many species have multiple calls and many are mimics. To give some indication of the difficulty of bird call recognition, a state-of-the-art commercial system using an ASR approach that has been under development for more than a decade, achieves, on unseen test vocalisations of 54 species, an average accuracy of 65% to 75% (Agranat 2009).

One approach to the automated recognition of bird/animal calls is to build a one-classifier-recognizes-all. This is the approach used by those who apply ASR methods (MFCC cepstral coefficient features and HMM classifiers) to the problem. We have not found this approach to be successful for a number of reasons. First, HMMs have many degrees of freedom and require a lot of training data. In many cases, particularly with cryptic species, training data in the form of a wide range of species vocalisations is not available. Second, MFCC features are inappropriate for some bird call features, notably pure tone whistles. Third, the results of an HMM are sensitive to the selected noise model and it is not practical to have a separate noise model for each of the many situations that occur in an uncontrolled recording. Note that the MFCC-HMM approach was developed for ASR under conditions where noise and recording conditions are tightly controlled. Fourth, an all-in-one-recognizer must be retrained every time the user decides to omit or include another call from the study. The retraining of HMMs is not a trivial exercise and it makes more sense to train recognizers only once as they are required.

The opposite approach might be to train a unique recognizer for every call type. However this would also involve a lot of duplicated effort. Thus for all the above reasons our approach was to build comparatively few recognizers capable of recognizing generic features such as oscillations, whistles, whips and stacked harmonics. Recognizers can be trained for individual call types by supplying appropriate parameters. Furthermore, not all noise types and all species occur at all locations so it is possible to achieve useful recognition results without building a universal-classifier.

While some animal and bird calls have complex structures (Somervuo, Harma and Fagerlund 2006), species recognition does not necessarily require recognition of an entire call. For example it is not necessary to model the complex structure of 30 second male Koala (*Phascolarctos cinereus*) bellow. Instead the oscillatory characteristic of its exhalations provides a suitable feature on which to train a recogniser. Likewise the Bush Stone Curlew (*Burhinus grallarius*) has a multi-syllable call structure with harmonics, but recognition can be limited to detection of a single characteristic formant. Even highly variable bird calls such as that of the Golden Whistler (*Pachycephala pectoralis*) may be confined to a particular frequency band and have characteristic frequency modulated whistles. Many multi-syllable calls consist of the same repeated syllable (e.g. the cane toad (*Bufo marinus*)) or different syllables varying in pitch (e.g. the ground parrot (*Pezoporus wallicus*)), duration or both (e.g. the whistle and whip of the Eastern Whipbird (*Psophodes olivaceus*)).

While all these call types exhibit some form of variability, nevertheless each has an invariant feature to which a recogniser can be tuned. Representative examples of recognition techniques we have implemented include:

MFCC features + HMMs: We have found this technique to be suitable only for high quality single-syllable calls. We used the Hidden Markov Model Tool Kit (HTK) (Young et al. 2006) and applied it to the recognition of Pied Currawong (*Strepera graculina*) calls. The Hidden Markov Model Toolkit is a suite of software development tools for constructing and manipulating hidden Markov models, traditionally used for speech recognition research.

Oscillation Detection (OD): We used a Discrete Cosine Transform to find repeating or oscillating elements of calls within a user specified bandwidth. This method is highly sensitive and does not require prior noise removal. For more details see (Towsey et al. 2012).

Event Pattern Recognition (EPR): This technique models a call as a 2D distribution of acoustic events in the spectrogram. Step 1: Acoustic Event Detection (AED). Extract acoustic events from the spectrogram. Each call syllable should be isolated as a single event. Step 2: Detect a 2D pattern of events whose distribution matches a template. Note that the content of the syllables themselves is *not* modelled. The advantage of this method is that it is resistant to background noise and other acoustic events. For more details see (Towsey and Planitz 2010).

Syntactic Pattern Recognition (SPR): this technique models a call as a symbol sequence, each symbol selected from a finite alphabet representing 'primitive' elements of the composite pattern. In our case the primitives are short straight-line segments at different angles in the spectrogram. Step 1: Isolate Spectral Peak Tracks (SPTs) which appear as ridges in the spectrogram. Step 2: Describe the spectral tracks as piece-wise straight line segments. We apply this technique to Eastern Whipbird calls that can be modelled as a series of horizontal line segments (the whistle) followed by a series of near-vertical line segments (the whip).

To test these methods we used data sets selected by an ecologist based on judgements as to what selection of recordings at different times of the day would provide interesting information about the locality. An ecologist tagged all calls of interest, even those at the limits of audibility and not expected to be detected by automated means. Our objective was to devise experimental conditions that would reflect how an ecologist would use the acoustic workbench. Results are displayed in Table 1. We use the following definitions of recall and precision:

recall = TP/(TP+FN)

precision = TP/(TP+FP)

Where TP is True Positive, FP is False Positive and FN is False Negative.

Table 1. Recogniser results from experiments using four automated recognition techniques.

Call structure	**Recognition technique**	**Call type**	**Recordings (Files in Datasets)**	**# Files with Calls**	**Recall**	**Precision**	**Accuracy**
Single syllable	MFCC features + HMM	Currawong	29 x 4-mins	7	28.6%	100%	75.9%
Oscillating single syllables in time domain	Detection of temporal oscillations within a characteristic frequency band of the STFT.	Cane Toad	337 x 2-mins	55	92.5%	98.0%	98.5%
		Asian House Gecko	270 x 2-mins	77	90.9%	89.7%	94.4%
		Male Koala (bellows)	115 x 4-mins	12	75.0%	75.0%	94.8%
Static pattern in time and frequency	Detection of a characteristic pattern of acoustic events in the STFT. (AED + EPR)	Ground Parrot (one call type)	405 x 1-min	23	87.0%	87.0%	98.5%
Complex single/ multiple-line patterns	Detect whistle followed by whip using	Whipbirds	38 x 2-mins	14	100%	66.7%	81.6%

	Syntactic Pattern Recognitio n.						

Accuracy is defined as the total number of correctly classified 1-4-minute file segments in the test set. We adopted the convention that where a recogniser detected a true positive (TP) in a single 1-4 minute file yet made an error in the same file (either a false positive - FP - or false negative - FN) we labelled that file correctly classified. On the other hand we observed many instances where multiple TPs were obtained in one recording but offset by a single error in another file. The most common errors were FN due to a distant call or call lost in noise. We chose this form of presenting accuracy because it is more efficient for ecologists using the acoustic workbench to work with audio segments of 1-4 minute rather than manipulate hours of recording. Furthermore birds tend to call in clusters and reporting on a file basis reduces the length of a report.

It is notable that the use of MFCCs and HMMs was the least successful technique tested (Table 1). This was due to the inadequacy of the noise model for the detection of Currawong calls. Although the accuracy figures presented should only be regarded as general indications of performance in a real operational environment, they nevertheless demonstrate that useful accuracy rates can be achieved for automated recognition when appropriate algorithms are selected for specific vocalisations. At the present time, selection of an appropriate algorithm must be done by an experienced user who inspects the call's spectrogram and determines which of its features (oscillations, stacked harmonics, etc.) would be most amenable to which algorithm. A call could well have features detectable by more than one algorithm. In this instance, the generic classifiers can be utilised in sequence and the results aggregated to improve the likelihood for detection.

3.5.3 HUMAN-IN-THE-LOOP ANALYSIS

Human-in-the-loop analysis provides a hybrid approach which addresses the respective strengths and weaknesses of the manual and automated techniques. Manual analysis utilises the sophisticated recognition capabilities of a human user, but cannot be efficiently scaled to process the volumes of data collected in long-term sensor deployments. Automated techniques are effective for identifying some targeted species in large volumes of data, but they require a high degree of skill to develop and are currently not able to cope with the variability found in animal calls.

Combining manual and automated approaches provides users with the ability to analyse large volumes of acoustic data interactively and systematically. Human-in-the loop analysis recognises that: a) many species (particularly avian species) have a broad range of vocalisations and these vocalisations may have significant regional variation; b) environmental factors such as wind, rain, vegetation and topography can attenuate, muffle and distort vocalisations considerably and c) human analysis capabilities are currently superior to that of automated computational analysis tools. The human-in-the-loop technique provides users with the ability to:

- Associate many different vocalisations with a single species.
- Automate repetitive annotation tasks.
- Leverage expert user time by searching a set of recordings with a number of identifying vocalisations.
- Locate vocalisations which have not been identified i.e. identify novelty.
- Develop a comprehensive, geographical-specific library of vocalisations to apply to other recordings

To illustrate this technique, the following is an example of a typical human-in-the-loop scenario.

A user is tasked with producing a species list and associated call frequency data for avian species in a seven day (168 hour – 9.1GB) continuous acoustic recording. The user is also tasked with building up a library of representative calls of interest in the recording. This library could be used later to assist call identification in other recordings at the same geographic location.

The recording is first uploaded to the workbench using web-based tools and processed segment-wise to remove background noise. The analysis process begins by performing a manual scan of the first minutes of the recording to identify calls of interest. These calls are manually tagged and placed in the call library. At present we use a binary matrix to represent the shape of calls in a spectrogram. These steps are represented in Figure 3 as the arrows from 'Start' to 'New Tags' to 'Library of Calls'.

The automated component of the human-in-the-loop process (the top section of Figure 3) is to scan the entire recording with the templates in the call library. The recall/precision trade-off is controlled with a sensitivity parameter. At present we use a nearest-neighbour recogniser but in principle a number of recognition algorithms could be used. This automated step returns a list of 'hits', some number of which will be false positive errors. The recogniser will also have missed some true calls (false negatives).

The user now identifies and corrects errors (see Error Correction box in Figure 3) and adds new examples of calls including those incorrectly identified in the previous scan. The expanded library is now used as the basis for a second scan of the entire recording.

The above process is iterated until all vocalisations of interest have been annotated. Note that iterative identification and annotation of vocalisations builds up a call library that not only covers the species range but also the variation within species for that location. Since calls in the library are annotated with their location, filtering for geographic proximity reduces the number of vocalisations to be compared.

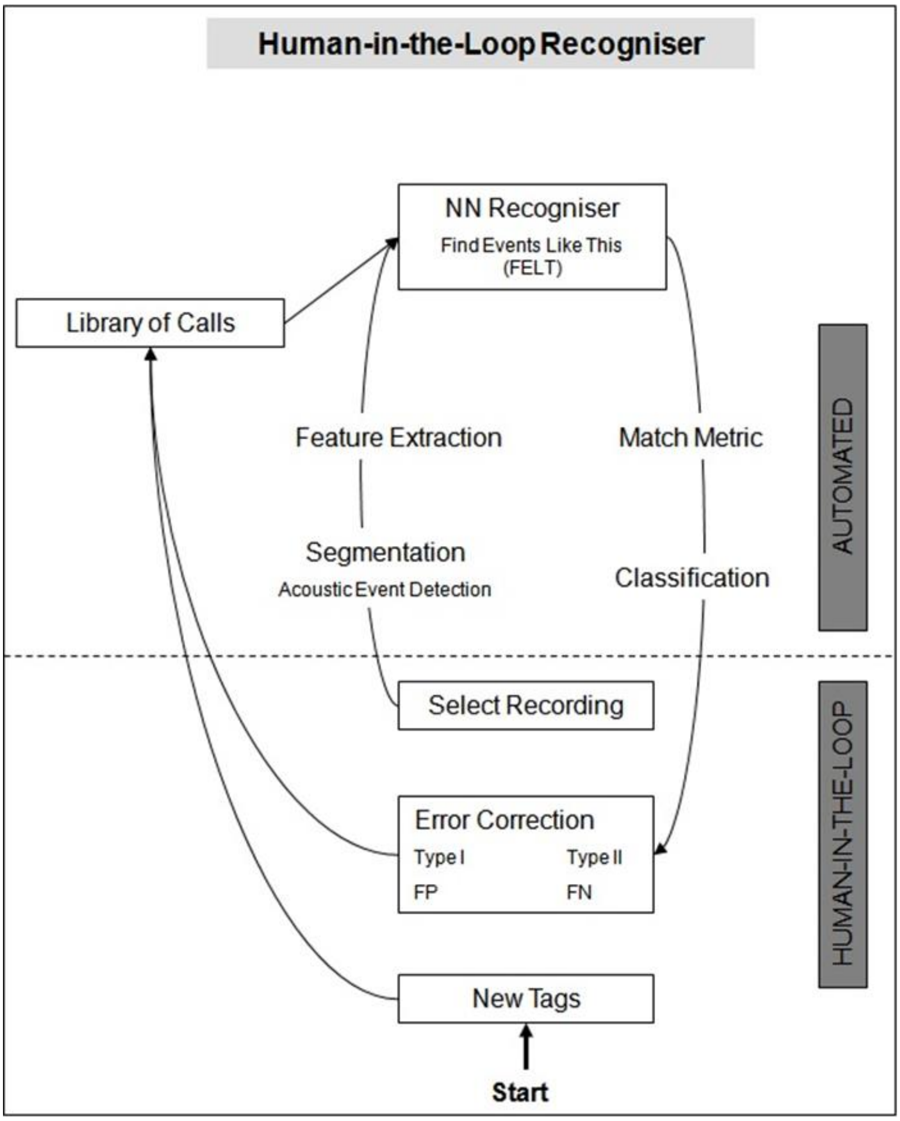

Figure 3. Semi-automated analysis (human-in-the-loop)

To give some idea of the performance of the nearest-neighbour recogniser (which also requires any similarity measure to exceed a threshold for positive identification) we used it to detect Bush Stone Curlew calls in a two hour recording. We used a single template describing just one of the several syllable types characteristic of a Bush Stone Curlew call. Dividing the recording into 4-minute segments, the single syllable recogniser achieved a recall rate of 63%, precision of 100% and accuracy of 76%. The addition of more syllables to the call library would increase recognition performance correspondingly.

3.6 SYSTEM IMPLEMENTATION

Figure 4 shows an overview of the system architecture.

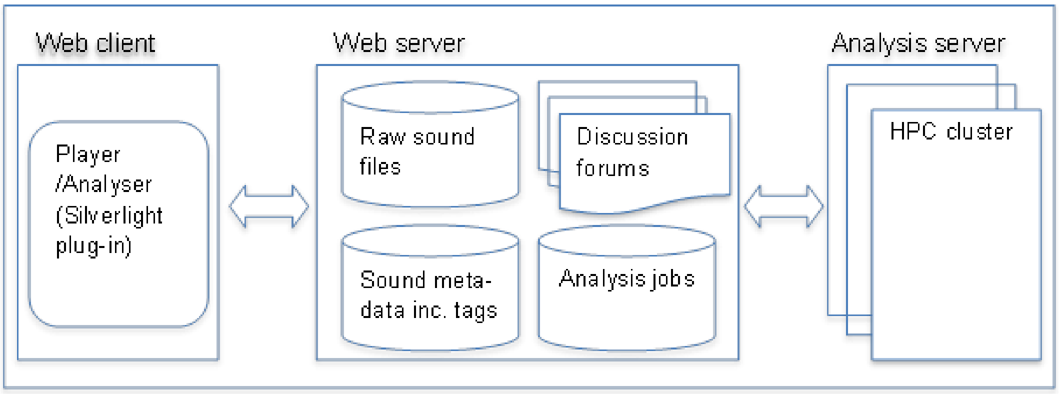

Figure 4. System Architecture

All data is stored centrally and accessed through a web based interface (Mason et al. 2008). The centralised data store and web interface support a collaborative interface. For example the results of analyses can be collaboratively reviewed. The web interface is realised by a mixture of conventional HTML for authenticating navigating projects and sites etc. and a custom Silverlight control for playing and annotating data. The player control is similar to a standard media play but with additional features for displaying a high resolution spectrogram and for creating and viewing annotations. Silverlight was chosen because of the rich features available for playing sound, viewing images and annotating spectrograms. Flash technology could equally have been used.

Data is stored on a central server; raw sound is stored in a file system and sound metadata, tags and other data are stored in a database. In this way large sound files can be stored efficiently in a regular file system: currently this is hosted by a dedicate file server. The simple file based interface lends itself to more sophisticated hosting for example by portioning across a set of file servers or even a cloud based solution. On the other hand meta-data is stored in a relational database (SQL Server) permitting the efficient querying and selection of meta-data. This is important to enable fast and efficient navigation to data on the web server. It also permits complex data sets to be formed through relational joining of metadata.

The automated analysis of large quantities of sound is computationally expensive. The approach we adopted is to break sound up into fixed size segments of two minutes and to process these on a high performance computing (HPC) cluster computer. The sound can be cached on the cluster and all processing is independent hence the problem becomes embarrassingly parallel. Other solutions might be to use GPUs or a hybrid cloud based system for undertaking the analyses (Mateescu, Gentzsch and Ribbens 2011). The computation is a mixture of regular and custom digital signal processing (DSP) tasks including Fast Fourier transforms. These are potentially well suited to a GPU implementation. However they would have necessitated rewriting the analysis code; the partition data and computation over a cluster was deemed a simpler and hence more attractive option. This is demand driven based on the analyses requested by the user.

In addition to the web user interface the web server also presents a lightweight REST-style web service interface. These simple web service interfaces enable applications to query the server and upload and download data; for example the Silverlight control uses this to communicate with the server accessing audio data and spectrogram images. A similar interface is used to communicate with the HPC server and to upload sound data into the system. All data and metadata can be addressed by

URLs. This facilitates linking of data, meta-data and discussions through sharing of URLs; it also simplifies the web client and other web service consumers. Developing clients for REST style web interfaces is simple and supported across different platforms. This allows different sensors, applications and web clients to communicate with the audio servers through a common interface.

One drawback of the current web-based system is the need to download all sound data onto clients for playing sound. Where users have fast and unlimited broadband access this is not a problem. For other more remote users such a system can stress download quotas and bandwidth. To alleviate this problem we support the local caching of raw sound data. This can be transmitted out of band to the user, for example on a portable hard drive/DVD through the postal system.

3.7 RELATED SYSTEMS

A number of other systems exist to analyse acoustic data. The Cornell Lab of Ornithology RAVEN sound analysis software provides extensive support for viewing spectrograms, playing audio, automated detection and spectrogram annotation. RAVEN provides user configurable detection algorithms based on amplitude or band limited energy. An extensible detection application programming interface (API) is also provided to allow users to develop custom detection algorithms in Java or Python. RAVEN automated analysis suffers from the same automated analysis issues as the online workbench. The presence of high background noise, low signal strength, signal complexity or clutter all have a detrimental effect on the accuracy of detection.

XBAT (http://xbat.org/home.html) is also developed and made available by the Cornell Lab of Ornithology. XBAT is a MATLAB extension for the sophisticated analysis of acoustic data with a GUI development environment. XBAT offers a rich and powerful suite of tools for visualising, filtering, detecting, measuring and annotating acoustic data. While XBAT is made available as open-source software under the GPL, the requirement for a licensed version of MATLAB and MATLAB development skills may restrict the widespread use of XBAT as an acoustic sensor data analysis tool.

Song Scope (http://www.wildlifeacoustics.com) is a commercial acoustic analysis application developed by Wildlife Acoustics. Song Scope has rich support for long audio recordings, spectrogram visualisation, annotation and interactive automated detection development. Using training data (representative vocalisations for the target species), Song Scope can generate a custom detection algorithm which can be used to analyse large volumes of data. As with other automated detection algorithms and tools which operate on unconstrained recordings of the natural environment, the presence of high levels of noise, signal strength and variation compete with the detection accuracy. Wildlife acoustics claim a typical 80% detection rate for complex, variable vocalisations in noisy environments (http://www.wildlifeacoustics.com/songscope.php).

There are a number of notable differences and similarities between RAVEN, XBAT, Song Scope and the online workbench. Firstly, RAVEN, XBAT and Song Scope are standalone applications which have limited online collaboration capabilities. The online workbench is specifically designed to allow large numbers of users to collaborate online to collect, store and analyse large volumes of acoustic data. RAVEN and XBAT allow the user to interactively adjust detection parameters to improve detection performance for a given environment as does the online workbench. Because of their standalone nature, XBAT, RAVEN and Song Scope provide a rich and mature sound analysis environment with a greater range of visualisation and analysis tools than is currently available in the online workbench. A comparison of the performance characteristics of a number of existing automated analysis tools and the online workbench detection tools is planned as part of future research into automated acoustic analysis tools.

3.8 DISCUSSION AND FUTURE WORK

Acoustic sensors are set to play an important role in protecting biodiversity as we face increasing environmental challenges. Sensors provide scientists with the capability to collect data over large spatial and temporal scales, far exceeding what would be traditionally possible using manual methods. With this ability however comes the problem of analysing large volumes of data. Collecting, storing and analysing large volumes of data is becoming increasingly challenging with large-scale eScience applications (Fiore and Aloisio 2011). This research has adopted a 'toolbox' approach to the analysis of acoustic data, providing scientists with an online environment to store, access and collaborate on data collected from acoustic sensors. Ultimately, these tools are aimed at providing scientists with the ability to detect and identify species in large volumes of acoustic data. These data can be analysed over time to observe fluctuations in species richness, detect the presence of rare or invasive species, and to monitor the effects of climate change on the environment.

e-Science systems such as this are necessarily cross-disciplinary, usually combining the skills of many non-IT disciplines. While IT is, at the most fundamental level a cross-disciplinary profession, there are many challenges in developing systems that take traditional methods of scientific investigation (such as ecology) and attempt to redefine the ways in which that investigation is conducted. At its core, this system attempts to move the estimation of avian species composition from the field (i.e. ecologists in the field making visual and auditory observations of avian species) to cyberspace, and to the masses, using acoustic sensors. This is a fundamental paradigm shift for many ecologists, and developing strategies to ensure that e-Science projects such as this maintain the appropriate levels of scientific rigour is essential. To this end, we have engaged extensively and comprehensively with ecologists to ensure that the objectives of traditional ecological research are able to be met through the use of the system. Analysis verification processes which ensure data accuracy, and online species identification libraries which improve the performance of novice users are classic examples of contributions from ecologists to this system.

We have taken an agile approach to the research, design and development of the system; system components have been iteratively researched, built and evaluated with input and feedback from ecologists at each stage of development. Team members have actively participated in ecological studies utilising the system, and research students have been jointly supervised by ecologists and computer scientists. In this way the system's research has been kept 'ecologically honest'. As is often the case in e-Science, key research problems are often found to be different from those originally envisaged. The acid test is whether the system allows ecologists to conduct research in new or innovative ways. Another somewhat surprising finding is that ecologists are very tolerant of a new system providing it enables them to undertake new otherwise infeasible research.

The automated recognition of animal calls has not yet reached a level of reliability that allows ecologists to use the methods without careful verification of results. Any application which offers analysis tools to ecologists must necessarily offer graded levels of utility from fully manual to fully automated. Thus our manual and semi-automated tools offer an adjustable degree of user interaction with the data.

To this end, the automated recognisers in our Acoustic Environmental Workbench have a number of features that adapt them to the real world of manual and semi-automated classification as opposed to the optimised world of a specialised machine learning laboratory. In particular:

We have developed collaboration and manual species identification tools to allow for large scale manual analysis of acoustic data utilising novice users. In recent years there has been enormous growth in participatory sensing and the popularity of many amateur environmental activities such as bird watching. This means there are a large number of amateur enthusiasts who may be willing to assist with the analysis of large volumes of sensor data (Greenwood 2007). The rise of internet-enabled citizen science projects has led to masses of information being collected and analysed across numerous fields. Web-based tools and processes allow citizen scientists to contribute more effectively to environmental monitoring. Further development of tools and technology to support reputation modelling, consistency and accuracy checking specifically for acoustic sensor data analysis will be critical to the wide-spread adoption of collaborative sensor data analysis (West et al. 2011).

1. We have constructed generic classifiers that respond to a particular feature which is common to many animal calls. The most obvious example in our work is the Oscillation Detector. Another feature of our generic recognisers is that they have parameters whose tuning is relatively intuitive. The only exception to this rule is the use of HMMs in HTK. These classifiers require IT expertise to construct. Reporting the accuracy of call classifiers based on carefully prepared data sets is not an accurate reflection of the typical ecologist’s requirements.
2. Except for our HMM classifiers, we have prepared generic classifiers that can be ‘trained’ with very few (even just one) instance. This is necessary because many bird species of interest are cryptic. As more calls are identified, the classifier can be improved in a boot-strap manner.

3. We have constructed classifiers that can be used in *both* a multi-class context (e.g. as a nearest-neighbour classifier) or as stand-alone binary classifiers. The latter option is necessary because in many situations an ecologist is interested in a particular species and has no need of a classifier that recognisers multiple species. The difficulty to be solved in order to achieve this outcome is to normalise classification scores independently over a broad range of call types.

The identification of animal calls in arbitrary recordings of the environment remains a difficult task. We believe that it is fundamentally more difficult than human speech recognition, which is only just becoming a reliable technology after three decades and huge investment. From an economic standpoint alone, it is most unlikely that automated recognition of animal vocalisations will be achieved in the near future, certainly not having sufficient accuracy to replace human identification. Consequently large scale manual collaborative and human-in-the-loop analysis will be required for analysis of environmental acoustic data for the foreseeable future. Our workbench recognises this reality, however, we anticipate that we will continue to improve the effectiveness of our manual, semi-automated and fully-automated tools. These features will be added to the online acoustic workbench as they become available. The workbench can be accessed at sensor.mquter.qut.edu.au.

3.9 ACKNOWLEDGMENTS

The Microsoft QUT eResearch Centre is funded by the Queensland State Government under a Smart State Innovation Fund (National and International Research Alliances Program), Microsoft Research and QUT. This research was conducted with the support of the QUT Institute of Sustainable Resources and the QUT Samford Ecological Research Facility.

Chapter 4: Assessing bird biodiversity with acoustic sensors – Insights from avian surveys in South-East Queensland.

Title: Assessing Bird Biodiversity with Acoustic Sensors – Insights from Avian Surveys in SE Queensland.

Authors: Jason Wimmer[a], Paul Roe[a], and Ian Williamson[a]

Affiliations:

[a]Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

Email: (j.wimmer, p.roe, i.williamson)@qut.edu.au

Corresponding Author: Jason Wimmer

Corresponding Author Address: School of Electrical Engineering and Computer Science, QUT Gardens Point, Brisbane, Queensland, 4000, Australia. Ph: +61 7 3138 9485 Fax: +61 7 3138 9390

4.1 STATEMENT OF CONTRIBUTION OF CO-AUTHORS

The authors listed below have certified* that:

1. they meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the Australasian Research Online database consistent with any limitations set by publisher requirements.

In the case of this chapter: **Assessing Biodiversity with Acoustic Sensors – Insights from Avian Surveys in SE Queensland.**

Publication title and date of publication or status: Assessing Biodiversity with Acoustic Sensors – Insights from Avian Surveys in SE Queensland (Submitted to *Austral Ecology*, 2013).

Contributor	Statement of Contribution*
Name: Jason Wimmer	Wrote manuscript, experimental design, analysis.
Signature:	
Date: 11/6/2013	
Co-author: Prof. P. Roe	Experimental design. Manuscript review.
Co-author: Dr. I. Williamson	Experimental design. Manuscript review.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all Co-authors confirming their certifying authorship.

Professor Paul Roe		11/6/2013
Name	Signature	Date

4.2 ABSTRACT

Acoustic sensors have a promising and important role to play in long term biodiversity monitoring. They can extend the spatial and temporal scale of ecological observations, however the cost of analysing acoustic sensor data can be high due to the large volumes of data collected, and the lack of effective automated analysis tools for a large numbers of species. Efficient sampling methods are needed to make acoustic sampling a viable way of assessing biodiversity. This study made a detailed analysis of acoustic sensor recordings from four sites, over five days in south-east Queensland, with the aim of assessing how bird calling patterns might provide insights for efficient acoustic sampling.

Over the duration of the survey period, 96 bird species were identified, with 75% of species detected by 7am on day one of the survey. A total of 87 species called during the dawn period, and the majority of species that called at other times of the day also called at dawn. The number of calls detected from each species overall, varied considerably with the majority of species calling very infrequently. Five species were detected calling only once, and 35 species (36% of total species) were detected calling less than 50 times out of 28,800 one minute segments. 26 species (27% of total species) were detected calling greater than 1000 times, and two species were detected over 6000 times. Wind had a significant effect on calling behaviour with stronger winds causing an average reduction of 25% in call detections across all species and sites. This study demonstrates that unique insights can be gained from the analysis of acoustic sensor data which can inform our planning, monitoring and natural resource management efforts.

Keywords:

Acoustic sensor; biodiversity monitoring; bird survey, species richness

4.3 INTRODUCTION

Acoustic sensors are being used increasingly to monitor biodiversity in the terrestrial environment. They have a number of well documented advantages over traditional surveys. For example, they can remain deployed for extended periods of time continuously recording sounds of the environment, they can provide an indelible record of the area in which they were deployed, and recordings can be reanalysed to verify the presence of particular species (Parker 1991; Acevedo and Villanueva-Rivera 2006; Mellinger et al. 2007; Moore et al. 2006). Perhaps because of these advantages, a greater number of species can usually be detected from acoustic sensor data, which in turn provides a more accurate assessment of species richness (Celis-Murillo, Deppe and Allen 2009; Haselmayer and Quinn 2000).

Acoustic sensors are not a silver bullet for biodiversity monitoring, however. They are generally incapable of providing accurate estimates of abundance without complicated localisation equipment and accurate time coordination between devices (Ali et al. 2009; Stevenson et al. 2015). They have an obvious bias towards vocal species, and acoustic sensor data can be complex and difficult to analyse. Manual analysis of acoustic data requires significant effort, and while progress is being made, automated methods for identifying a significant number of avian or anuran species are unlikely to be available in the near future (Swiston and Mennill 2009; Rempel et al. 2005).

Notwithstanding these advantages and disadvantages, many ecologists and long term ecological research programs, such as NEON in the USA (www.neoninc.org), TERN (tern.org.au) in Australia and AMIBIO in the EU (www.amibio-project.eu) are using acoustic sensors to collect and retain an historical record of the environmental soundscape. As automated methods become available, these collections will become a valuable source of historical environmental information, and coupled with other sensing devices (e.g. soil, air, water etc), will provide unique insights into the natural environment.

But not all monitoring programs are long-term, and many cannot defer data analysis until technology matures. Many environmental surveys use a ‘snapshot’ approach for characterising flora and fauna diversity. Floristic surveys are usually undertaken using a standard vegetation assessment protocol appropriate to the region or authority undertaking the survey (e.g. Habitat Hectares (Parkes, Newell and Cheal 2003) and BioCondition (Wimmer, Towsey, Roe, et al. 2013)). Fauna surveys are generally conducted using traditional sampling, capture and release or observational approaches. Bird surveys are increasingly being conducted with the use of acoustic sensors. Acoustic bird survey data can be analysed in a manual or semi-automated way, albeit with a considerable amount of effort. A number of commercial and open-source tools are available which can assist with analysis, by rendering spectrograms, playing sound and annotating calls (e.g. Cornell Raven (Charif, Ponirakis and Krein 2006), Avisoft SASLab Pro (Eyre et al. 2006), SongScope; Wildlife Acoustics Inc., Concord, Massachusetts).

Having conducted acoustic sensor surveys and analysed the data, what insights beyond species richness, can acoustic sensors provide? This work investigates data derived from manually analysed acoustic sensor data to demonstrate that acoustic sensor data can provide much more information than species richness. Specifically, we investigate call frequency, the effect of weather, and detectability of bird species across temporal and spatial scales.

4.4 METHODS

4.4.1 SITE DESCRIPTION

Acoustic sensor surveys were conducted in four locations over five days at the Queensland University of Technology (QUT) Samford Ecological Research Facility (SERF). SERF is a 51ha patch of remnant vegetation located in the Samford valley in south east Queensland, Australia (-27.388992,152.878103).

The predominant 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 Samford Creek, in the western corner within *Melaleuca* woodland, and in the southern corner where open forest bordering cleared pasture (Figure 5). Each site was 100m x 200m and marked with flagging tape. In addition, a weather station was located in the northern section of the property.

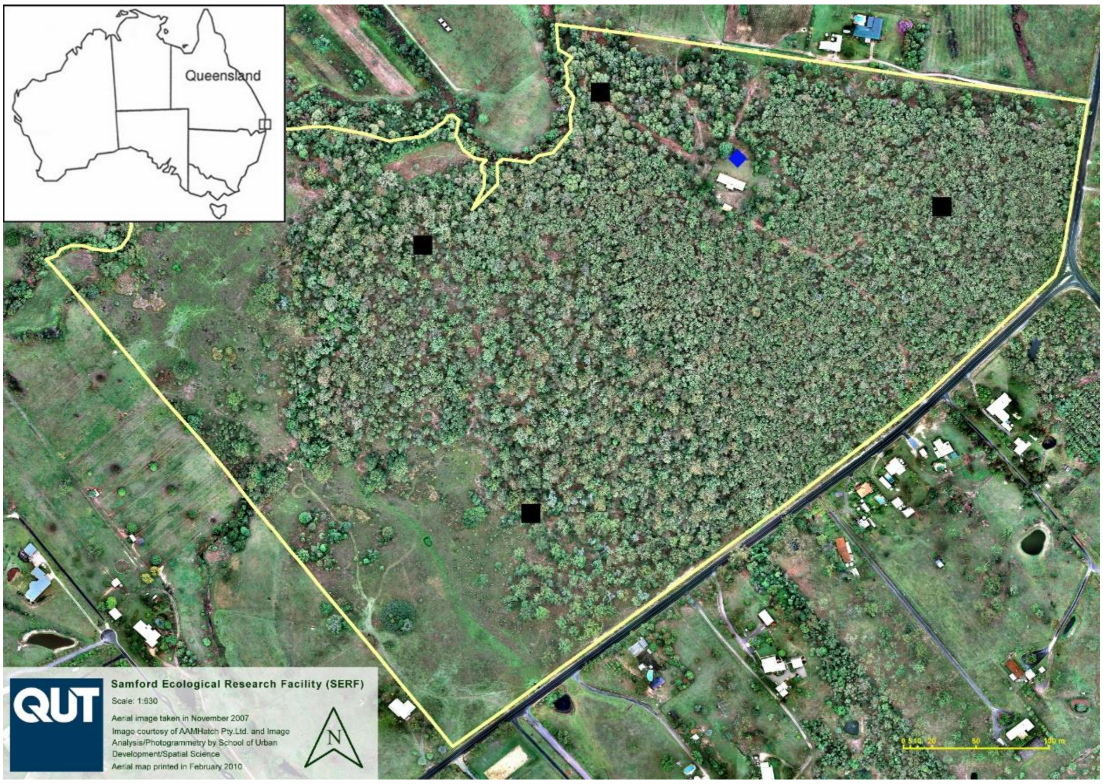

Figure 5. Samford Ecological Research Facility (SERF) with survey site postions marked with black squares and weather station position marked with a blue diamond.

4.4.2 ACOUSTIC SENSORS

Acoustic sensors were located at the centre of each survey site and configured to record continuously for five consecutive days from the 13th – 17th October 2010. Sensors were located a minimum of 300m apart.

Sensors used for this study were custom-developed using commercially available, low cost digital recording equipment. Recording equipment consisted of Olympus DM-420 (Olympus, Pennsylvania, USA) digital recorders and external omni-directional electret microphones. Data were stored internally in stereo MP3 format (128 Kbit/s, 22.05 KHz) on high capacity 32GB Secure Digital memory cards. The units were stored in weatherproof cases and powered by four D cell batteries, providing up to 20 days of continuous recording.

4.4.3 ACOUSTIC SENSOR DATA ANALYSIS

At the completion of the survey, sensor data were split into one minute segments (henceforth referred to as segments) and analysed manually by experienced surveyors utilising a custom-developed online acoustic workbench (Wimmer, Towsey, Planitz, et al. 2013). The workbench played audio and displayed a spectrogram, which allowed the user to visualise and hear recordings, and to annotate species vocalisations.

To identify, mark and record species vocalisations within recordings, the workbench provided the ability to annotate spectrograms. Annotation involved selecting the portion of the spectrogram image which contained the specific vocalisation, using a rectangular marquee tool in the audio player. A tag was then assigned to the selection, which identified the species. The upper and lower frequency bands, start time, end time, duration and species name were associated with the selection. Figure 6 shows an example of a spectrogram annotated with a Bush Stone Curlew (*Burhinus grallarius*) vocalisation in the audio player.

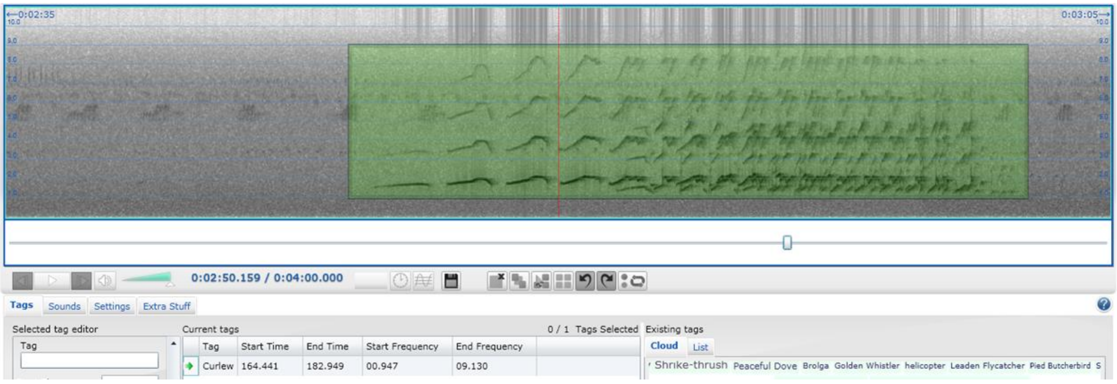

Figure 6. Spectrogram with annotated Bush Stone Curlew (*Burhinus grallarius*) call (http://sensor.mquter.qut.edu.au/)

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 at each site, and the need to have detailed information on the number of species calling at a particular time of the day.

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 investigate species richness, call frequency and species accumulation patterns for all species detected.

4.4.4 METEOROLOGICAL DATA

Meteorological data were also collected over the five days of the survey period using a Davis Vantage Pro2 (Davis Instruments Corp., Hayward, California, USA) weather station, recording observations at 5 minute intervals. The weather station was positioned in the centre of the northern part of SERF (Figure 5).

4.4.5 STATISTICAL ANALYSIS

Statistical analyses were performed using the IBM SPSS Statistics package (Version 20). The mean proportion of total species detected per day were compared using a one-way ANOVA with sites as replicates. Analysis of covariance was calculated to examine the effect of wind speed on calling rates of bird species.

To examine the effect of time of day on calling frequency, each day was split into four periods; dawn (4:15 – 8:14), day (8:15 – 14:54), dusk (14:55 – 18:54) and night (18:55 – 4:14). The number of calls detected for each species and for each period was compared using a paired samples t-test.

Chao2 species richness estimates were calculated using the EstimateS 8.2 package (Chao 1987; Colwell 2009). Chao2 is a nonparametric richness estimator, which estimates total species richness based on occurrence data. Chao2 species richness estimates were calculated to estimate bird species richness for each site.

4.5 RESULTS

4.5.1 RICHNESS AND SIMILARITY

Across the four sites and five days, a total of 28,800 one minute segments were manually analysed. Fifty-six per cent (16,019) of total segments contained calls, and from these, 63,089 bird calls were identified and annotated. A total of 96 unique species were identified across all four sites over the five-day acoustic sensor survey period. The total species detected at each site ranged from 75 to 80 species, with the mean number of species recorded per site per day across the five-day period ranging from 57 to 59 (Figure 7).

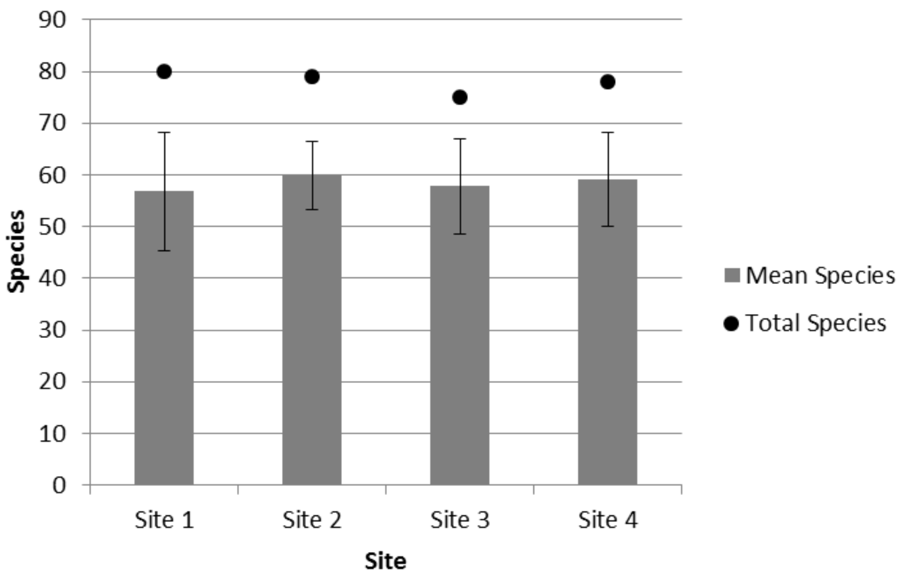

Figure 7. Mean and total number of bird species detected daily (± 95% CI) at each site.

An average of 78% of species were detected in the first day across all sites, with at least 75% of species detected by 7am on the first day at all sites (Figure 8). The Chao2 species richness estimate for the combined sites was 101 species, suggesting that a high proportion of species that were able to be detected across the four sites were detected over the five days (Figure 8).

The Chao2 estimates for individual sites showed some variation with estimates ranging from 77 (Site 3) to 101 (Site 1). The Chao2 estimate for Site 3 did not differ from the actual number of species detected (77 sp.), while the Chao2 estimate for Site 1 suggested 18 further species might be detected. Chao2 estimates for Sites 2 (92 sp.) and 4 (90 sp.) suggested nine to ten additional species respectively.

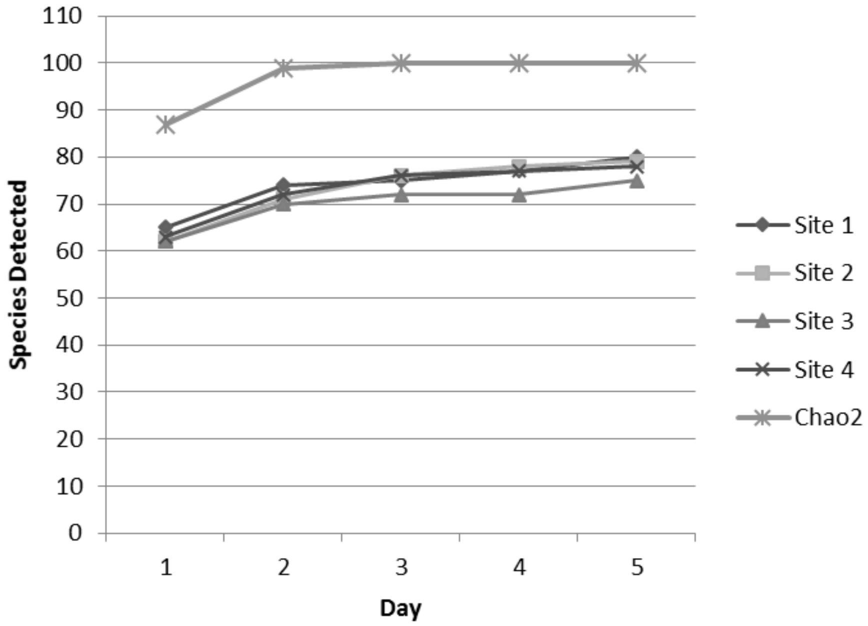

Figure 8. Species accumulation curves and Chao2 estimate of species richness for all sites across five days.

There was very little variation in species composition across the four sites for the duration of the survey period, with 93% of species found at all sites. This was not unexpected as the sites were within approximately 300m of each other. Seven species were not detected at all four sites; Pale-vented Bush-hen *(Amaurornis moluccana)*, Tawny Grassbird (*Megalurus timoriensis)*, White-breasted Woodswallow *(Artamus leucorynchus)*, Glossy Black Cockatoo *(Calyptorhynchus lathami)*, Welcome

Swallow *(Hirundo neoxena)*, White-naped Honeyeater *(Melithreptus lunatus)* and Common Myna *(Sturnus tristis)*.

The species composition between days at each site remained relatively consistent over the survey period, however some variation was observed. Species common to all days ranged from 78% (Site 1) to 87% (Site 3). Sites 2 and 4 both recorded 82% species common to all days.

Species composition within days was also examined. When data were split into four time periods (dawn, day, noon and dusk), the dawn period contained the highest proportion of species (87 species - 91%), followed by day (81 species - 84%), dusk (71 species - 74%) and night (30 species- 31%). Of the 81 species detected in the day, all but two were also detected at dawn. Similarly, 70 of the 71 species that called at dusk also called at dawn. Species detected at night differed most from dawn callers, but even then only 6 of the 30 species calling at night were detected only at that time (Noisy Pitta (*Pitta versicolour*), Plumed Whistling Duck (*Dendrocygna eytoni*), Dusky Moorhen (*Gallinula tenebrosa*), Australian Masked Owl (*Tyto novaehollandiae*), Lewin's Rail (*Lewinia pectoralis*), and Pale-vented Bush-hen (*Amaurornis moluccana*)). The other 24 species calling at night also called at dawn.

4.5.2 CALL FREQUENCY

The total number of calls detected over the survey period varied considerably from species to species. Five species were detected only once over the five day period at all four 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 vocalised in only one of the 28,800 segments, these species exhibited a very low probability of detection.

The most detected species was Rufous whistler (*Pachycephala rufiventris*) which was detected in 6941 segments over the five day period, followed by Scarlet Honeyeater (*Myzomela sanguinolenta*) which was detected in 6239 segments. Both species were detected at all sites.

Across all sites over the duration of the survey period, 70 species were detected calling in less than 500 segments out of 28,800 and four species were detected calling in greater than 4000 segments (Figure 9).

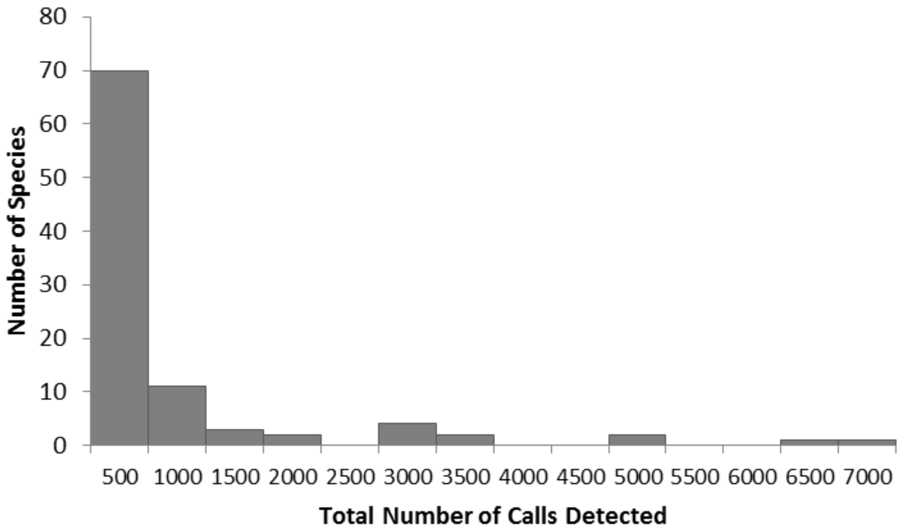

Figure 9. Call frequency distribution for all species over the survey period.

Of the 70 species detected less than 500 times, 35 species (36% of total species detected) were detected calling in less than only 50 segments out of 28,800 (Figure 10). However, the detectability of these species could be slightly higher given the tendency for higher call rates at dawn. A majority of the 70 species that called in less than 500 minutes, called during the during the dawn period (87%) and in the day (79%). Of the 35 species that called in less than 50 minutes, most were detected in the dawn period (74%) and during the day (60%).

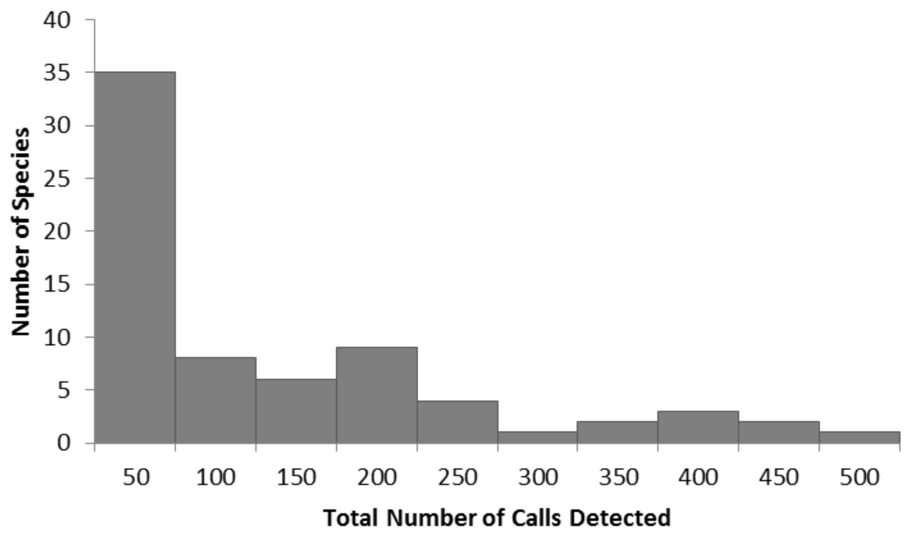

Figure 10. Call frequency distribution for species with less than 550 calls detected over the survey period.

4.5.3 VARIATION IN CALLING

Overall Pattern

As expected, higher calling rates were found during the day than at night. Split into one minute segments, each day constituted 1,440 segments. Sunrise to sunset (5:15am – 5:54pm) constituted 760 one minute segments (53% of the total day) and sunset to sunrise (night) constituted 680 one minute segments (47% of the total day).

Across all sites and days, an average of 91% of segments contained calls during the day, and 16% of segments contained calls during the night. 92% of total species were detected during the daytime period and 77% detected during the night. A high proportion of those species detected between sunset and sunrise were detected in the hour after sunset and the hour before sunrise (48%). When these hours are excluded only 30% of total species were detected in the night time period.

Time of day had an effect on both the number of species calling, and the calling behaviour of individual species (and therefore detectability). The calling rate for species that called at different times of the day was generally higher for the dawn period. For example, for the 79 species that called both at dawn and during the day, the average call rate (proportion of minutes detected) was significantly higher for dawn (dawn (mean +/- sd) = 0.07+/- 0.10) than day (0.04 +/- 0.09) (paired t_{78} = 5.64, p<0.001). Similarly, calling rates were higher for birds calling at dawn versus dusk (70 species: dawn = 0.07 +/- 0.10; dusk = 0.06 +/- 0.06) (paired t_{69} = 6.02, p<0.001), and dawn versus night (24 species: dawn = 0.09 +/- 0.10; dusk = 0.003 +/- 0.005) (paired t_{23} = 4.08, p<0.001)

Species Detected per Minute

A distinctive diurnal pattern was observed in the minute by minute observations (Figure 11), which featured a sharp rise in the number of species detected around sunrise, followed by a steady decline towards the middle of the day. There were also small increases in species detected around the middle of the day and prior to sunset, and a rapid decline following sunset. The highest number of species detected in any one minute segment was 15 unique species, detected at 5:35am on day five at site three. In any hour during daylight an average of at least two to three species were likely to be detected, compared to less than one species during the night.

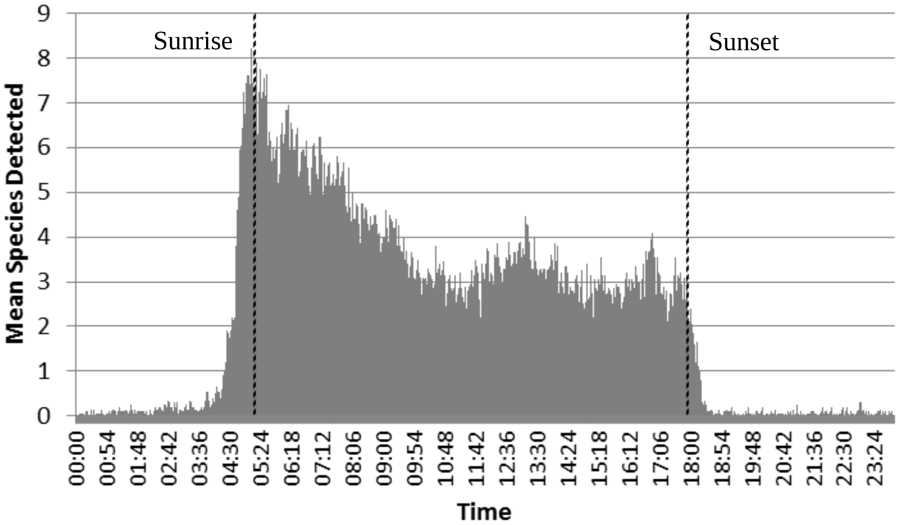

Figure 11. Mean species detected per minute across four sites and five days.

Species Detected per Hour

The diurnal pattern of calling activity is also seen in the plot of the number of species calling per hour (Figure 12). The average number of species calling per hour ranged from 34 (dawn period) to less than two for most of the night time hours.

The maximum number of species recorded in any one hour period across the five days and four sites was 43 species in the hour 6:00am to 7:00am at Site two on day five, with similar numbers recorded in the dawn period at other sites (Site one = 40 species 6 to 7am Day 1; Site three = 42 species 7 to 8am Day 1; Site four = 42 species 7 to 8 am Day 1).

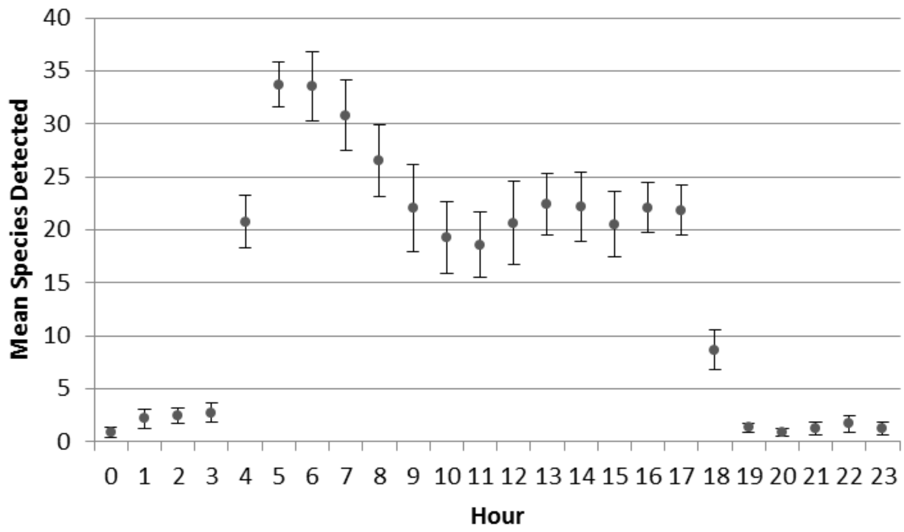

Figure 12. Mean bird species detected per hour (± 95% CI) across four sites and five days.

Species Detected per Day

The number of species detected per day across all sites remained relatively consistent over the five day period, with the exception of day four, which had a pronounced drop in number of species detected (Figure 13). A one-way ANOVA confirmed that the number of species detected on day four was lower than all other days (F (4, 15) = 11.847, $p < 0.05$; Tukey post hoc < 0.05).

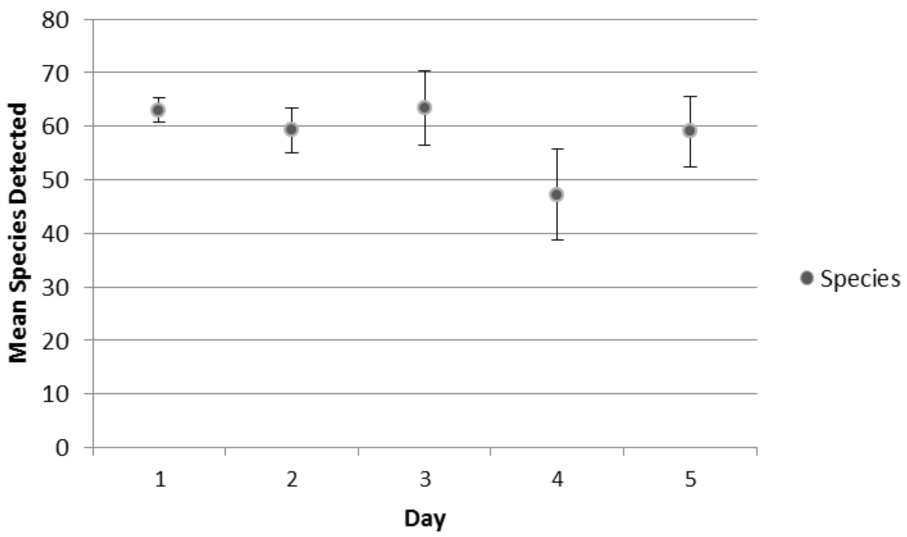

Figure 13. Mean species detected per day (sites as replicates)

at all sites (± 95% CI).

Effect of Wind Speed

Reliable wind speed data was only available for daylight hours, however these data demonstrated a clear difference between and within days. Day four experienced higher average wind speeds than all other days (Figure 14).

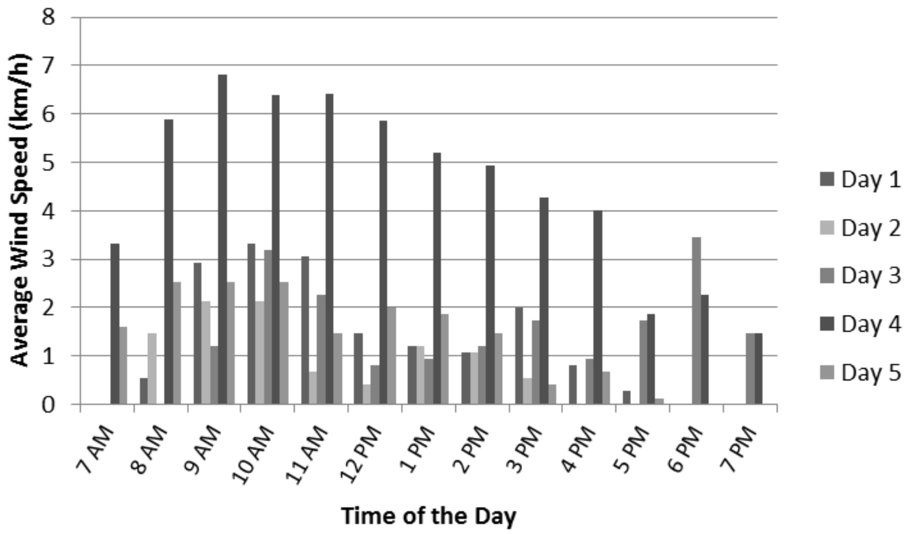

Figure 14. Average wind speed for each day over the 5 day survey period.

Because time of day influences number of species calling, the effect of wind speed on number of species detected was examined using analysis of covariance (factor = time of day, covariate = wind speed). There was a strong negative effect of wind speed (F (1,221) = 162.4, $p < 0.001$), as well as an effect of time of day (F (2,221) = 31.7, $p < 0.001$). However, there was no interaction between time of day and wind speed (F (2,221) = 1.8, $p = 0.164$) on the number of species detected, indicating that the reduction in number of species detected with increased wind speed was independent of the time of day (Figure 15).

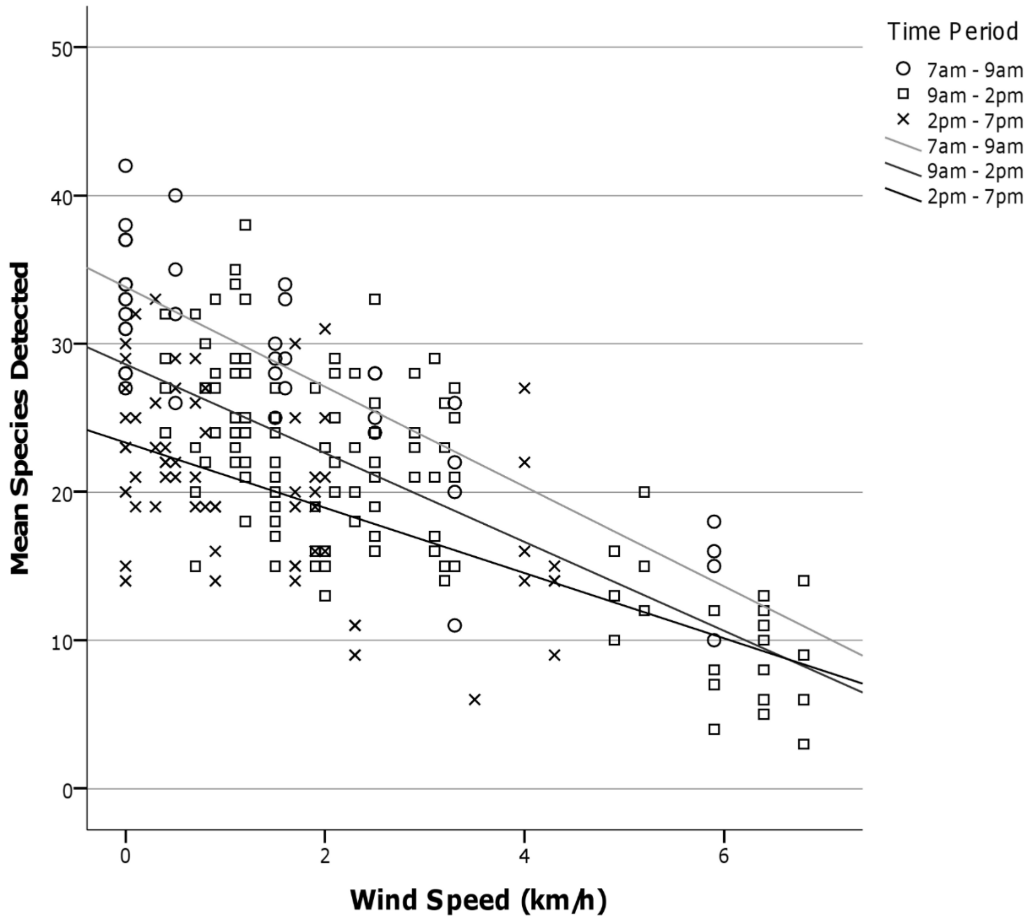

Figure 15. The relationship between numbers of species detected and average wind speed per hour, for three different periods of the day (7-9am; 9am-2pm; and 2-7pm).

4.6 DISCUSSION

Acoustic sensors are being used increasingly to monitor terrestrial biodiversity. They have a number of advantages over traditional monitoring techniques, such as the ability to remain deployed over extended periods of time, continuously recording the sounds of the environment. Aside from increasing the temporal and spatial resolution of observations however, acoustic sensors can provide other insights which cannot typically be obtained from traditional survey methods. This study examined some of the insights that can be obtained from analysis of five days of continuous acoustic sensor deployment.

The call frequency of many of the species detected varied considerably across the five day period. Low calling rates were the norm. Out of the 96 species detected, five species were detected vocalising only once in 28,800 one minute segments. A further 35 species (36% of total species) vocalised less than 50 times over the survey period. Overall, the number of calls detected for most species were relatively low, with only 26 species (27% of total species) vocalising more than 1000 times. This represents approximately 3.5% of the 28,800 one minute segments over the five day period. In comparison 20 minute traditional surveys conducted at dawn, noon and dusk over a five day period would constitute 300 minutes (60 minutes per day x 5 days) or ~1% of the total survey time.

A large number of species were detected rapidly on day one across all sites, with 75% of species detected by 7am. Call detection rates peaked in the hour following sunrise, and reduced considerably during the night time period. Most species (92% of total species) were detected during the day, with six species detected calling only during the night. While dawn is widely recognised as the period of the day with the highest number of species vocalising (Keast 1994), the number of species calling at dawn, and their detailed calling behaviour have rarely been quantified in the Australian context (Lindenmayer, Cunningham and Lindenmayer 2004). This study has collected detailed calling behaviour for 96 species in south-east Queensland, Australia. These data confirm that the highest number of species exhibit the highest call frequency in the period following sunrise (dawn). Call frequencies increased rapidly at dawn, peaking at sunrise, before reducing gradually throughout the day, and declining rapidly at sunset. The night period contained the least number of species, vocalising the least number of times.

Wind speed had a dramatic effect on the detectability of species. Day four of the survey had a significant increase in wind speed, with a corresponding decrease in the number of species detected across all sites. Previous studies have found that some bird species reduce calling rates in response to wind and rain (Lengagne and Slater 2002; Keast 1994), and others increase calling rates and call amplitude in response to anthropogenic noise (Brumm 2004; Slabbekoorn and Peet 2003). Whether bird species reduce their calling rates in response to increases in wind speed, or the increased noise from wind decreases the ability to detect calls from sensor recordings is unclear.

Acoustic sensors can provide rich insights into the calling behaviour and call frequency of species which go beyond simple species richness estimates. Understanding the effect of weather on calling behaviour of bird species, estimating calling rates and variations in diurnal calling patterns can be important when designing biodiversity monitoring programs. In this study, we have collected detailed calling rate data for 96 species over a five day period. These data identify periods of the day in which the likelihood of detecting any individual species is highest, and periods of the day in which the likelihood of detecting the greatest number of species is highest. Targeting specific periods of the day or night, based on calling rates increases the probability of detection, and decreases effort.

Traditional survey methods such as point count surveys of fauna are currently the mainstay of biodiversity monitoring, however acoustic sensors have a promising and important role to play now and in the future. Sampling methods have been shown to be effective for estimating species richness from large volumes of acoustic sensor data (Lengagne and Slater 2002), however comprehensive analysis such as the analyses performed here have the potential to provide much richer insights into changes occurring in the environment.

ACKNOWLEDGEMENTS

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

Chapter 5: Do the eyes have it? – A comparison of traditional bird surveys and acoustic sensor surveys.

Title: Do the eyes have it? – A comparison of traditional bird surveys and acoustic sensor surveys.

Authors: Jason Wimmer[a], Paul Roe[a], Peter Grace[b] and Ian Williamson[a]

Affiliations:

[a]Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

[b]Institute for Future Environments, Queensland University of Technology, Brisbane, Australia

Email: (j.wimmer, p.roe, pr.grace, i.williamson)@qut.edu.au

Corresponding Author: Jason Wimmer

Corresponding Author Address: School of Electrical Engineering and Computer Science, QUT Gardens Point, Brisbane, Queensland, 4000, Australia. Ph: +61 7 3138 9485 Fax: +61 7 3138 9390

5.1 STATEMENT OF CONTRIBUTION OF CO-AUTHORS

The authors listed below have certified* that:

1. they meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the Australasian Research Online database consistent with any limitations set by publisher requirements.

In the case of this chapter: **Do the eyes have it? – A comparison of traditional bird surveys and acoustic sensor surveys.**

Publication title and date of publication or status: Do the eyes have it? – A comparison of traditional bird surveys and acoustic sensor surveys (Submitted to *Methods in Ecology and Evolution*, 2013).

Contributor	Statement of Contribution*
Name: Jason Wimmer	Wrote manuscript, experimental design, analysis.
Signature:	
Date: 11/6/2013	
Co-author: Prof. P. Roe	Experimental design. Manuscript review.
Co-author: Prof. P. Grace	Experimental design. Manuscript review.
Co-author: Dr. I. Williamson	Experimental design. Manuscript review.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all Co-authors confirming their certifying authorship.

Professor Paul Roe	PRoe	11/6/2013
Name	Signature	Date

5.2 ABSTRACT

This study compares the results of traditional bird field surveys and acoustic sensor surveys conducted concurrently over a five day period. We compared the number of species detected by each method, the differences in species composition, the effect of observers on bird calling frequency and the cost of each method.

Acoustic sensor surveys consistently detected a higher number of species than traditional surveys conducted concurrently at the same location. The greatest difference in number of species detected was recorded on day one of a five day survey.

While detection of species increased using acoustic sensors, the overall cost of analysis also increased by a factor of two. However, the cost of sensor surveys reduces as the deployment length increases.

The 20 minute periods before, during and after traditional surveys were examined to establish if the presence of observers in the field had an effect on the calling behaviour of species (and hence detectability). Of 43 species analysed, only three species demonstrated significant changes in calling behaviour.

These results provide important guidance for researchers and managers considering the use of acoustic sensing technology for biodiversity monitoring. When compared to traditional surveys, acoustic sensor surveys consistently detect a higher number of bird species. Issues relating to the detection range of acoustic sensors should be considered however, when making comparisons between traditional and acoustic sensor methods. The presence of observers in the field does not appear to have an effect on the detectability of most bird species. The cost associated with acoustic sensor data analysis is currently prohibitive for large volumes of data; however automated methods are evolving rapidly. The ability to verify and reanalyse acoustic sensor data is also a considerable advantage.

Keywords:

Acoustic sensor; biodiversity monitoring; observer bias; survey method comparison, bird survey

5.3 INTRODUCTION

The ability to monitor biodiversity at large spatial and temporal scales is becoming increasingly important as the effects of climate change and habitat loss threaten the natural environment (Pereira and David Cooper 2006). In recent years, rapid advances in consumer electronics have led to the availability of low-cost, digital recording devices that serve as acoustic sensors for monitoring the sounds of the environment (Mennill et al. 2012). Acoustic sensors have the potential to increase environmental observations by providing a cost-effective, continuous, *in situ* recording capability across large areas, for extended periods of time (Penman, Lemckert and Mahony 2005; Gage, Napoletano and Cooper 2001; Porter et al. 2005). They can also provide an indelible, long term record of the environment in which they were deployed. While these factors make acoustic sensors appealing, objective comparisons of acoustic sensors and traditional survey methods are needed. In this paper we compare acoustic sensor surveys and traditional bird surveys to determine the effectiveness of acoustic sensors as a means for collecting data on bird species richness and abundance.

Traditional bird survey methods such as point count surveys are currently the mainstay for collecting data on bird species richness and abundance (Bibby et al. 2000). They provide valuable observation data, and require little in the way of specialised equipment; however, they require experienced observers, and are subject to a number of known biases. Observers vary significantly in their expertise in identifying and counting birds, and many factors contribute to the accuracy of any individual survey (Alldredge, Simons and Pollock 2007b; Cunningham et al. 1999), including the survey design and sampling method, habitat, and season (Bibby et al. 2000), and species attributes such as singing rate (Alldredge, Simons and Pollock

2007b). Observer presence and clothing colour has also been found to affect song rate or other bird behaviours (Gutzwiller and Marcum 1997; Riffell and Riffell 2002), although one study that used an array of GPS time synchronised recording units found no difference in either bird location, singing behaviour or bird species detected with observers present (Frommolt and Tauchert (2014).

Correct identification of species can also be a considerable source of observer bias in bird surveys (Lindenmayer, Wood and MacGregor 2009). Field observations cannot usually be independently verified and can be subject to inconsistencies due to observer experience, vegetation type, distance from observer and other factors (Cunningham et al. 1999; Diefenbach, Brauning and Mattice 2003). The ability to review acoustic sensor data can be a considerable advantage, allowing for independent verification of observations, and providing a permanent record of the environment. The lack of appropriately trained and skilled observers, the potential for observer bias to negatively impact survey results and the ability of acoustic sensors to scale observations (spatially and temporally), has increased interest in acoustic sensor technology for species surveys.

Determining the accuracy and effectiveness (in both time and resources) of acoustic sensors compared to traditional survey methods is important for understanding the appropriate application of this technology, but the small number of comparisons of sensor-based and field surveys have yielded conflicting results. Haselmayer and Quinn (2000) demonstrated that acoustic sensing yielded better results in areas with high species richness, due to the ability of observers conducting analysis to replay recordings and identify individual species amongst vocalisations of other species. Acevedo and Villanueva-Rivera (2006) compared traditional surveys to acoustic sensor data collected from the same sites, using a seven minute sampling regime over 24 hours. Their results indicated that the acoustic sensor data detected a higher number of species, provided a permanent record of species detected, and caused minimal disturbance to wildlife. There was however greater effort involved in analysing acoustic sensor data, and difficulty in obtaining density estimates. Similarly, Celis-Murillo et al. (2009) demonstrated that analysis of acoustic sensor data required greater time and effort, however the analysis resulted in a faster rate-of-detection of species and different species composition. Hobson et al. (2002) found that a greater number of species were detected in sensor recordings later analysed by an experienced observer than in field surveys in Boreal forests.

Conversely, when acoustic data recorded during traditional bird surveys were analysed, Hutto and Stutzman (2009) found that acoustic data failed to detect a significant proportion of species detected by field observers, who also used visual cues to perceive and identify birds. Studies of recordings taken from Breeding Bird Surveys found that listeners detected similar numbers of species to field observers, when recordings were listened to only once (Acoustics 2014). Both traditional methods and acoustic sensor data analysis failed to detect all species however. Similarly, both Venier et al. (2012) and Hobson et al. (2002) found no significant difference in species detected from sensor and traditional surveys.

The limited number of studies comparing acoustic sensors with traditional surveys, and the variation in findings, indicate that further comparisons are needed. In an earlier paper (Wimmer et al, 2013) we made some comparisons of traditional surveys with five continuous days (120 hours) of acoustic sensor data from a patch of open forest in south-east Queensland, Australia. In this paper we compare species richness estimates from traditional bird surveys and acoustic sensor surveys from the same survey, but focussing on information collected by each method for the same times. In addition we compared the costs associated with traditional and sensor surveys, and the effect of in-the-field observers on the calling behaviour of bird species.

5.4 METHODS

5.4.1 SITES

Traditional avian surveys and acoustic sensor surveys were conducted at the 51ha, Queensland University of Technology (QUT) Samford Ecological Research Facility (SERF) in the Samford valley in south east Queensland, Australia. SERF vegetation is predominantly open forest consisting of *Eucalyptus tereticornis*, *E. crebra* , *Corymbia intermedia*, *Lophostemon suavolens* and *Melaleuca quinquenervia*. A small patch of closed forest (notophyll vine forest) borders Samford Creek along the north-western edge of the property, and the southern and western sections consist of previously grazed pasture.

Samples were taken at four sites over five consecutive days from 13th October 2010 – 17th October 2010. The four sites were positioned in the north-east corner within open forest, the north-west corner in closed forest along the Samford creek, in the west corner within *Melaleuca* woodland, and in the southern corner bordering open pasture (Figure 16).

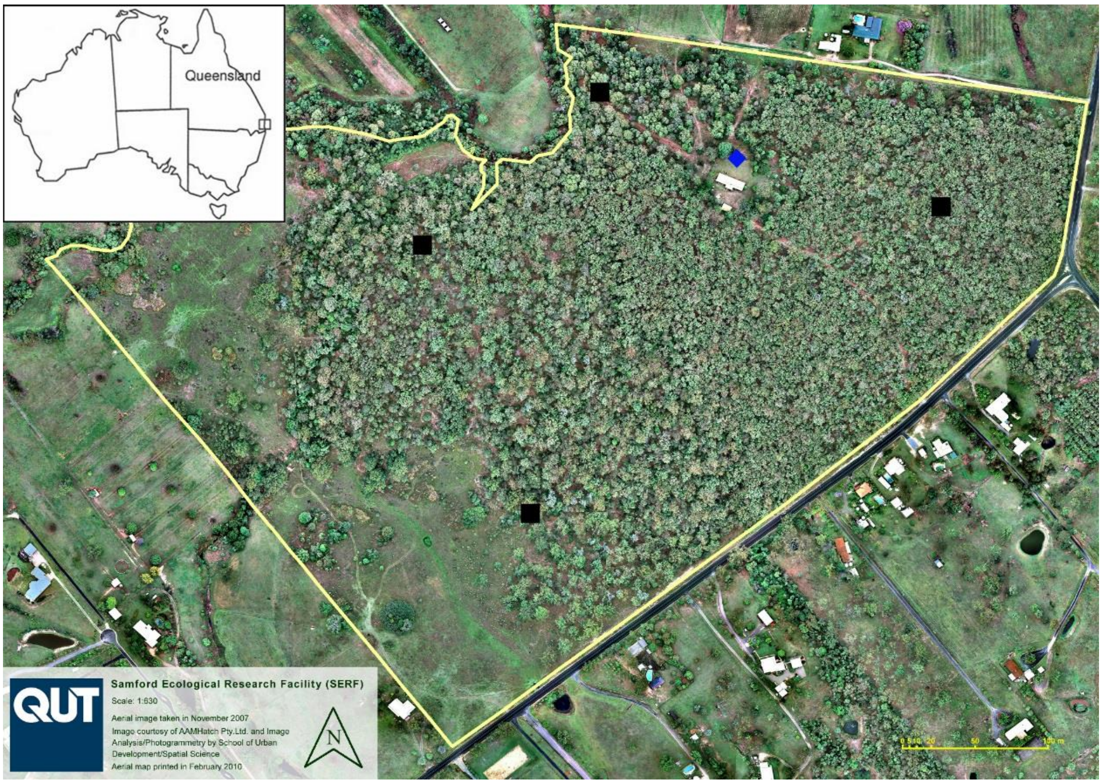

Figure 16. Samford Ecological Research Facility with survey sites indicated as black squares.

5.4.2 TRADITIONAL BIRD SURVEYS

Traditional bird surveys were conducted at dawn, noon and dusk sequentially at each site using a modified area search (Loyn 1985). All birds observed within the 200m x 100m sites were recorded as seen, heard, or seen and heard over a 20-minute period. Surveys were carried out by two observers with over 20 years of combined experience bird watching in the south-east Queensland area.

5.4.3 ACOUSTIC SENSORS

Acoustic sensors were located at the centre of each survey site and configured to record continuously for five consecutive days. Sensors used for this study were custom-built using commercially available, low cost digital recording equipment. Acoustic data were recorded using Olympus DM-420 digital recorders (Olympus, Pennsylvania, USA) and external omni-directional electret microphones. Data were stored internally in stereo MP3 format (128 Kbit/s, 22.05 KHz) on 32GB Secure

Digital memory cards. The units were stored in a weatherproof case and powered by four D cell batteries.

5.4.4 ACOUSTIC DATA ANALYSIS

Sensor data were analysed after completion of the five days of traditional surveys and recordings. Recordings were reviewed by two experienced observers (the same observers who conducted the traditional surveys) to identify species calling in each one minute segment. Observers analysed five days from two sites each, processing one minute segments starting from day one. A call library containing examples of each species vocalising was developed to ensure species were annotated consistently. These calls were verified and crosschecked with reference material (Morcombe 2004). To ensure species were annotated accurately each observer was allocated 1,440 random one minute segments (10% of total data analysed by each surveyor) to audit. Results from the audits found that less than 5% of total annotations were incorrectly identified. In total, each observer analysed approximately 10 full days of acoustic data (14,400 one minute segments).

Calls were annotated online using acoustic analysis software which allows users to play audio, view spectrograms and annotate species vocalisations (Wimmer, Towsey, Planitz, et al. 2013). Annotation involved selecting the portion of the spectrogram representing the bird vocalisation and assigning a species name to it. At the completion of analysis, annotations were downloaded in CSV format which included the site name, date, time and species name of all annotations.

5.4.5 COMPARISONS

Statistical analyses were performed using the IBM SPSS Statistics package (Version 20). Using analysis of variance (ANOVAs) the following comparisons were made between acoustic sensor and traditional surveys.

- The number of species detected from traditional surveys at dawn, noon and dusk, and the corresponding sensor recording times.
- The number of unique species detected daily from aggregated dawn, noon and dusk results for both sensor and traditional surveys.
- The number of species detected over the 5 day survey period from aggregated dawn, noon and dusk results for both sensor and traditional surveys.
- The number of species detected overall from continuous recordings spanning the period of the traditional surveys (5 days x 24 hour recordings), and the number of species from traditional surveys.
- Estimated costs of acoustic sensor deployment and subsequent data analysis, and estimated costs of traditional surveys.

To determine whether surveyors had an impact on the calling behaviour of birds, recordings corresponding to the periods 20 minutes before the arrival of surveyors on site, the 20 minutes while the surveyors were on site, and 20 minutes after surveyors departed were analysed using repeated measures analysis of variance (ANOVAs). Across the five-day survey period 3,600 1 minute segments corresponding to 20 minute periods before, during and after the 60 surveys were analysed to determine if species calling rates decreased or increased.

Species accumulation curves are effective for illustrating how quickly species are detected in a particular habitat using a particular survey method. They can also be used to visually represent the point at which further sampling effort is unlikely to result in further detection of species (the asymptote). For this study, we used species accumulation curves to highlight the differences in the rate of species detection for sensor and traditional field surveys.

We compared the species accumulation over the five day survey period for the field surveys, the sensor data corresponding to the field survey times (i.e. the same times corresponding to dawn, noon and dusk surveys) and the full sensor data (i.e. 24 hours per day).

5.5 RESULTS

5.5.1 SURVEY PERIOD COMPARISON

The total number of species detected over the five days and four sites was 66 for the traditional survey method and 74 for the sensor method (for corresponding traditional and sensor time periods). Traditional surveys detected between 34 and 49 species per site across the five day survey period. Acoustic sensors detected between 46 and 49 species per site, for times corresponding to traditional surveys. Full analysis of all sensor data (not restricted to traditional survey periods) detected up to 80 species (Figure 17).

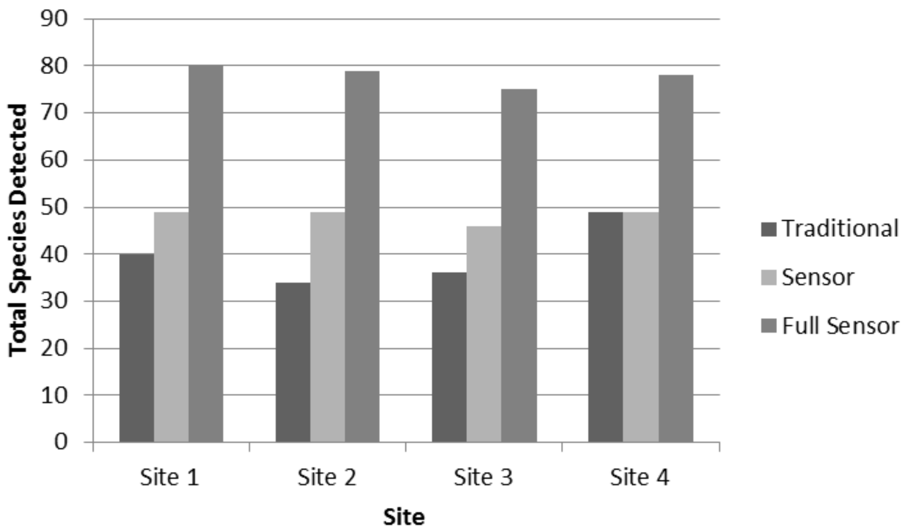

Figure 17. Number of unique species detected per site over five days by traditional surveys, sensor surveys corresponding to traditional survey times, and full sensor surveys.

Figure 18 shows the species accumulation curves for the two methods over the five days. The greatest difference in number of species detected by each method was recorded on day one, with the sensor surveys corresponding to traditional survey times recording an additional 21 species. By day five, the difference reduced to eight and 38 species for sensor surveys corresponding to traditional survey times, and full day sensor surveys respectively. These data suggest that acoustic sensors detect higher numbers of species initially, and add new species at a slightly slower rate, whereas traditional surveys detect fewer species initially, and tend to accumulate more new species over each survey day.

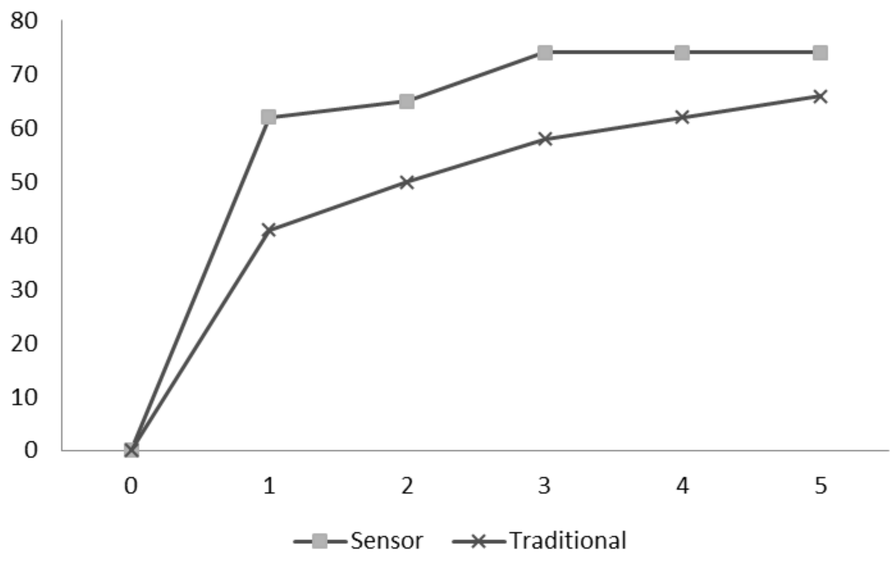

Figure 18. Species accumulation curves for Sensor and Traditional surveys (for corresponding 20 minute dawn, noon and dusk survey periods). Points are total number of species detected across all sites.

Comparisons made within days: Comparisons based on daily observations (using mean species detected per day, and sites as replicates) indicated that more species were detected at dawn than at noon or dusk, and more species were detected from sensor surveys than from traditional surveys (Figure 19).

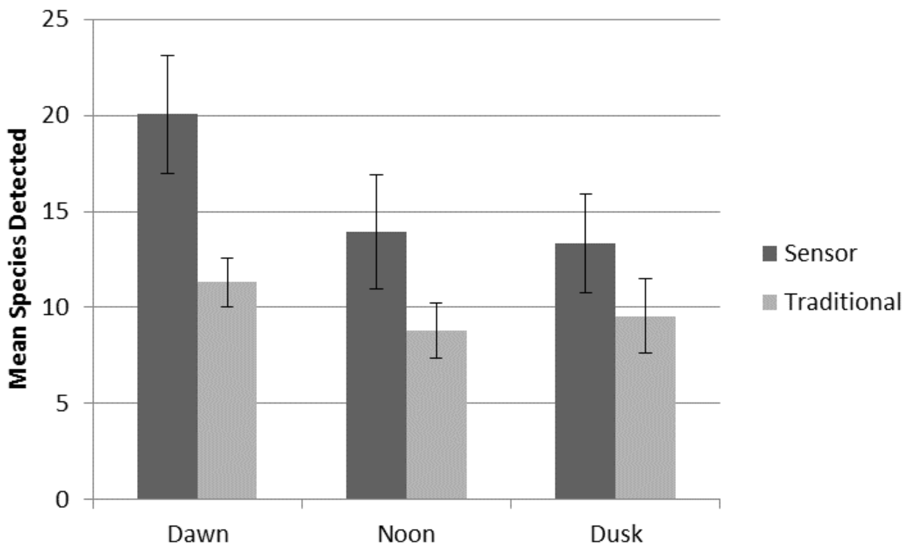

Figure 19 Mean number of species detected from sensor and traditional surveys for corresponding 20 minute dawn, noon and dusk survey periods (± 95% CI).

However, the level of difference between traditional and sensor surveys depended on time and day (2 way ANOVA, Period x Method Interaction: F (2,8) = 3.79, p = 0.042). The difference between traditional and sensor methods was lower at dusk and higher at dawn (Figure 19).

A similar analysis based on total species found at the site over 5 days (sites as replicates) the same trend was observed, however the interaction between period and method was not significant (F (2,18) = 2.77, p = 0.09). More species were detected from the sensor surveys (F (1,18) = 22.6, p < 0.001), and more species were detected at dawn (F (2,18) = 11.3, p = 0.001). Post hoc tests (Tukey: p < 0.05) showed a difference between dawn and other periods, but no difference between noon and dusk.

Comparisons made between days: Comparisons were also be made between the combined dawn, noon and dusk surveys for each method on each day (i.e. a tally of species from 3 x 20 minute surveys each day; sites as replicates). There was a significant difference in number of species detected between methods (F(1,30) = 37.3,

$p < 0.001$). Sensors consistently detected more species per day than traditional surveys (Figure 20).

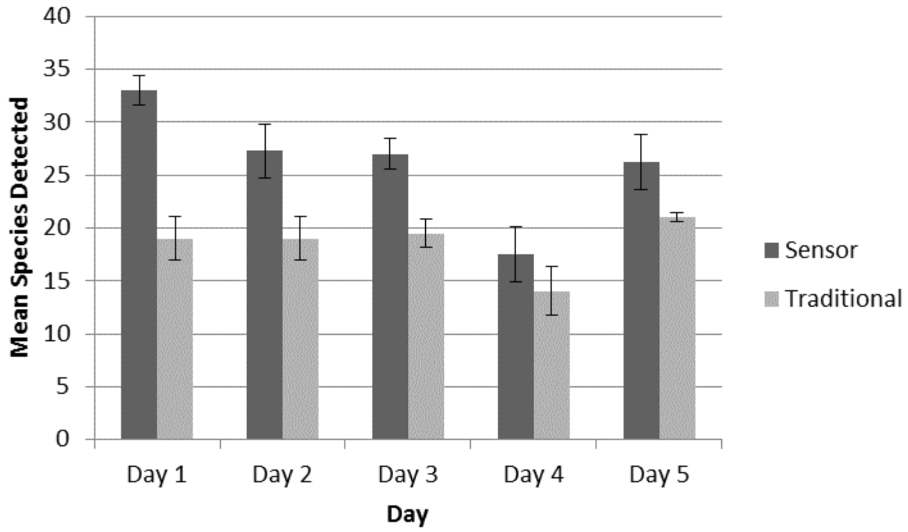

Figure 20. Mean number of species detected daily (aggregated from dawn, noon and dusk survey periods) for traditional and sensor surveys (± SEM).

There was also a significant difference in the number of species detected between days ($F(4,30) = 7.53$, $p < 0.001$), but the magnitude of the difference in the number of species detected between methods did not vary between days (Day x Method interaction: $F(4,30) = 2.00$, $p = 0.12$).

5.5.2 DIFFERENCES IN SPECIES COMPOSITION

Of the 74 species detected by sensor surveys and 66 species detected by traditional surveys, 52 species were detected by both methods, 22 species were detected by acoustic sensors and not by traditional surveys, and 14 species were detected by traditional surveys and not by sensors.

Of the 22 species, 13 could be described as loud callers (Morcombe 2004), and may therefore have called from outside the 200 x 100m traditional survey area, and been excluded from the traditional surveys (e.g. Australian Magpie *Gymnorhina tibicen*, Channel-billed Cuckoo *Scythrops novaehollandiae*, Grey Butcherbird

Cracticus torquatus, Masked Lapwing *Vanellus miles* and Pied Butcherbird *Cracticus nigrogularis*).

Of the remaining nine species, six were detected in fewer than 100 out of 28,800 one minute segments, and three species were detected vocalising in between 100 and 329 out of 28,800 one minute segments over the entire survey period. These species had a very low probability of detection, and for Painted Buttonquail *Turnix varia* calls, which called in four one minute segments (out of 28,800), the probability of detection was less than 0.01%. The probability of detection was <2% for Little Fiarbird *Philemon citreogularis*, which called in 329 one minute segments.

Of the 14 species detected only by traditional surveys, two species were observed as 'heard only'. Reanalysis of the sensor recordings corresponding to the times these species were observed failed to detect them. Of the remaining 12 species that were recorded as 'seen', three are described as being 'silent', or having 'quiet calls' (Topknot Pigeon *Lopholaimus antarcticus*; Little Pied Cormorant *Microcarbo melanoleucos* and Little Black Cormorant *Phalacrocorax sulcirostris*) (Morcombe 2004). The remaining nine species were difficult to characterise in terms of their calling behaviour. These species may have either not vocalised during the survey period, or their vocalisations may have been faint and not detected.

Even though field surveys and concurrent sensor recordings constituted 5 hours of the total 120 hours per site covered by whole sensor survey, there were only 17 species (18% of total species) detected by the full sensor survey that were not detected during the field survey periods. Of these, three species were nocturnal and therefore unlikely to call during daylight periods in which the surveys were conducted (i.e. Australian Masked Owl *Tyto novaehollandiae*, Australian Owlet-nightjar *Aegotheles cristatus* and Bush Stone-curlew *Burhinus grallarius*). Fourteen other species (15% of total species detected) were recorded calling 10 times or less over the entire study (e.g. Azure Kingfisher *Alcedo azurea*, Collared Sparrowhawk *Accipiter cirrhocephalus*, Dusky Moorhen *Gallinula tenebrosa*, Forest Kingfisher *Todiramphus macleayii*, Glossy Black Cockatoo *Calyptorhynchus lathami*, Lewin's Rail *Lewinia pectoralis*, Pale-vented Bush-hen *Amaurornis moluccana* and Plumed Whistling Duck *Dendrocygna eytoni*). These species had a very low probability of detection (on average less than 0.04%).

5.5.3 EFFECT OF OBSERVERS ON CALLING BEHAVIOUR

The continuous recordings made at each site (Wimmer et al, 2013) allowed a comparison of calling rates immediately before, during, and immediately after traditional surveys. There were a total of 3,600 one-minute segments across the four sites and five days for the 20 minutes before, 20 minutes during, and 20 minutes after the surveys. In total, 16,253 calls were annotated and 74 unique species identified in these 3,600 one-minute segments. Of these, 31 species called in fewer than 10 *before*, *during* and *after* periods, and were excluded from analysis. Repeated measures ANOVAs were performed on the remaining 43 species to determine if the presence of observers during the survey period had an effect on calling behaviour (as measured by the proportion of the 20 minute segments in which a species called).

Of the 43 species tested, only three species showed significant differences in calling rates. These were the Australian Magpie *Gymnorhina tibicen* (Sphericity Assumed: $F(2, 38) = 5.86$, $p < 0.006$), Leaden Flycatcher *Myiagra rubecula* (Greenhouse-Geisser corrected: $F(1.47, 22.01) = 6.693$, $p < 0.009$), and Scaly-breasted Lorikeet *Trichoglossus chlorolepidotus* (Greenhouse-Geisser corrected: $F(1.262, 25.24) = 11.33$, $p < 0.006$). Post hoc tests using the Bonferroni correction were performed for the three species. The Australian Magpie decreased calling during the period in which the observers where present (p < 0.002), and while calling rates increase slightly in the period following the departure of observers, this was not significant (p = 0.487). The Scaly-breasted Lorikeet (p < 0.000) and Leaden Flycatcher (p < 0.007) both increased calling during the period in which the observers were present. In the period following the departure of observers, both species also reduced calling rates, however these were not significantly different to the survey period in which observers were present (p = 0.940, p = 0.374).

Noise created by the observers was relatively low across the survey periods. On average, 15% of total traditional survey time (three, one-minute segments out of 20) contained noise disturbance attributable to the observers. These included faint verbal communication and rustling vegetation noise. To get an indication of the overall impact of the noise from observers, disturbance was classified as 'faint', 'moderate' or 'loud'. Ninety one per cent of disturbance was classified as 'faint', with no disturbance classified as 'loud'; therefore overall observers were relatively quiet while conducting surveys.

5.5.4 COST COMPARISON

These results compare the cost of traditional surveys and acoustic sensor surveys. The cost of manual analysis of acoustic sensor data was not consistent across all times of the day (Figure 21).

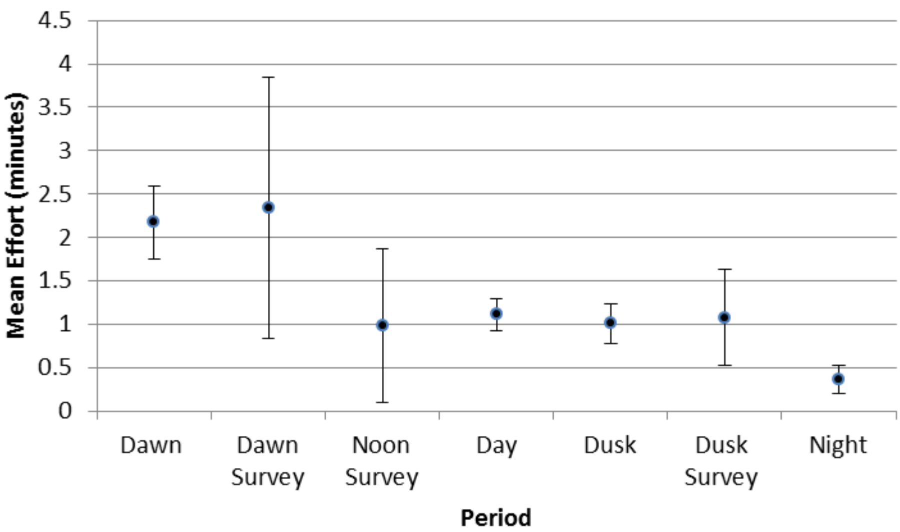

Figure 21. Mean number of minutes (and standard error) taken to manually analysis one minute of acoustic sensor data at different times of the day. Values for Dawn, Noon and Dusk Survey periods were calculated using one minute segments corresponding to the 20 minute traditional surveys.

The dawn chorus is a complex period, with many species vocalising simultaneously and repeatedly, and analysis of sensor recordings for this period took the most time (>2 minutes per recorded minute). Conversely, periods through the night contained few vocalisations, and therefore analysis took less time (<0.5 minutes per recorded minute). The time taken to analyse day and dusk sensor data was approximately one minute per recorded minute. The average analysis times for the periods corresponding to the three field survey times were similar to the corresponding acoustic survey periods from the whole survey analysis, though confidence limits were larger due to lower sample size. (Figure 21).

Costs of surveys include travel and preparation time, time in the field, and data collation and upload. Acoustic analysis is an additional cost for the sensor method. For longer surveys, travel costs to and from survey sites are generally lower for sensor surveys than traditional surveys. This is because sensors need to be deployed and collected once over the duration of the survey, whereas traditional surveys usually requiring travel to and from the site each day.

Assuming all other costs are generally similar for both methods, and the main comparison is between traditional field surveys and sensor data analysis corresponding to the same times, then the costs for either method (3 x 20 minute traditional surveys per day versus 3 x 20 minute sensor analysis per day) are similar (2 persons per traditional survey minute versus 1 person taking 2 minutes analysis per recorded sensor minute). Sensor data analysis of the full 24 hour periods detected a higher number of species; however at the 2:1 ratio observed (2 minutes to analyse one minute of sensor data) the cost of full analysis is prohibitive.

5.6 DISCUSSION

Acoustic sensors consistently detected a higher number of species than traditional surveys, for both the periods corresponding to the traditional surveys, and from full day acoustic sensor data comparisons. As expected, the difference between sensor and traditional surveys was greatest when traditional surveys were compared to full day sensor data. These results are consistent with previous studies comparing traditional and sensor survey methods (Celis-Murillo, Deppe and Allen 2009; Haselmayer and Quinn 2000).

Most of the difference in species detected between the survey methods can be attributed to the number of species detected on day 1 of the survey. After this, species accumulated at approximately the same rate for each method.

Sensor surveys detected a higher proportion of unique species compared to traditional surveys (30% compared to 23%). With the exception of Spotted Dove *Streptopelia chinensis*, and Tree Martin *Petrochelidon nigricans*, which were observed as ‘heard only’, all species unique to the traditional surveys were observed as ‘seen’. Reanalysis of the recording segments failed to detect species designated as ‘heard only’ by field observers.

Detection range is an important factor to consider when interpreting these results. The detection range for traditional surveys is usually set by the boundaries of the survey area (in this case a 100m x 200m site). For acoustic sensor surveys, the detection range for a specific species’ vocalisation, in varying environmental, vegetation and topographic conditions is very difficult to estimate. Subsequently, all bird vocalisations discernible and identifiable in recordings are included in survey results. Clearly this skews the results in favour of acoustic sensor surveys, as traditional surveys naturally exclude species seen or heard outside of the survey area (although, there is a significant body of literature describing inaccuracies associated with range estimation, particularly with bird vocalisations (Alldredge, Simons and Pollock 2007a; Alldredge et al. 2008; Simons et al. 2009; Nadeau and Conway 2012)).

‘Loud’ species accounted for 13 out of the 22 species (59%) detected only by sensor surveys. The remaining nine species are more difficult to characterise in terms of being more amenable to detection by sensor surveys, or less amenable to detection by traditional surveys. Given that 14 of the species not detected by field surveys were recorded in sensor surveys on 10 or fewer one minute segments over the entire survey period (10 out of 28,800 one minute segments), it is possible that these infrequent callers were simply not detected.

The effect of observers on estimates of species richness (leading to either under or overestimation) has been well documented for fish species (Dearden, Theberge and Yasué 2010; Cole et al. 2007; Kulbicki 1998). Some bird species are known to modify their calling behaviour in response to the presence of observers wearing brightly coloured clothing (Gutzwiller and Marcum 1997; Riffell and Riffell 2002); however the general effect of observers on the calling behaviour of birds (and thus their detectability) is less well understood (but see (Frommolt and Tauchert 2014)). Given that bird detections based on calls can constitute over 50% of bird observations in the field (Sauer, Peterjohn and Link 1994; Dobkin and Rich 1998), changes in either calling rates or detectability could lead to under or overestimations.

We examined call frequency data for 43 species before, during and after traditional surveys were conducted, to determine if the presence of observers had an effect on the calling behaviour of bird species. Of the 43 species, only three species showed a significant difference in mean calling rates for the 20 minute periods corresponding to before, during and after periods. This result warrants further investigation in different habitat types to determine if these findings are consistent across different species assemblages. It does however indicate that the presence of observers conducting surveys (relatively quietly) in the field is unlikely to account for the reduced number of species detected by traditional surveys.

When compared to the cost of traditional surveys, it is clear that full manual analysis (i.e. analysing 24 hours) of acoustic sensor data is currently prohibitive. We observed a 2:1 ratio of sensor analysis time to minutes of recorded data at dawn in this study (i.e. 2 minutes to analyse one minute of data). During night time periods when the number of species and their calling rates were reduced, the time taken to analyse one minute of data reduced to 0.5 of a minute. Given rapid advances in automated and semi-automated analysis, we believe there is significant advantage in conducting acoustic sensor surveys in conjunction with traditional surveys. As automated methods mature, historical records will provide an invaluable resource for future comparisons. In addition, semi-automated methods which can find potential vocalisations at night and remove periods of silence or noise (e.g. wind or rain), while assisting in the correct identification of species, may be of assistance in manually analysing large volumes of data in the near term.

For traditional dawn and dusk surveys conducted over one day only, the costs associated with travelling to and from sites, and for deploying and collecting sensors are roughly equivalent. When surveys are conducted over multiple days however, the overall travel costs for acoustic sensor surveys are less. This is because, irrespective of the number of days that surveys are conducted over, sensors require deploying and retrieving only once per survey period. Traditional surveys over multiple days generally require repeated visits to the site for each survey. This is consistent with previous studies based on acoustic sensor surveys of frogs (Penman, Lemckert and Mahony 2005), although there a no previous comparable sensor-based bird survey studies.

Comparisons between acoustic sensors and traditional surveys are in some ways arbitrary. The increased detection range of acoustic sensors has probably skewed the comparison between acoustic and traditional surveys in this research. We have demonstrated however that acoustic sensor surveys can at least produce results comparable with (or better than) results from traditional surveys. The greater issue is that of enhancing our capability to monitor biodiversity at larger spatial and temporal scales. In this regard, capturing an indelible historical record of the soundscape, which can later be analysed and verified, is a significant advantage.

Traditional surveys are typically constrained by time, effort and area so that meaningful comparisons can be made between surveys. With acoustic sensing, we remove some of these constraints, most notably time and area. Acoustic sensors can theoretically remain deployed indefinitely in large numbers over large areas, recording the sounds of any species with vocalisations loud enough to be detected. Even with very large scale citizen science initiatives such as the North American Breeding Bird Survey (Sauer et al. 1997) and the British Breeding Bird Surveys (Noble, Raven and Baillie 2001) traditional surveys lack the accuracy and capability to achieve this scale of continuous monitoring.

The adoption of a new technology to enhance our monitoring capability requires a rethink of the ways in which we interpret the results. Given that bird species vocalise to protect territory (amongst other reasons) (Catchpole and Slater 2008), detection range could likely be considered as a proxy for territory, and therefore for occupation. Conversely, attributing occupation based on call detection could lead to incorrectly assuming presence in a particular habitat type. This may be accentuated in areas with high edge effects, or ecotones. Where traditional surveys exclude calls outside the survey area (to preserve effort so that meaningful comparisons can be made between surveys), the inclusion of all calls in acoustic sensor surveys may provide a more accurate assessment of biodiversity in the detection range of the sensor. Calibrating sensors, standardising analysis methods and establishing the detection range of sensors under different environmental conditions is therefore critical to allow for meaningful comparisons to be made between acoustic sensor surveys.

ACKNOWLEDGEMENTS

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 analysing acoustic sensor data.

Chapter 6: Sampling environmental acoustic recordings to determine species richness.

Title: Sampling environmental acoustic recordings to determine species richness.

Authors: Jason Wimmer[a], Michael Towsey[a], Paul Roe[a], and Ian Williamson[a]

Affiliations:

[a]Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

Email: (j.wimmer, m.towsey, p.roe, i.williamson)@qut.edu.au

Corresponding Author: Jason Wimmer

Corresponding Author Address: School of Electrical Engineering and Computer Science, QUT Gardens Point, Brisbane, Queensland, 4000, Australia. Ph: +61 7 3138 2240 Fax: +61 7 3138 9390

6.1 STATEMENT OF CONTRIBUTION OF CO-AUTHORS

The authors listed below have certified* that:

1. they meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
3. there are no other authors of the publication according to these criteria;
4. potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
5. they agree to the use of the publication in the student's thesis and its publication on the Australasian Research Online database consistent with any limitations set by publisher requirements.

In the case of this chapter: **Sampling environmental acoustic recordings to determine species richness.**

Publication title and date of publication or status: Sampling environmental acoustic recordings to determine species richness (Accepted for publication in *Ecological Applications*, 2013).

Contributor	Statement of Contribution*
Name: Jason Wimmer	Wrote manuscript, experimental design, analysis.
Signature:	
Date: 11/6/2013	
Co-author: Dr. M. Towsey	Experimental design. Manuscript review.
Co-author: Prof. P. Roe	Experimental design. Manuscript review.
Co-author: Dr. I. Williamson	Experimental design. Manuscript review.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all Co-authors confirming their certifying authorship.

Professor Paul Roe	PRoe	11/6/2013
Name	Signature	Date

6.2 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 analysed 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 analysing large volumes of acoustic sensor data, while retaining high levels of species detection accuracy. Utilising five days of manually analysed 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 segments 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 segments, 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 analysing large volumes of acoustic sensor data efficiently and accurately. Development of automated and semi-automated techniques are required to assist in analysing large volumes of acoustic sensor data.

Keywords:

Acoustic Sensing, Sampling, Biodiversity Monitoring, Acoustic Data Analysis

6.3 INTRODUCTION

Acoustic sensors provide an effective means for monitoring biodiversity at large spatial and temporal scales (Haselmayer and Quinn 2000; Celis-Murillo, Deppe and Allen 2009; Acevedo and Villanueva-Rivera 2006; Thompson, Schwager and Payne 2009; Penman, Lemckert and Mahony 2005). They can record large volumes of acoustic data continuously and passively over extended periods. However, these recordings must be analysed to detect the presence of vocal species. Acoustic recordings can be analysed automatically by specially designed call-recognition software, or manually by humans to identify species-specific calls (Wimmer, Towsey, Planitz, et al. 2013; Acevedo et al. 2009; Celis-Murillo, Deppe and Allen 2009; Brandes 2008). 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 (Towsey et al. 2012; Swiston and Mennill 2009). Manual analysis can produce accurate results, however the time and effort required to process recordings can make manual analysis prohibitive (Swiston and Mennill 2009; Rempel et al. 2005). Continuous acoustic sensor deployments 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 interrogate the data in a meaningful way.

Many studies have identified the issues of efficiently analysing large amounts of acoustic data collected in the field (Acevedo and Villanueva-Rivera 2006; Corn, Muths and Iko 2000; Haselmayer and Quinn 2000; Brandes 2008; Mason et al. 2008; Collins et al. 2006). The amount of effort required to analyse acoustic data depends on the objective of the analysis. These objectives fall broadly into two categories: Single species surveys that analyses acoustic recordings of the vocalisations of a single species to assess aspects of that species' ecology or behaviour; or species richness surveys that analyse 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 vocalisations), or automatically using custom developed software or existing tools such as Raven (Charif, Ponirakis and Krein 2006). Automated detectors for species with distinctive vocalisations such as the Koala (*Phascolarctos cinereus*) and Cane Toad (*Bufo marinus*) have been developed and used successfully for a number studies (Ellis et al. 2011; Ellis et al. 2010; Grigg et al. 2006). Due to the larger number of species (and therefore range of vocalisations), species richness analyses typically require much greater time and effort. Irrespective of the objective, efficient analysis methods must be developed which 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 vocalisations of individual species in recordings. Perhaps due to the importance of birds as indicator species of environmental health (Carignan and Villard 2002a), there is a significant body of literature relating to the automated detection of bird vocalisations (Brandes 2008; Acevedo et al. 2009; Cai, Ee, Binh, et al. 2007; Juang and Chen 2007; Chen and Maher 2006; Kwan et al. 2004; McIlraith and Card 1997; Somervuo, Harma and Fagerlund 2006; Anderson, Dave and Margoliash 1996; Kasten, McKinley and Gage 2007; Bardeli et al. 2010; Sueur et al. 2008) . 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 (Schrama et al. 2008; Farnsworth, Gauthreaux and Blaricom 2004). Other approaches have focused on cataloguing and characterisations 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; Brandes 2008; Baker and Logue 2003) .

Manual analysis typically involves listening to recordings and identifying individual species vocalising in the recordings. This can be augmented by the use of tools to visualise the audio in the form of spectrograms, and by providing ‘reference calls’ which can be used to assist in species identification (Wimmer, Towsey, Planitz, 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 analyse 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 analysed 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.

6.4 MATERIALS AND METHODS

6.4.1 STUDY SITE

Traditional avian area searches modified from Loyn (Loyn 1985) and acoustic sensor surveys were conducted simultaneously at the Queensland University of Technology (QUT) Samford Ecological Research Facility (SERF). SERF is 51ha site located in the Samford valley in south east Queensland, Australia (-27.388992,152.878103).

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 in open woodland, the northern corner in closed forest along Samford Creek, in the western corner within *Melaleuca* woodland, and in the southern corner where open woodland borders cleared pasture (Figure 22).

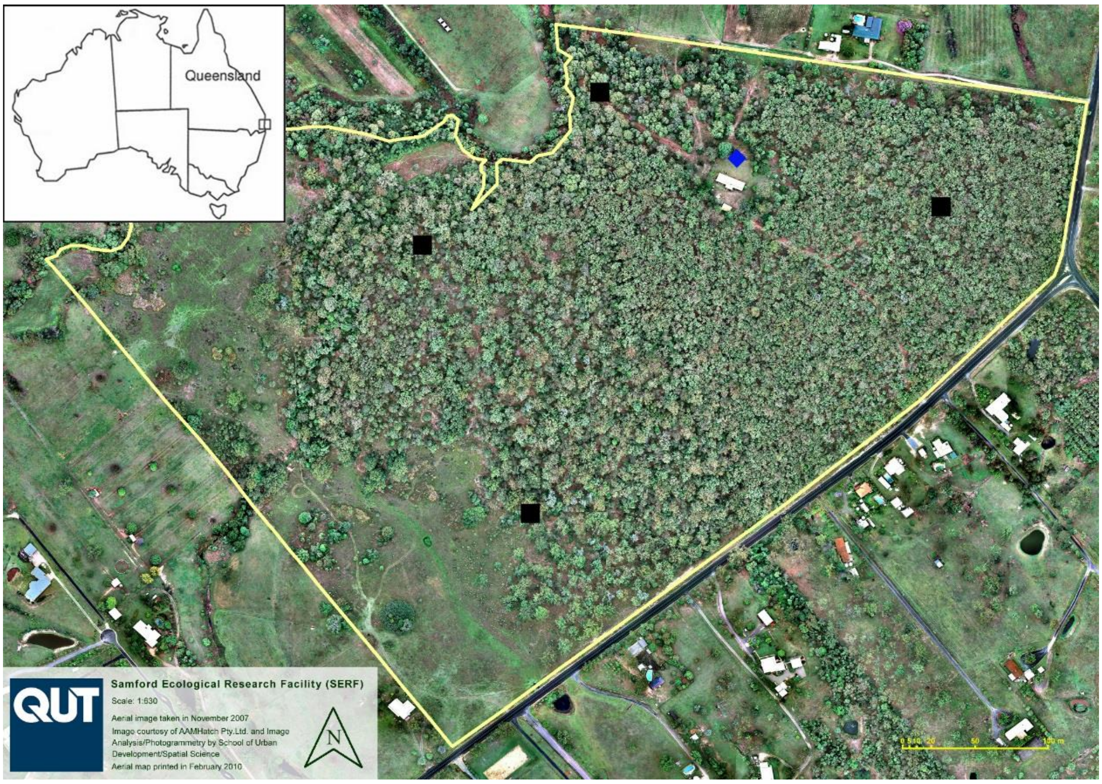

Figure 22. Samford Ecological Research Facility (SERF) with survey site positions.

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

6.4.2 ACOUSTIC SENSORS

Acoustic sensors were located at the centre of each survey site and configured to record continuously for five consecutive days. Sensors used for this study were custom-developed using commercially available, low cost digital recording equipment. Acoustic data were recorded using Olympus DM-420 digital recorders (Olympus, Pennsylvania, USA) and external omni-directional electret microphones. Data were stored internally in stereo MP3 format (128 Kbit/s, 22.05 KHz) on 32GB

Secure Digital memory cards. The units were stored in a weatherproof enclosure and powered by four D cell batteries.

6.4.3 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. In addition, surveyors were randomly allocated 1,440 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. In total, each surveyor analysed 14,400 one minute segments and 63,089 calls were annotated.

Calls were annotated using a custom online acoustic workbench designed to manage the process of acoustic data analysis (Wimmer, Towsey, Planitz, et al. 2013). The workbench plays audio and displays a spectrogram, which allows the user to visualise and hear audio simultaneously. Bird vocalisations were identified aurally and visually by listening to the recording with headphones and observing the corresponding spectrogram. To mark species vocalisations within recordings, the workbench provided the ability to annotate spectrograms. Annotation involved selecting the portion of the spectrogram image that contained the specific vocalisation, 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 vocalisations, and a single vocalisation 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 analyse 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.

6.4.4 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 segments selected randomly from the full 24-hour periods;
- **Dawn** – one minute segments selected randomly from 3 hours after dawn (05:15 – 08:14);

- **Dusk** – one minute segments selected randomly from 3 hours before dusk (14:55 – 17:54);
- **Dawn + Dusk** – one minute segments 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 7,200 one minute 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 1,800 one minute 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 2 minutes every hour). This constituted 240 one minute segments over the five-day survey period for each site.

For each sampling method, the required number 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 7,200 one minute recordings over five days, and counting the unique species detected in the n samples. This sampling was repeated 1,000 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 1,000 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 7,200 one minute samples from a site), and from traditional survey methods.

6.4.5 TRADITIONAL AREA SEARCH SURVEYS

Traditional bird surveys were conducted at each site using a modified area search survey method (Loyn 1985). A 200m x 100m 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 x 20 minutes) and each day constituted 120 minutes of effort (two surveyors x 20 minutes x three surveys). Over the five-day period at each site, the traditional surveys constituted 10 person hours of effort.

6.4.6 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 minimise 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.

6.5 RESULTS

6.5.1 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 28,800 one minute segments were manually analysed. Fifty-six per cent (16,019) of total segments contained calls, and from these, 63,089 birdcalls were identified and annotated (~ 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 77 to 83 species, while traditional surveys ranged from 34 to 49 species (Figure 23). 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) (Figure 23). Chao2 estimates from traditional surveys varied considerably, with estimates ranging from 41 (Site 3) to 110 (Site 2) (Figure 23).

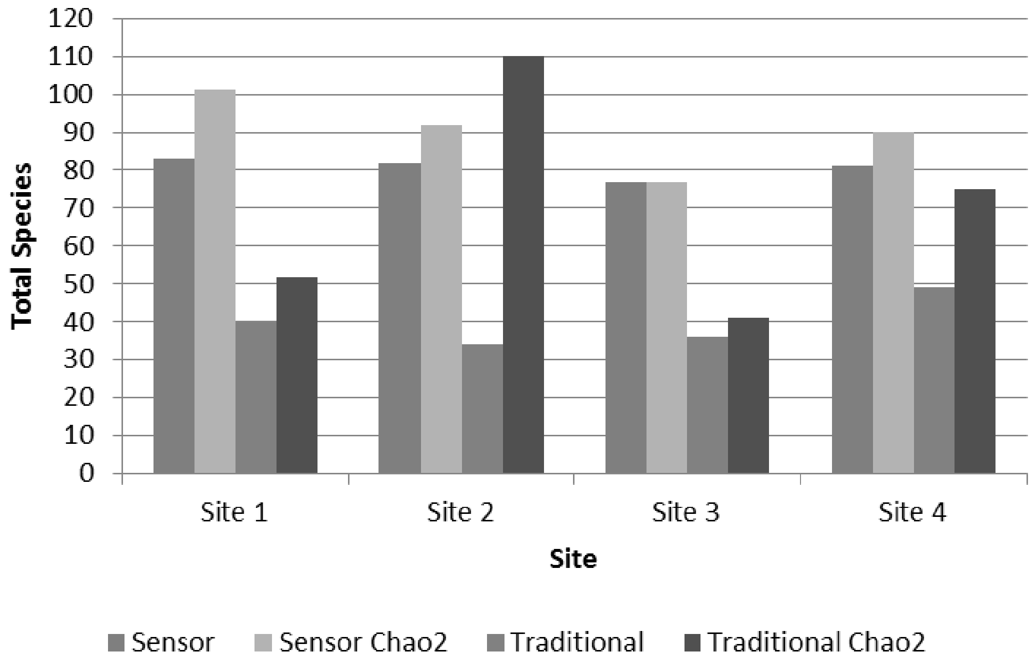

Figure 23. Total number of unique bird species detected and Chao2 species richness estimates for full acoustic sensor data analysis and traditional survey, for each site over the five-day survey period.

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 (Figure 24). The mean number of species recorded per site per day from traditional surveys across the five-day period ranged from 15 to 20 (Figure 24).

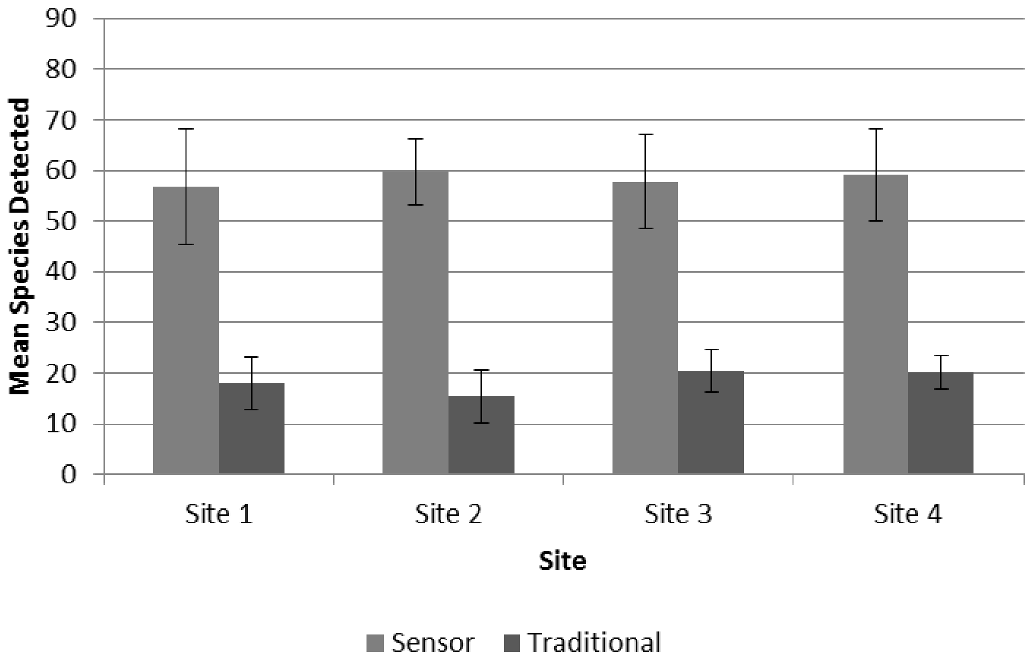

Figure 24. Mean number of bird species detected daily from full acoustic sensor data analysis and traditional survey for each site over the five-day survey period (± 95% CI).

Figure 25 shows the mean number of species detected from sensor data analysis per hour across all sites for all hours of the day.

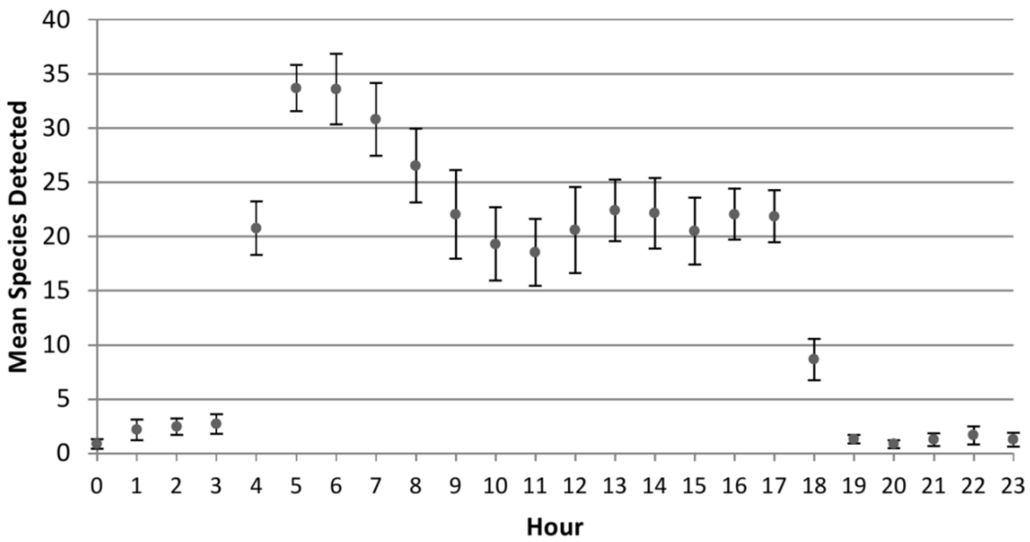

Figure 25. Mean number of species detected per hour from full analysis of acoustic sensor data across all sites (± 95% CI).

The dawn period had the greatest number of species, with a lull around midday and a less-pronounced peak towards 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 7am 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 vocalised in one out of 28,800 one minute segments, these species had a very low probability of detection. In contrast, the most frequently detected species was Rufous whistler (*Pachycephala rufiventris*), which was detected in 6941 one minute segments over the five-day period at all sites.

6.5.2 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 2).

Table 2. The maximum number and percentage of species detected [square brakets] for each sampling method from full manual analysis of sensor data, along with the minimum number of samples required to detect the maximum number of species (greedy algorithm). Results are presented for each site, and the mean of all sites.

Sampling Method	**Site 1**	**Site 2**	**Site 3**	**Site 4**	**Mean**
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)

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 optimisation algorithm (Cormen et al. 2009). 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.

Figure 26 shows the mean percentage of total species that were detected by each sampling method in relation to the number of one minute samples examined.

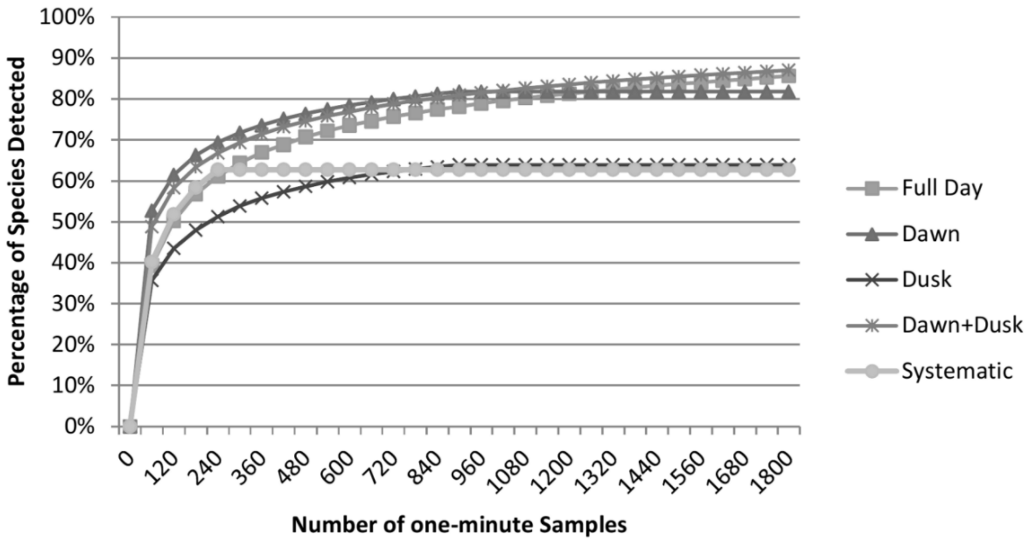

Figure 26. Mean percentage of total species detected for each sampling method for the associated number of minutes sampled (Data combined over sites).

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 x one minute samples (2 samples per hour x 24 hours x 5 days per site), whereas Dawn sampling had 900 samples (180 minutes per day x 5 days per site). Dawn plus Dusk sampling had 1,800 minutes of sampling available (combined dawn 180 minutes and dusk 180 minutes per day x 5 days per site). Only sampling from the Full Day method did not reach its asymptote in Figure 26 (24 hours x 60 minutes per hour x 5 days = 7,200 samples).

Systematic sampling detected an average of 63% of species, and the Dusk sampling period comprised 64% of species (Figure 26). An average of 82% of species were detected at Dawn, compared to 87% from the combined Dawn and Dusk sampling period (Figure 26) (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 1,080 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 total number of one minute samples in the Dawn and Dusk period) (Figure 26).

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 analyse 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 analyse 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 vocalisations. Hence, one minute of effort to analyse observations from acoustic sensor data is equivalent to two minutes of traditional survey observation effort.

For traditional surveys, each site had 120 person-minutes of effort per day (three 20-minute surveys x 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).

Figure 27 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)).

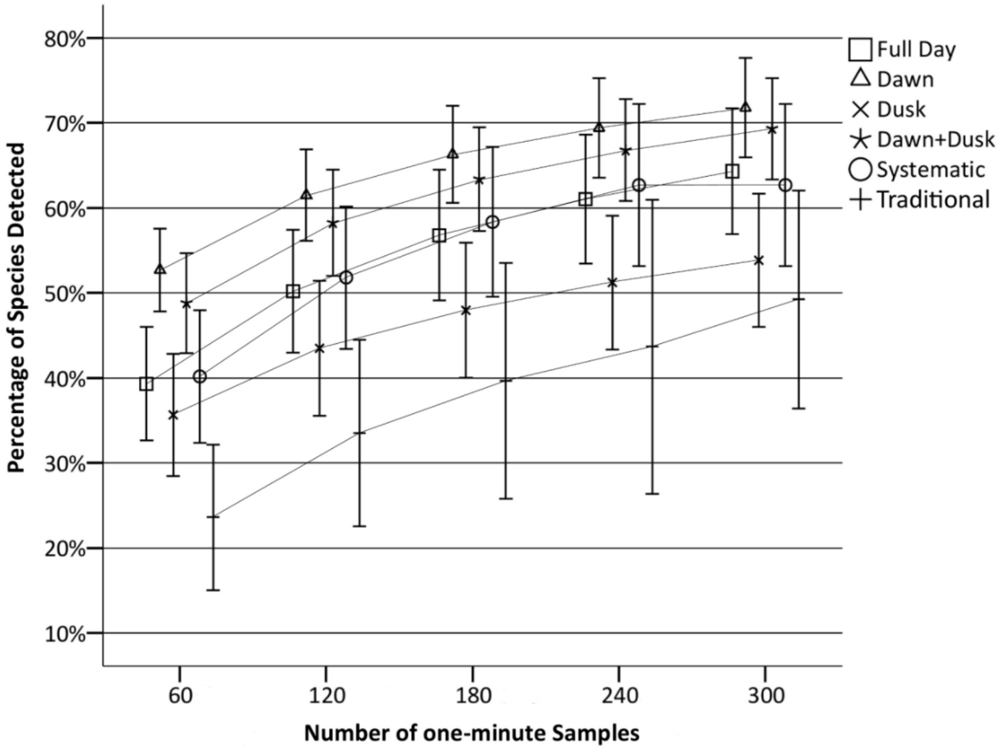

Figure 27. Mean percentage of total species detected by each sampling method for the associated number of minutes sampled. Error bars for each group of samples have been offset for clarity.

At all levels of sampling effort there was a significant difference in the number of species detected in relation to the sampling method (60 min - $F_{(5,18)} = 21.32$, $p < 0.001$; 120 min - $F_{(5,18)} = 16.145$, $p < 0.001$; 180 min - ($F_{(5,18)} = 12.783$, $p < 0.001$); 240 min - ($F_{(5,18)} = 9.956$, $p < 0.001$); 300 min - ($F_{(5,18)} = 10.461$, $p < 0.001$). Post hoc tests (Tukey; $p < 0.05$) indicated that traditional surveys detected significantly lower numbers of species than all acoustic sampling methods at 60 minutes sampling effort, and all sampling methods/sampling effort with the exception of Dusk (Table 3).

Table 3. Tukey post hoc test results for traditional survey against each sensor survey sampling method, and sampling effort up to 300 samples. Results are significant ($p < 0.05$) for all sampling methods and sampling effort with the exception of Dusk at 120 samples and higher.

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

6.6 DISCUSSION

Acoustic sensors are being used increasingly to augment traditional field survey methods. They can increase the spatial and temporal scales of observations (Brandes 2008; Parker 1991), 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 one minute 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; Celis-Murillo, Deppe and Allen 2009; Acevedo and Villanueva-Rivera 2006; Penman, Lemckert and Mahony 2005; Swiston and Mennill

2009), however there are issues relating to the detection range of acoustic sensors which 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 300m), 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 analyse 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, all species at each site could be detected in less than 50 samples (see greedy algorithm results: Table 2). 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 analysing 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 vocalisations. 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 vocalisations, 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.

6.7 ACKNOWLEDGEMENTS

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 analysing acoustic sensor data. Special thanks to Dr William Ellis and Dr 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.

Chapter 7: Conclusions

7.1 SUMMARY AND CONTRIBUTIONS

Effective environmental management requires an understanding of complex environmental systems. This understanding is based on observations of the environment, which are traditionally carried out in the field by experienced observers. Many aspects of environmental monitoring are becoming automated with the increasing availability of monitoring equipment which can repeatedly sample and log observations. Terrestrial fauna biodiversity monitoring is no exception, and acoustic sensing (particularly for bird species) is becoming widespread in the ecological community. Acoustic sensors allow us to increase the scale and scope of fauna observations and can provide an indelible record of the environment for future comparison or analysis.

Analysis and interpretation of acoustic sensor data presents some new and unique challenges for biodiversity monitoring. Acoustic sensor data (audio recordings of the environment) can be complex and opaque, with periods of the day, such as dawn, containing many species vocalising simultaneously. Noise such as wind and rain can also 'pollute' the acoustic soundscape and make the detection of individual species difficult. In addition, many species (particularly bird species) can exhibit a high degree of variation in their calling. Automated analysis methods are evolving, however this complexity and variation makes analysis tools costly to develop and difficult to characterise in terms of accuracy and precision. In the meantime, users of acoustic sensor technology require an efficient means to analyse and interpret acoustic sensor data. They also require an objective assessment of the typical performance of acoustic sensors, compared to traditional survey methods.

Analysis of acoustic sensor data can be performed manually or automatically. Manual analysis requires tools to assist in data management, visualisation, annotation and data summary. As part of this research, I have developed and refined an online *acoustic workbench* which manages large volumes of sensor data, provides visualisation, audio and annotation tools to marquee individual vocalisations and assign species tags. I have demonstrated that providing spectrogram visualisation tools significantly improved the ability of observers to find and annotate calls in audio recordings (Wimmer, Towsey, Planitz, et al. 2013). In addition, I have developed and implemented a comprehensive online call reference library and discussion and review facility, which assisted both with annotation consistency and accuracy in species identification. While more systems are now emerging to facilitate analysis of acoustic sensor data (Charif, Ponirakis and Krein 2006; Eyre et al. 2006), this system was the first of its kind, and supported the manual analysis of five days (480 hours) of continuous acoustic sensor data. To our knowledge, this is the largest and most comprehensively manually annotated dataset of its kind. It has subsequently been used to compare sensor surveys and traditional surveys, to test sampling strategies to reduce analysis effort, and has facilitated further acoustic sensing research in crowdsourcing and automated analyses (Shufei et al. 2011; Truskinger et al. 2011; Cottman-Fields et al. 2011; Towsey et al. 2012). In total, using the workbench, 480 hours of sensor data took 1,440 hours to analyse (180 days, or 36 working weeks).

Rich data such as audio or video recordings provide more than simple scalar data which is derived from most traditional observations. For example, traditional avian field surveys typically result in a species list and a count of individuals over the duration of the survey period. The visual observation and/or auditory detections made by the observers are effectively analysed on the spot by the observer, and then lost. Subsequently, it cannot be re-interpreted, re-analysed or verified in any way. In contrast, acoustic sensor data is rich data that has been captured in the field in a relatively raw state (assuming it has been recorded at the correct sampling frequency) and later analysed. In addition, because the data can be reanalysed and reinterpreted, we can make observations and attain insights that would otherwise be impossible.

For this research, acoustic sensors were deployed at four sites in south east Queensland for five consecutive days in October 2010. Data was subsequently manually analysed to identify calling patterns and the distribution of bird calls throughout a 24 hour period. The distribution and variation of bird calling behaviour over the five day period demonstrated a distinctive diurnal pattern, with a sharp peak at dawn and a pronounced lull through the night time periods. A far greater proportion of daytime one minute segments contained calls compared to night time segments. In addition, a greater number of species were detected calling through the day, compared to night. With a higher number of species vocalising many more times, there is significantly higher probability of detecting species during the day.

The vast majority of species were detected vocalising relatively few times which demonstrates one of the key advantages of acoustic sensing; namely, the ability to remain deployed for extended periods of time, passively recording the sounds of the environment. Cryptic species, or species which call infrequently are more likely to be detected by acoustic sensors than by infrequent traditional surveys. The results from Chapter 5 support this.

Acoustic sensors are being used increasingly to monitor terrestrial biodiversity (particularly bird species). To understand the appropriate application and biases of the technology, we require an objective assessment of its performance compared to traditional methods. Studies comparing the effectiveness of traditional and sensor surveys have yielded conflicting results, with some studies detecting greater numbers of species and some detecting less. As part of this research, I conducted concurrent sensor and traditional surveys over a five day period at four sites and compared the results of both methods. Acoustic sensors consistently detected a greater number of species than traditional methods for corresponding survey periods and overall. This confirms that acoustic sensor technology can be an effective tool for biodiversity monitoring.

There are a number of possible explanations for higher detection rates in sensor surveys than traditional surveys. An obvious explanation is that traditional surveys exclude observations (seen or heard) that are outside of the defined survey area; whereas all vocalisation detected in acoustic sensor surveys are included. Over 50% of species detected in sensor surveys and not detected in traditional surveys can been characterised as having ‘loud’ calls, which could have conceivably originated from outside the survey area, and subsequently disregarded by observers. There were also however, a number of species (12% of species detected only by sensor surveys) which were either nocturnal (and therefore unlikely to be detected by surveys conducted at dawn, noon and dusk) or cryptic/secretive making them potentially difficult to detect. Detection range and species specific behaviour can account for ~64% of species detected by sensor surveys. The remaining 36% of species are more difficult to characterise in terms of being more amenable to detection through acoustic sensor surveys.

To investigate another potential cause for higher detection rates using acoustic sensor surveys compared to traditional surveys, I examined whether bird species increase or decrease calling behaviour in response to the presence of human observers in the field. Using recordings from acoustic sensors, we compared the 20 minute periods before, during and after traditional survey periods and found that only three species out of 74 had a significant change in their calling rate. This is the first study of its kind to our knowledge that has compared the effect of human observers conducting bird surveys on the calling rates of a large number of bird species. The fact that only three of the 74 species observed demonstrated a change in calling rates, suggests that the physical presence of observers in the field does not account for the lower detection rates from traditional surveys.

This area requires further investigation; however we can deduce that the higher number of species detected by acoustic sensor surveys may be attributable to a combination of factors. These may include having the ability to replay recordings to detect fleeting calls and to discriminate between species calling simultaneously, and having access to periods of the day and night which would not typically be surveyed.

Analysis of acoustic sensor data is complex and time consuming. During the dawn period when the acoustic environment was particularly complex with high numbers of species exhibiting high call frequencies, on average it took over two minutes to analyse one minute of data. In contrast, during the night periods, with much lower numbers of species calling, on average one minute of data was analysed in 30 seconds. Over the entire day, the average was just over one minute to analyse one minute of data. This means that manual analysis of 24 hours of data will take, on average, 24 hours to analyse (3 x 8 hour working days). Given that the perceived value of acoustic sensing lies in the ability of the devices to remain deployed for extended periods continuously monitoring the environment, the amount of effort required to analyse large volumes of data is not cost effective.

Sampling is a well-accepted and commonly used technique in ecology to provide species diversity and population estimates. Taking a full census of any population is usually technically infeasible or prohibitive in terms of cost. The same is true of full manual analysis of large volumes of acoustic sensor data. Using a fully annotated set of acoustic sensor data from five days at four sites, I examined a number of random and systematic acoustic sensor data sampling methods to reduce cost, while maintaining high levels of species detection.

One minute segments were randomly sampled from the full day, dawn, dusk and a combination of dawn and dusk periods over a five day period at four sites. In addition, one minute segments were selected systematically on the hour and half hour. Up to 1,080 samples, the dawn period consistently detected a higher number of species than the other methods. The dusk and systematic methods consistently detected the lowest number of species overall.

To compare the results of random sampling of sensor data with traditional surveys, the time taken to conduct a traditional survey was used as a baseline of effort. Comparing the number of species detected for acoustic sensors and the results from traditional surveys using the equivalent effort, all random sampling methods (with the exception of the dusk period) consistently detected a higher number of species. Specifically, random sampling from the dawn period detected on average 20% more species than traditional surveys, for equivalent survey effort.

One of the core themes of this research was utilising technology to increase the temporal and spatial scale of biodiversity observations. At large scales, the sheer volume of acoustic data generated by acoustic sensors will eventually require automated acoustic sensor data analysis techniques. Automated techniques will continue to evolve and improve as interest in acoustic sensing increases. This thesis however, has consciously focused on the ecological aspects of acoustic sensing, and comparisons between manual analysis and traditional survey methods, rather than the development of automated methods.

This research presents a series of related works which together demonstrate the acoustic sensing biodiversity monitoring lifecycle from data collection, to comparisons between sensor and traditional methods, to analysis and sampling methods to reduce data analysis effort. This study is the first of its kind to compare a large volume of manually analysed acoustic sensor data with traditional surveys. This is also the first study of its kind to demonstrate that random sampling of acoustic sensor data can reduce manual acoustic data analysis effort, and produce results comparable to traditional surveys, for equivalent effort. This is an important contribution, because it also demonstrates that acoustic sensors are a viable bird survey technique, even in the absence of comprehensive automated analysis tools.

Another key contribution of this research has been the creation of 480 hours of fully annotated acoustic sensor data which will continue to provide insights into the calling behaviour of 96 bird species, and assist in ongoing research into automated analysis tools. Development of automated analysis tools necessarily requires a large number of example calls, both to develop analysis tools and then to test them. It is the development of these tools and the characterisation of their accuracy and precision that this data set will continue to assist with.

Bibliography

Acevedo, Miguel A., Carlos J. Corrada-Bravo, Héctor Corrada-Bravo, Luis J. Villanueva-Rivera and T. Mitchell Aide. 2009. "Automated classification of bird and amphibian calls using machine learning: A comparison of methods." *Ecological Informatics* 4 (4): 206-214. http://www.sciencedirect.com/science/article/B7W63-4X0W4WR-1/2/dada6a7a59cd874bd0babb94eb899919. doi: doi: 10.1016/j.ecoinf.2009.06.005.

Acevedo, Miguel A. and Luis J. Villanueva-Rivera. 2006. "Using Automated Digital Recording Systems as Effective Tools for the Monitoring of Birds and Amphibians." *Wildlife Society Bulletin* 34 (1): 211-214.

Acoustics, Wildlife. 2014. *Song Scope* 4.1.3. Maynard, MA: Wildlife Acoustics.

Agranat, Ian. 2009. "Automatically Identifying Animal Species from their Vocalizations." Paper presented at the Fifth International Conference on Bio-Acoustics, Holywell Park. Accessed 10 June 2010. http://bioacoustics2009.lboro.ac.uk/abstract.php?viewabstract=57.

Akyildiz, Ian F., Dario Pompili and Tommaso Melodia. 2005a. "Underwater acoustic sensor networks: research challenges." *Ad Hoc Networks* 3 (3): 257-279. http://www.sciencedirect.com/science/article/pii/S1570870505000168. doi: 10.1016/j.adhoc.2005.01.004.

Akyildiz, IF, D Pompili and T Melodia. 2005b. "Underwater acoustic sensor networks: research challenges." *Ad Hoc Networks* 3 (3): 257-279.

Ali, AM, S Asgari, TC Collier, M Allen, L Girod, RE Hudson, K Yao, CE Taylor and DT Blumstein. 2009. "An empirical study of collaborative acoustic source localization." *Journal of Signal Processing Systems* 57 (3): 415-436.

Alldredge, Mathew W., Krishna Pacifici, Theodore R. Simons and Kenneth H. Pollock. 2008. "A novel field evaluation of the effectiveness of distance and independent observer sampling to estimate aural avian detection probabilities." *Journal of Applied Ecology* 45 (5): 1349-1356. http://dx.doi.org/10.1111/j.1365-2664.2008.01517.x. doi: 10.1111/j.1365-2664.2008.01517.x.

Alldredge, Mathew W., Theodore R. Simons and Kenneth H. Pollock. 2007a. "A Field Evaluation of Distance Measurement Error in Auditory Avian Point Count Surveys." *The Journal of Wildlife Management* 71 (8): 2759-2766. http://www.jstor.org/stable/4496400. doi: 10.2307/4496400.

Alldredge, MW, TR Simons and KH Pollock. 2007b. "Factors affecting aural detections of songbirds." *Ecological Applications* 17 (3): 948-955.

Anderson, SE, AS Dave and D Margoliash. 1996. "Template-based automatic recognition of birdsong syllables from continuous recordings." *The Journal of the Acoustical Society of America* 100 (2): 1209-1219.

Australian Government Bureau of Meterology. 2012. "Climate Statistics for Samford CSIRO." Accessed 12 March 2012. http://www.bom.gov.au/climate/averages/tables/cw_040241.shtml.

Baker, Myron C. and David M. Logue. 2003. "Population Differentiation in a Complex Bird Sound: A Comparison of Three Bioacoustical Analysis Procedures." *Ethology* 109 (3): 223-242. http://dx.doi.org/10.1046/j.1439-0310.2003.00866.x. doi: 10.1046/j.1439-0310.2003.00866.x.

Balmford, Andrew and Kevin J. Gaston. 1999. "Why biodiversity surveys are good value." *Nature* 398 (6724): 204-205. http://dx.doi.org/10.1038/18339.

Bardeli, R., D. Wolff, F. Kurth, M. Koch, K. H. Tauchert and K. H. Frommolt. 2010. "Detecting bird sounds in a complex acoustic environment and application to bioacoustic monitoring." *Pattern Recognition Letters* 31 (12): 1524-1534. http://www.sciencedirect.com/science/article/pii/S0167865509002487. doi: 10.1016/j.patrec.2009.09.014.

Barlow, Jay and Barbara L. Taylor. 2005. "Estimates of sperm whale abundance in the northeastern temperate pacific from a combined acoustic and visual survey." *Marine Mammal Science* 21 (3): 429-445. http://dx.doi.org/10.1111/j.1748-7692.2005.tb01242.x. doi: 10.1111/j.1748-7692.2005.tb01242.x.

Bart, Jonathan. 2005. "Monitoring the abundance of bird populations." *Auk (American Ornithologists Union)* 122 (1): 15-25. http://gateway.library.qut.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=afh&AN=17460621&site=ehost-live.

Begon, M, CR Townsend and JL Harper. 2006. *Ecology: from individuals to ecosystems*. 4th ed. Malden: Wiley-Blackwell.

Bibby, C.J., N.D. Burgess, D.A Hill and S.H. Mustoe. 2000. *Bird census techniques*. 2nd ed. London: Academic Press.

Boer, M. M. and J. Puigdefábregas. 2003. "Predicting potential vegetation index values as a reference for the assessment and monitoring of dryland condition." *International Journal of Remote Sensing* 24 (5): 1135 - 1141. Accessed June 07, 2011. http://www.informaworld.com/10.1080/0143116021000026788.

Bosch, J. and I. De la Riva. 2004. "Are frog calls modulated by the environment? An analysis with anuran species from Bolivia." *Canadian Journal of Zoology* 82 (6): 880-888. http://gateway.library.qut.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=afh&AN=14541817&site=ehost-live. doi: 10.1139/z04-060.

Boulinier, Thierry, James D. Nichols, John R. Sauer, James E. Hines and K. H. Pollock. 1998. "Estimating species richness: the importance of heterogeneity in species detectability." *Ecology* 79 (3): 1018-1028. http://www.esajournals.org/doi/abs/10.1890/0012-9658%281998%29079%5B1018%3AESRTIO%5D2.0.CO%3B2. doi: doi:10.1890/0012-9658(1998)079[1018:ESRTIO]2.0.CO;2.

Brandes, S.T. 2008. "Automated sound recording and analysis techniques for bird surveys and conservation." *Bird Conservation International* 18 (SupplementS1): S163-S173. doi: doi:10.1017/S0959270908000415.

Bridges, Andrew S. and Michael E. Dorcas. 2000. "Temporal Variation in Anuran Calling Behavior: Implications for Surveys and Monitoring Programs." *Copeia* 2000 (2): 587-592. http://www.jstor.org/stable/1448212.

Brumm, Henrik. 2004. "The impact of environmental noise on song amplitude in a territorial bird." *Journal of Animal Ecology* 73 (3): 434-440. http://dx.doi.org/10.1111/j.0021-8790.2004.00814.x. doi: 10.1111/j.0021-8790.2004.00814.x.

Cai, J, D Ee, B Pham, P Roe and J Zhang. 2007. "Sensor network for the monitoring of ecosystem: Bird species recognition." In *Third International Conference on Intelligent Sensors, Sensor Networks and Information Processing, Melbourne*, edited, 293–298: Citeseer.

Cai, J, D. Ee, Pham Binh, P. Roe and Zhang Jinglan. 2007. "Sensor Network for the Monitoring of Ecosystem: Bird Species Recognition." In *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on, 3-6 Dec. 2007*, edited, 293-298. doi: 10.1109/issnip.2007.4496859.

Carignan, V and MA Villard. 2002a. "Selecting indicator species to monitor ecological integrity: a review." *Environmental Monitoring and Assessment* 78 (1): 45-61.

Carignan, Vincent and Marc-André Villard. 2002b. "Selecting Indicator Species to Monitor Ecological Integrity: A Review." *Environmental Monitoring and Assessment* 78 (1): 45-61. http://dx.doi.org/10.1023/A:1016136723584. doi: 10.1023/a:1016136723584.

Catchpole, Clive and Peter Slater. 2008. "Bird Song : Biological Themes and Variations". Leiden: Cambridge University Press.

Celis-Murillo, A, JL Deppe and MF Allen. 2009. "Using soundscape recordings to estimate bird species abundance, richness, and composition." *Journal of Field Ornithology* 80 (1): 64-78.

Chao, Anne. 1987. "Estimating the Population Size for Capture-Recapture Data with Unequal Catchability." *Biometrics* 43 (4): 783-791. http://www.jstor.org/stable/2531532.

Charif, RA, DW Ponirakis and TP Krein. 2006. *Raven Lite 1.0 User's Guide.* Ithaca, NY: Cornell Laboratory of Ornithology. http://www.birds.cornell.edu/brp/RavenLite/RavenLite10UsersGuide.pdf.

Chen, Z and RC Maher. 2006. "Semi-automatic classification of bird vocalizations using spectral peak tracks." *The Journal of the Acoustical Society of America* 120: 2974.

Cohen, Warren B. and Samuel N. Goward. 2004. "Landsat's Role in Ecological Applications of Remote Sensing." *BioScience* 54 (6): 535-545. http://www.jstor.org/stable/10.1641/0006-3568%282004%29054%5B0535%3ALRIEAO%5D2.0.CO%3B2.

Cole, R. G., C. Syms, N. K. Davey, N. Gust, P. Notman, R. Stewart, C. A. Radford, G. Carbines, M. H. Carr and A. G. Jeffs. 2007. "Does breathing apparatus affect fish counts and observations? A comparison at three New Zealand fished and protected areas." *Marine Biology* 150 (6): 1379-1395. http://dx.doi.org/10.1007/s00227-006-0420-3. doi: 10.1007/s00227-006-0420-3.

Collier, T.C., A.N.G. Kirschel and C.E. Taylor. 2010. "Acoustic localization of antbirds in a Mexican rainforest using a wireless sensor network." *The Journal of the Acoustical Society of America* 128: 182 - 189.

Collins, Scott L., Luís MA Bettencourt, Aric Hagberg, Renee F. Brown, Douglas I. Moore, Greg Bonito, Kevin A. Delin, et al. 2006. "New opportunities in ecological sensing using wireless sensor networks." *Frontiers in Ecology and the Environment* 4 (8): 402-407.

Colwell, R. K. 2009. "EstimateS: Statistical estimation of species richness and shared species from samples. Version 8.2. User's Guide and application published at: http://purl.oclc.org/estimates.

Cooper, Caren B., Janis Dickinson, Steve Kelling, Tina Phillips, Kenneth V. Rosenberg, Jennifer Shirk and Rick Bonney. 2009. "Citizen Science: A Developing Tool for Expanding Science Knowledge and Scientific Literacy." *BioScience* 59 (11): 977-984. http://gateway.library.qut.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=anh&AN=46986686&site=ehost-live. doi: 10.1525/bio.2009.59.11.9.

Cormen, T.H., C.E. Leiserson, R.L. Rivest and C. Stein. 2009. *Introduction to Algorithms, Third Edition*. 3rd ed. Massachusetts: MIT Press. http://books.google.com.au/books?id=VK9hPgAACAAJ.

Corn, Paul Stephen, Erin Muths and William M. Iko. 2000. "A Comparison in Colorado of Three Methods to Monitor Breeding Amphibians." *Northwestern Naturalist* 81 (1): 22-30. http://www.jstor.org/stable/3536896.

Cottman-Fields, M., A. Truskinger, J. Wimmer and P. Roe. 2011. "The Adaptive Collection and Analysis of Distributed Multimedia Sensor Data." In *E-Science (e-Science), 2011 IEEE 7th International Conference on, 5-8 Dec. 2011*, edited, 218-223. doi: 10.1109/eScience.2011.38.

Cunningham, R. B., D. B. Lindenmayer, H. A. Nix and B. D. Lindenmayer. 1999. "Quantifying observer heterogeneity in bird counts." *Australian Journal of Ecology* 24 (3): 270-277. http://dx.doi.org/10.1046/j.1442-9993.1999.00971.x. doi: 10.1046/j.1442-9993.1999.00971.x.

Darwin, Charles. 2012. "On the Origin of Species, 1859". Hoboken: Taylor and Francis.

Dawson, Deanna K. and Murray G. Efford. 2009. "Bird population density estimated from acoustic signals." *Journal of Applied Ecology* 46 (6): 1201-1209. http://dx.doi.org/10.1111/j.1365-2664.2009.01731.x. doi: 10.1111/j.1365-2664.2009.01731.x.

Dearden, P., M. Theberge and M. Yasué. 2010. "Using underwater cameras to assess the effects of snorkeler and SCUBA diver presence on coral reef fish abundance, family richness, and species composition." *Environmental Monitoring and Assessment* 163 (1-4): 531-538. http://dx.doi.org/10.1007/s10661-009-0855-3. doi: 10.1007/s10661-009-0855-3.

Dejong, Michael J. and John T. Emlen. 1985. "The Shape of the Auditory Detection Function and Its Implications for Songbird Censusing." *Journal of Field Ornithology* 56 (3): 213-223. http://www.jstor.org/stable/4513018.

Depraetere, Marion, Sandrine Pavoine, Fréderic Jiguet, Amandine Gasc, Stéphanie Duvail and Jérôme Sueur. 2011. "Monitoring animal diversity using acoustic indices: Implementation in a temperate woodland." *Ecological Indicators* In Press, Corrected Proof. http://www.sciencedirect.com/science/article/pii/S1470160X11001361. doi: 10.1016/j.ecolind.2011.05.006.

Diefenbach, Duane R., Daniel W. Brauning and Jennifer A. Mattice. 2003. "Variability in Grassland Bird Counts Related to Observer Differences and Species Detection Rates." *The Auk* 120 (4): 1168-1179. http://www.jstor.org/stable/4090287. doi: 10.2307/4090287.

Dobkin, David S. and Adam C. Rich. 1998. "Comparison of Line-Transect, Spot-Map, and Point-Count Surveys for Birds in Riparian Habitats of the Great Basin." *Journal of Field Ornithology* 69 (3): 430-443. http://www.jstor.org/stable/4514340.

Ellis, W. A., S. I. Fitzgibbon, P. Roe, F. B. Bercovitch and R. Wilson. 2010. "Unraveling the mystery of koala vocalisations: acoustic sensor network and GPS technology reveals males bellow to serenade females." *Integrative and Comparative Biology* 50: E49-E49.

Ellis, W., F. Bercovitch, S. FitzGibbon, P. Roe, J. Wimmer, A. Melzer and R. Wilson. 2011. "Koala bellows and their association with the spatial dynamics of free-ranging koalas." *Behavioral Ecology*. http://beheco.oxfordjournals.org/content/early/2011/02/04/beheco.arq216.abstract. doi: doi:10.1093/beheco/arq216.

Endler, John A. 1993. "Some General Comments on the Evolution and Design of Animal Communication Systems." *Philosophical Transactions: Biological Sciences* 340 (1292): 215-225. http://www.jstor.org/stable/55796.

Eyre, Teresa J, Annie Kelly, VJ Neldner, BA Wilson, DJ Ferguson, MJ Laidlaw and AJ Franks. 2006. *Biocondition: a terrestrial vegetation condition assessment tool for biodiversity in Queensland, field assessment manual*: Environmental Protection Agency.

Farnsworth, Andrew, Jr Sidney A. Gauthreaux and Donald van Blaricom. 2004. "A comparison of nocturnal call counts of migrating birds and reflectivity measurements on Doppler radar." *Journal of Avian Biology* 35 (4): 365-369. http://dx.doi.org/10.1111/j.0908-8857.2004.03180.x. doi: 10.1111/j.0908-8857.2004.03180.x.

Fiore, S. and G. Aloisio. 2011. "Special section: Data management for eScience." *Future Generation Computer Systems* 27 (3): 290-291. http://www.sciencedirect.com/science/article/pii/S0167739X10001664. doi: 10.1016/j.future.2010.08.012.

Fletcher, N. 1997. "Sound in the Animal World." *Acoustics Australia* 25: 69-74.

Fletcher, N.H. 2004. "A simple frequency-scaling rule for animal communication." *The Journal of the Acoustical Society of America* 115: 2334.

Freitag, Lee E. and Peter L. Tyack. 1993. "Passive acoustic localization of the Atlantic bottlenose dolphin using whistles and echolocation clicks." *The Journal of the Acoustical Society of America* 93 (4): 2197-2205. doi: 10.1121/1.406681.

Frommolt, Karl-Heinz and Klaus-Henry Tauchert. 2014. "Applying bioacoustic methods for long-term monitoring of a nocturnal wetland bird." *Ecological Informatics* 21 (0): 4-12. http://www.sciencedirect.com/science/article/pii/S1574954113001301. doi: http://dx.doi.org/10.1016/j.ecoinf.2013.12.009.

Frommolt, KH, KH Tauchert and M. Koch. 2008. "Advantages and Disadvantages of Acoustic Monitoring of Birds—Realistic Scenarios for Automated Bioacoustic Monitoring in a Densely Populated Region, Computational bioacoustics for assessing biodiversity." In *Proceedings of the International Expert meeting on IT-based detection of bioacoustical patterns, Isle of Vilme, Germany, December 2007*, edited, 83-92.

Gage, Stuart H., Brian M. Napoletano and Michael C. Cooper. 2001. "Assessment of ecosystem biodiversity by acoustic diversity indices." *The Journal of the Acoustical Society of America* 109 (5): 2430-2430.

Golder, Scott A. and Bernardo A. Huberman. 2006. "Usage patterns of collaborative tagging systems." *Journal of Information Science* 32 (2): 198-208. http://jis.sagepub.com/content/32/2/198.abstract. doi: 10.1177/0165551506062337.

Greenwood, Jeremy. 2007. "Citizens, science and bird conservation." *Journal of Ornithology* 148 (0): 77-124. http://dx.doi.org/10.1007/s10336-007-0239-9. doi: 10.1007/s10336-007-0239-9.

Grigg, G., A. Taylor, H. McCallum and L. Fletcher. 2006. "Monitoring the impact of cane toads (Bufo marinus) on Northern Territory frogs–a progress report. Pages 47 - 54 in Science of Cane Toad Invasion and Control. Proceedings of the Invasive Animals CRC/CSIRO/Qld NRM&W Cane Toad Workshop, Brisbane, June 2006, edited by K. L. Molloy and W. R. Henderson. Canberra: Invasive Animals Cooperative Research Centre. , edited.

Gutzwiller, Kevin J. and Heidi A. Marcum. 1997. "Bird Reactions to Observer Clothing Color: Implications for Distance-Sampling Techniques." *The Journal of Wildlife Management* 61 (3): 935-947.

Hamilton, Michael P., Eric A. Graham, Philip W. Rundel, Michael F. Allen, William Kaiser, Mark H. Hansen and Deborah L. Estrin. 2007. "New Approaches in Embedded Networked Sensing for Terrestrial Ecological Observatories." *Environmental Engineering Science* 24 (2): 192-204. Accessed 2011/06/07. http://dx.doi.org/10.1089/ees.2006.0045. doi: 10.1089/ees.2006.0045.

Harma, A. 2003. "Automatic identification of bird species based on sinusoidal modeling of syllables." In *Acoustics, Speech, and Signal Processing, 2003. Proceedings. (ICASSP '03). 2003 IEEE International Conference on, 6-10 April 2003*, edited, V-545-8 vol.5.

Haselmayer, John and James S. Quinn. 2000. "A Comparison of Point Counts and Sound Recording as Bird Survey Methods in Amazonian Southeast Peru." *The Condor* 102 (4): 887-893.

Havlik, Denis, Sven Schade, Zoheir A. Sabeur, Paolo Mazzetti, Kym Watson, Arne J. Berre and Jose Lorenzo Mon. 2011. "From Sensor to Observation Web with Environmental Enablers in the Future Internet." *Sensors* 11 (4): 3874-3907. http://www.mdpi.com/1424-8220/11/4/3874/.

Ho, Clifford, Alex Robinson, David Miller and Mary Davis. 2005. "Overview of Sensors and Needs for Environmental Monitoring." *Sensors* 5 (1): 4-37. http://www.mdpi.com/1424-8220/5/1/4/.

Hobson, Keith A., Robert S. Rempel, Greenwood Hamilton, Brian Turnbull and Steven L. Van Wilgenburg. 2002. "Acoustic Surveys of Birds Using Electronic Recordings: New Potential from an Omnidirectional Microphone System." *Wildlife Society Bulletin* 30 (3): 709-720.

Hu, Wen, Nirupama Bulusu, Chun Tung Chou, Sanjay Jha, Andrew Taylor and Van Nghia Tran. 2009. "Design and evaluation of a hybrid sensor network for cane toad monitoring." *ACM Transactions on Sensor Networks.* 5 (1): 1-28. doi: 10.1145/1464420.1464424.

Hunter, ML and JP Gibbs. 2007. *Fundamentals of conservation biology*. 3rd ed. Malden: Wiley-Blackwell.

Huse, Ingvar and Rolf Korneliussen. 2000. "Diel variation in acoustic density measurements of overwintering herring (Clupea harengus L.)." *ICES Journal of Marine Science: Journal du Conseil* 57 (4): 903-910. http://icesjms.oxfordjournals.org/content/57/4/903.abstract. doi: 10.1006/jmsc.2000.0577.

Hutto, Richard L. and Ryan J. Stutzman. 2009. "Humans versus autonomous recording units: a comparison of point-count results." *Journal of Field Ornithology* 80 (4): 387-398.

IUCN. 2010. "IUCN Red List version 2010. Numbers of threatened species by major groups of organisms (1996 - 2010). http://www.iucnredlist.org/documents/summarystatistics/2010_1RL_Stats_Table_1.pdf. (accessed on 23 February 2011).".

Juang, CF and TM Chen. 2007. "Birdsong recognition using prediction-based recurrent neural fuzzy networks." *Neurocomputing* 71 (1-3): 121-130.

Kasten, E. P., P. K. McKinley and S. H. Gage. 2007. "Automated Ensemble Extraction and Analysis of Acoustic Data Streams." In *Distributed Computing Systems Workshops, 2007. ICDCSW '07. 27th International Conference on, 22-29 June 2007,* edited, 66-66. doi: 10.1109/icdcsw.2007.25.

Kasten, Eric P., Stuart H. Gage, Jordan Fox and Wooyeong Joo. 2012. "The remote environmental assessment laboratory's acoustic library: An archive for studying soundscape ecology." *Ecological Informatics* 12 (0): 50-67. http://www.sciencedirect.com/science/article/pii/S157495411200088X. doi: http://dx.doi.org/10.1016/j.ecoinf.2012.08.001.

Keast, A. 1994. "Temporal Vocalization Patterns in Members of a Eucalypt Forest Bird Community: the Effects of Weather on Song Production." *Emu* 94 (3): 172-180. http://www.publish.csiro.au/paper/MU9940172. doi: http://dx.doi.org/10.1071/MU9940172.

Kendall, William L. 1999. "Robustness of Closed Capture-Recapture Methods to Violations of the Closure Assumption." *Ecology* 80 (8): 2517-2525. http://www.jstor.org/stable/177237.

Krebs, C.J. 1999. *Ecological methodology*. 2nd ed. Menlo Park, CA: Addison-Welsey Educational

Krebs, J.R. and R. Dawkins. 1984. "Animal signals: mind-reading and manipulation." In *Behavioural ecology: An evolutionary approach,* edited by J.R. Krebs and N.B. Davies, 380-402: Oxford: Blackwell Scientific Publications.

Kulbicki, Michel. 1998. "How the acquired behaviour of commercial reef fishes may influence the results obtained from visual censuses." *Journal of Experimental Marine Biology and Ecology* 222 (1–2): 11-30. http://www.sciencedirect.com/science/article/pii/S0022098197001330. doi: http://dx.doi.org/10.1016/S0022-0981(97)00133-0.

Kwan, C., G. Mei, X. Zhao, Z. Ren, R. Xu, V. Stanford, C. Rochet, J. Aube and K. C. Ho. 2004. "Bird classification algorithms: theory and experimental results." In *IEEE International Conference on Acoustics, Speech, and Signal Processing, 2004. Proceedings. (ICASSP '04). 17-21 May 2004*, edited, V-289-92 vol.5. 10.1109/ICASSP.2004.1327104.

Lengagne, Thierry and Peter J. B. Slater. 2002. "The effects of rain on acoustic communication: tawny owls have good reason for calling less in wet weather." *Proceedings of the Royal Society of London. Series B: Biological Sciences* 269 (1505): 2121-2125. http://rspb.royalsocietypublishing.org/content/269/1505/2121.abstract. doi: 10.1098/rspb.2002.2115.

Lieberzeit, Peter and Franz Dickert. 2007. "Sensor technology and its application in environmental analysis." *Analytical and Bioanalytical Chemistry* 387 (1): 237-247. http://dx.doi.org/10.1007/s00216-006-0926-z. doi: 10.1007/s00216-006-0926-z.

Lindenmayer, D. B., J. T. Wood and C. MacGregor. 2009. "Do observer differences in bird detection affect inferences from large-scale ecological studies?" *Emu* 109 (2): 100-106. http://dx.doi.org/10.1071/MU08029.

Lindenmayer, DB, RB Cunningham and BD Lindenmayer. 2004. "Sound recording of bird vocalisations in forests. II. Longitudinal profiles in vocal activity." *Wildlife Research* 31 (2): 209-217.

Liqian, Luo, Cao Qing, Huang Chengdu, T. Abdelzaher, J. A. Stankovic and M. Ward. 2007. "EnviroMic: Towards Cooperative Storage and Retrieval in Audio Sensor Networks." In *Distributed Computing Systems, 2007. ICDCS '07. 27th International Conference on, 25-27 June 2007*, edited, 34-34.

Loyn, R.H. 1985. "The 20-minute search: a simple method for counting forest birds." *Corella* 10: 58-60.

Luo, Liqian, Qing Cao, Chengdu Huang, Lili Wang, Tarek F. Abdelzaher, John A. Stankovic and Michael Ward. 2009. "Design, implementation, and evaluation of EnviroMic: A storage-centric audio sensor network." *ACM Trans. Sen. Netw.* 5 (3): 1-35. doi: 10.1145/1525856.1525860.

Magurran, Anne E. 2009. "Measuring Biological Diversity". Hoboken: Wiley-Blackwell.

Martinez, K., J. K. Hart and R. Ong. 2004. "Environmental sensor networks." *Computer* 37 (8): 50-56.

Mason, Richard, Paul Roe, Michael Towsey, Jinglan Zhang, Jennifer Gibson and Stuart Gage. 2008. "Towards an Acoustic Environmental Observatory." Paper presented at the Fourth IEEE International Conference on eScience. IEEE Computer Society. doi: http://dx.doi.org/10.1109/eScience.2008.16.

Mateescu, Gabriel, Wolfgang Gentzsch and Calvin J. Ribbens. 2011. "Hybrid Computing--Where HPC meets grid and Cloud Computing." *Future Generation Computer Systems* 27 (5): 440-453. http://www.sciencedirect.com/science/article/pii/S0167739X1000213X. doi: 10.1016/j.future.2010.11.003.

McCarthy, Jennifer L., Kyle P. McCarthy, Todd K. Fuller and Thomas M. McCarthy. 2010. "Assessing Variation in Wildlife Biodiversity in the Tien Shan Mountains of Kyrgyzstan Using Ancillary Camera-trap Photos." *Mountain Research and Development* 30 (3): 295-301. Accessed 2011/06/10. http://dx.doi.org/10.1659/MRD-JOURNAL-D-09-00080.1. doi: 10.1659/mrd-journal-d-09-00080.1.

McIlraith, A. L. and H. C. Card. 1997. "Birdsong recognition using backpropagation and multivariate statistics." *IEEE Transactions on Signal Processing* 45 (11): 2740-2748. 10.1109/78.650100.

Mellinger, DK, KM Stafford, S Moore, RP Dziak and H Matsumoto. 2007. "Fixed Passive Acoustic Observation Methods for Cetaceans." *Oceanography* 20 (4): 36.

Mennill, Daniel J., Matthew Battiston, David R. Wilson, Jennifer R. Foote and Stéphanie M. Doucet. 2012. "Field test of an affordable, portable, wireless microphone array for spatial monitoring of animal ecology and behaviour." *Methods in Ecology and Evolution* 3 (4): 704-712. http://dx.doi.org/10.1111/j.2041-210X.2012.00209.x. doi: 10.1111/j.2041-210X.2012.00209.x.

Mennill, Daniel J., John M. Burt, Kurt M. Fristrup and Sandra L. Vehrencamp. 2006. "Accuracy of an acoustic location system for monitoring the position of duetting songbirds in tropical forest." *The Journal of the Acoustical Society of America* 119 (5): 2832-2839. http://link.aip.org/link/?JAS/119/2832/1. doi: 10.1121/1.2184988.

Milne, D. J., M. Armstrong, A. Fisher, T. Flores and C. R. Pavey. 2004. "A comparison of three survey methods for collecting bat echolocation calls and species-accumulation rates from nightly Anabat recordings." *Wildlife Research* 31 (1): 57-63. http://www.publish.csiro.au/paper/WR03011. doi: doi:10.1071/WR03011.

Moore, Sue E., Kathleen M. Stafford, David K. Mellinger and John A. Hildebrand. 2006. "Listening for Large Whales in the Offshore Waters of Alaska." *BioScience* 56 (1): 49-55.

Morcombe, Michael. 2004. *Field guide to Australian Birds*. Archerfield, QLD: Steve Parish Publishing. http://qut.summon.serialssolutions.com/link/0/eLvHCXMwY2BQSExJNE00N0o0NkhNNTQyMzZPSUsEMpJSLQ0sUpNSjFEG25BKczdRBhk31xBnD93C0pJ46PBFPGiUAthINrE0FGNgAXaJUwGJ5Rfi.

Mundinger, PC. 1982. "Microgeographic and macrogeographic variation in acquired vocalizations in birds, p. 147–208 in D.E. Kroodsma and E.H. Miller, eds. ." In *Acoustic communication in birds*. New York: Academic Press.

Nadeau, Christopher P. and Courtney J. Conway. 2012. "Field evaluation of distance-estimation error during wetland-dependent bird surveys." *Wildlife Research* 39 (4): 311-320. http://dx.doi.org/10.1071/WR11161.

Nagy, Eric, John H. Porter, Timothy K. Kratz, Paul Hanson, Scott L. Collins and Peter Arzberger. 2009. "New Eyes on the World: Advanced Sensors for Ecology." *Bioscience* 59 (5): 385. http://gateway.library.qut.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=ulh&AN=39242284&site=ehost-live. doi: 10.1025/bio.2009.59.5.6.

Nielsen, S. E., E. M. Bayne, J. Schieck, J. Herbers and S. Boutin. 2007. "A new method to estimate species and biodiversity intactness using empirically derived reference conditions." *Biological Conservation* 137 (3): 403-414. http://www.sciencedirect.com/science/article/pii/S0006320707000912. doi: 10.1016/j.biocon.2007.02.024.

Noble, David G, MJ Raven and Stephen R Baillie. 2001. *The Breeding Bird Survey 2000*. Vol. 265, *BTO Research Report No. 265*. Thetford: British Trust for Ornithology.

Noss, Reed F. 1990. "Indicators for Monitoring Biodiversity: A Hierarchical Approach." *Conservation Biology* 4 (4): 355-364.

O'Farrell, Michael J., Bruce W. Miller and William L. Gannon. 1999. "Qualitative Identification of Free-Flying Bats Using the Anabat Detector." *Journal of Mammalogy* 80 (1): 11-23. http://www.jstor.org/stable/1383203.

Parker, Theodore A., III. 1991. "On the Use of Tape Recorders in Avifaunal Surveys." *The Auk* 108 (2): 443-444.

Parkes, David, Graeme Newell and David Cheal. 2003. "Assessing the quality of native vegetation: The 'habitat hectares' approach." *Ecological Management & Restoration* 4: S29-S38. http://dx.doi.org/10.1046/j.1442-8903.4.s.4.x. doi: 10.1046/j.1442-8903.4.s.4.x.

Parmesan, Camille. 2006. "Ecological and Evolutionary Responses to Recent Climate Change." *Annual Review of Ecology, Evolution, and Systematics* 37 (1): 637-669. http://www.annualreviews.org/doi/abs/10.1146/annurev.ecolsys.37.091305.110100. doi: doi:10.1146/annurev.ecolsys.37.091305.110100.

Patwari, N., J. N. Ash, S. Kyperountas, A. O. Hero, III, R. L. Moses and N. S. Correal. 2005. "Locating the nodes: cooperative localization in wireless sensor networks." *Signal Processing Magazine, IEEE* 22 (4): 54-69.

Payne, Katharine B., Mya Thompson and Laura Kramer. 2003. "Elephant calling patterns as indicators of group size and composition: the basis for an acoustic monitoring system." *African Journal of Ecology* 41 (1): 99-107. http://dx.doi.org/10.1046/j.1365-2028.2003.00421.x. doi: 10.1046/j.1365-2028.2003.00421.x.

Penman, TD, FL Lemckert and MJ Mahony. 2005. "A cost-benefit analysis of automated call recorders." *Applied Herpetology* 2 (4): 389-400.

Pereira, Henrique M. and H. David Cooper. 2006. "Towards the global monitoring of biodiversity change." *Trends in Ecology & Evolution* 21 (3): 123-129. http://www.sciencedirect.com/science/article/B6VJ1-4HJ47G5-1/2/7ab1b6961ebdf763bd97e12dd716a2c9. doi: 10.1016/j.tree.2005.10.015.

Peterson, C.R. and M.E. Dorcas. 2001. "The use of automated data-acquisition techniques in monitoring amphibian and reptile populations, p. 369 - 378. In: Wildlife 2001: populations. D.R. McCullough and R. Barrett (eds.). Elsevier Applied Science, London.

Pieretti, N., A. Farina and D. Morri. 2011. "A new methodology to infer the singing activity of an avian community: The Acoustic Complexity Index (ACI)." *Ecological Indicators* 11 (3): 868-873. http://www.sciencedirect.com/science/article/pii/S1470160X10002037. doi: 10.1016/j.ecolind.2010.11.005.

Porter, John, Peter Arzberger, Hans-Werner Braun, Pablo Bryant, Stuart Gage, Todd Hansen, Paul Hanson, et al. 2005. "Wireless Sensor Networks for Ecology." *BioScience* 55 (7): 561-572.

Rempel, Robert S., Keith A. Hobson, George Holborn, Steve L. van Wilgenburg and Julie Elliott. 2005. "Bioacoustic Monitoring of Forest Songbirds: Interpreter

Variability and Effects of Configuration and Digital Processing Methods in the Laboratory." *Journal of Field Ornithology* 76 (1): 1-11.

Riede, Klaus. 1993. "Monitoring Biodiversity: Analysis of Amazonian Rainforest Sounds." *Ambio* 22 (8): 546-548.

Riffell, Samuel K. and Ben D. Riffell. 2002. "Can Observer Clothing Color Affect Estimates of Richness and Abundance: An Experiment with Point Counts." *Journal of Field Ornithology* 73 (4): 351-359.

Roerink, G. J., M. Menenti, W. Soepboer and Z. Su. 2003. "Assessment of climate impact on vegetation dynamics by using remote sensing." *Physics and Chemistry of the Earth, Parts A/B/C* 28 (1-3): 103-109. http://www.sciencedirect.com/science/article/pii/S1474706503000111. doi: 10.1016/s1474-7065(03)00011-1.

Sauer, Jo R, JE Hines, G Gough, I Thomas and BG Peterjohn. 1997. "The North American Breeding Bird Survey Results and Analysis. Version 96.4." *Patuxent Wildlife Research Center, Laurel, Maryland*.

Sauer, John R., Bruce G. Peterjohn and William A. Link. 1994. "Observer Differences in the North American Breeding Bird Survey." *The Auk* 111 (1): 50-62. http://www.jstor.org/stable/4088504.

Schrama, T, M. Poot, M. Robb and H. Slabbekoorn. 2008. "Automated monitoring of avian flight calls during nocturnal migration." In *Proceedings of the International Expert meeting on IT-based detection of bioacoustical patterns, Isle of Vilme, Germany, December 2007*, edited by KH. Frommolt, R. Bardeli and M. Clausen, 132 - 134.

Shufei, Duan, M. Towsey, Zhang Jinglan, A. Truskinger, J. Wimmer and P. Roe. 2011. "Acoustic component detection for automatic species recognition in environmental monitoring." In *Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2011 Seventh International Conference on, 6-9 Dec. 2011*, edited, 514-519. doi: 10.1109/issnip.2011.6146597.

Silveira, L., A. T. A. Jacomo and J. A. F. Diniz. 2003. "Camera trap, line transect census and track surveys: a comparative evaluation." *Biological Conservation* 114 (3): 351-355. <Go to ISI>://000185371200005. doi: 10.1016/s0006-3207(03)00063-6.

Silvertown, Jonathan. 2009. "A new dawn for citizen science." *Trends in Ecology & Evolution* 24 (9): 467-471. http://www.sciencedirect.com/science/article/pii/S016953470900175X. doi: 10.1016/j.tree.2009.03.017.

Simons, Theodore R., Mathew W. Alldredge, Kenneth H. Pollock, John M. Wettroth and A. M. Dufty. 2007. "Experimental analysis of the auditory detection process on avian point counts." *The Auk* 124 (3): 986-999. Accessed 2012/02/13. http://dx.doi.org/10.1642/0004-8038(2007)124[986:EAOTAD]2.0.CO;2. doi: 10.1642/0004-8038(2007)124[986:eaotad]2.0.co;2.

Simons, Theodore R., Kenneth H. Pollock, John M. Wettroth, Mathew W. Alldredge, Krishna Pacifici and Jerome Brewster. 2009. "Sources of Measurement Error, Misclassification Error, and Bias in Auditory Avian Point Count Data." In *Modeling Demographic Processes In Marked Populations*, edited by David L. Thomson, Evan G. Cooch and Michael J. Conroy, 237-254: Springer US. http://dx.doi.org/10.1007/978-0-387-78151-8_10. doi: 10.1007/978-0-387-78151-8_10.

Slabbekoorn, Hans and Margriet Peet. 2003. "Ecology: Birds sing at a higher pitch in urban noise." *Nature* 424 (6946): 267-267. http://dx.doi.org/10.1038/424267a.

Somervuo, P., A. Harma and S. Fagerlund. 2006. "Parametric Representations of Bird Sounds for Automatic Species Recognition." *IEEE Transactions on Audio, Speech, and Language Processing* 14 (6): 2252-2263. 10.1109/TASL.2006.872624.

Southwood, T. R. E. and Peter A. Henderson. 2009. "Ecological Methods". Hoboken: Wiley-Blackwell.

Stein, Andrew, Todd Fuller and Laurie Marker. 2008. "Opportunistic use of camera traps to assess habitat-specific mammal and bird diversity in northcentral Namibia." *Biodiversity and Conservation* 17 (14): 3579-3587. http://dx.doi.org/10.1007/s10531-008-9442-0. doi: 10.1007/s10531-008-9442-0.

Stenseth, N.C., A. Mysterud, G. Ottersen, J.W. Hurrell, K.S. Chan and M. Lima. 2002. "Ecological effects of climate fluctuations." *Science* 297 (5585): 1292.

Stevenson, Ben C., David L. Borchers, Res Altwegg, René J. Swift, Douglas M. Gillespie and G. John Measey. 2015. "A general framework for animal density estimation from acoustic detections across a fixed microphone array." *Methods in Ecology and Evolution* 6 (1): 38-48. http://dx.doi.org/10.1111/2041-210X.12291. doi: 10.1111/2041-210X.12291.

Sueur, Jérôme, Sandrine Pavoine, Olivier Hamerlynck and Stéphanie Duvail. 2008. "Rapid Acoustic Survey for Biodiversity Appraisal." *PLoS ONE* 3 (12): e4065. http://dx.doi.org/10.1371%2Fjournal.pone.0004065. doi: 10.1371/journal.pone.0004065.

Sullivan, Brian L., Christopher L. Wood, Marshall J. Iliff, Rick E. Bonney, Daniel Fink and Steve Kelling. 2009. "eBird: A citizen-based bird observation network in the biological sciences." *Biological Conservation* 142 (10): 2282-2292. http://www.sciencedirect.com/science/article/pii/S000632070900216X. doi: 10.1016/j.biocon.2009.05.006.

Suri, Ankur, S. S. Iyengar and Eungchun Cho. 2006. "Ecoinformatics using wireless sensor networks: An overview." *Ecological Informatics* 1 (3): 287-293. doi: DOI: 10.1016/j.ecoinf.2006.02.008.

Sutherland, William J. 2006. "Predicting the ecological consequences of environmental change: a review of the methods." *Journal of Applied Ecology* 43 (4): 599-616. http://dx.doi.org/10.1111/j.1365-2664.2006.01182.x. doi: 10.1111/j.1365-2664.2006.01182.x.

Swiston, Kyle A. and Daniel J. Mennill. 2009. "Comparison of manual and automated methods for identifying target sounds in audio recordings of Pileated, Pale-billed, and putative Ivory-billed woodpeckers." *Journal of Field Ornithology* 80 (1): 42-50. http://dx.doi.org/10.1111/j.1557-9263.2009.00204.x. doi: doi:10.1111/j.1557-9263.2009.00204.x.

Szewczyk, Robert, Eric Osterweil, Joseph Polastre, Michael Hamilton, Alan Mainwaring and Deborah Estrin. 2004. "Habitat monitoring with sensor networks." *Commun. ACM* 47 (6): 34-40. doi: http://doi.acm.org/10.1145/990680.990704.

Taylor, A., G. Watson, G. Grigg and H. McCallum. 1996. "Monitoring Frog Communities: An Application of Machine Learning." In *Proceedings of The Eighth Annual Conference on Innovative Applications of Artificial Intelligence, Portland, Oregon, 5-7 August 1996*, edited: The AAAI Press.

Thomas, Chris D., Alison Cameron, Rhys E. Green, Michel Bakkenes, Linda J. Beaumont, Yvonne C. Collingham, Barend F. N. Erasmus, et al. 2004. "Extinction risk from climate change." *Nature* 427 (6970): 145-148. http://dx.doi.org/10.1038/nature02121. doi: http://www.nature.com/nature/journal/v427/n6970/suppinfo/nature02121_S1.html.

Thompson, ME, SJ Schwager and KB Payne. 2009. "Heard but not seen: an acoustic survey of the African forest elephant population at Kakum Conservation Area, Ghana." *African Journal of Ecology* 48 (1): 224-231.

Thompson, Mya E., Steven J. Schwager, Katharine B. Payne and Andrea K. Turkalo. 2010. "Acoustic estimation of wildlife abundance: methodology for vocal mammals in forested habitats." *African Journal of Ecology* 48 (3): 654-661. http://dx.doi.org/10.1111/j.1365-2028.2009.01161.x. doi: 10.1111/j.1365-2028.2009.01161.x.

Thompson, WL. 2004. *Sampling rare or elusive species: concepts, designs, and techniques for estimating population parameters*. Washington: Island Press.

Toresen, Reidar, Harald Gjøsæter and Pedro de Barros. 1998. "The acoustic method as used in the abundance estimation of capelin (Mallotus villosus Müller) and herring (Clupea harengus Linné) in the Barents Sea." *Fisheries Research* 34 (1): 27-37. http://www.sciencedirect.com/science/article/pii/S0165783697000775. doi: 10.1016/s0165-7836(97)00077-5.

Towsey, M and B Planitz. 2010. ***Technical Report: Acoustic analysis of the natural environment***. Brisbane: Queensland University of Technology.

Towsey, Michael, Jason Wimmer, Ian Williamson and Paul Roe. 2014. "The use of acoustic indices to determine avian species richness in audio-recordings of the environment." *Ecological Informatics* 21: 110-119.

Towsey, MW, BM Planitz, A Nantes, Jason Wimmer and P. Roe. 2012. "A Toolbox for Animal Call Recognition." *Bioacoustics* 21 (2): 107-125. http://eprints.qut.edu.au/.

Truskinger, Anthony Masters, Haofan Yang, Jason Wimmer, Jinglan Zhang, Ian Williamson and Paul Roe. 2011. "Large scale participatory acoustic sensor data analysis : tools and reputation models to enhance effectiveness." Paper presented at the 7th IEEE International Conference on eScience. IEEE Computer Society. http://eprints.qut.edu.au/45996/.

Underwood, AJ. 1994. "On beyond BACI: sampling designs that might reliably detect environmental disturbances." *Ecological applications* 4 (1): 3-15.

Venier, Lisa A, Stephen B Holmes, George W Holborn, Kenneth A Mcilwrick and Glen Brown. 2012. "Evaluation of an automated recording device for monitoring forest birds." *Wildlife Society Bulletin* 36 (1): 30-39.

Wark, T., P. Corke, P. Sikka, L. Klingbeil, Guo Ying, C. Crossman, P. Valencia, D. Swain and G. Bishop-Hurley. 2007. "Transforming Agriculture through Pervasive Wireless Sensor Networks." *Pervasive Computing, IEEE* 6 (2): 50-57.

West, Andrew G., Jian Chang, Krishna K. Venkatasubramanian and Insup Lee. 2011. "Trust in collaborative web applications." *Future Generation Computer Systems* In Press, Corrected Proof. http://www.sciencedirect.com/science/article/pii/S0167739X11000100. doi: 10.1016/j.future.2011.02.007.

Wimmer, J., M. Towsey, B. Planitz, P. Roe and I. Williamson. 2010. "Scaling acoustic data analysis through collaboration and automation." In *2010 IEEE Sixth International Conference on e-Science, Brisbane, Australia, 7-10 Dec. 2010*, edited, 308-315.

Wimmer, Jason, Michael Towsey, Birgit Planitz, Ian Williamson and Paul Roe. 2013. "Analysing environmental acoustic data through collaboration and automation." *Future Generation Computer Systems* 29 (2): 560-568. http://www.sciencedirect.com/science/article/pii/S0167739X1200057X. doi: http://dx.doi.org/10.1016/j.future.2012.03.004.

Wimmer, Jason, Michael Towsey, Paul Roe and Ian Williamson. 2013. "Sampling environmental acoustic recordings to determine bird species richness." *Ecological Applications* 23 (6): 1419-1428. Accessed 2014/11/18. http://dx.doi.org/10.1890/12-2088.1. doi: 10.1890/12-2088.1.

Xiaohong, Sheng and Hu Yu-Hen. 2005. "Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks." *Signal Processing, IEEE Transactions on* 53 (1): 44-53.

Young, S, G Evermann, M Gales, T Hain, D Kershaw, X Liu, G Moore, J Odell, D Ollason and D Povey. 2006. *The HTK book (for HTK version 3.4)*. Cambridge: Cambridge University Engineering Department.

Appendices

APPENDIX A: LIST OF SENSOR SURVEY SPECIES DETECTED

Australian Brush-turkey	*Alectura lathami*
Australian King Parrot	*Alisterus scapularis*
Australian Magpie	*Gymnorhina tibicen*
Australian Masked Owl	*Tyto novaehollandiae*
Australian Owlet-nightjar	*Aegotheles cristatus*
Australian White Ibis	*Threskiornis molucca*
Australian Wood Duck	*Chenonetta jubata*
Azure Kingfisher	*Alcedo azurea*
Bar-shouldered Dove	*Geopelia humeralis*
Black-faced Cuckoo-shrike	*Coracina novaehollandiae*
Blue-faced Honeyeater	*Entomyzon cyanotis*
Brown Cuckoo-Dove	*Macropygia amboinensis*
Brown Goshawk	*Accipiter fasciatus*
Brown Honeyeater	*Lichmera indistincta*
Brown Quail	*Coturnix ypsilophora*
Brown Thornbill	*Acanthiza pusilla*
Brush Cuckoo	*Cacomantis variolosus*
Bush Stone-curlew	*Burhinus grallarius*
Channel-billed Cuckoo	*Scythrops novaehollandiae*
Cicadabird	*Coracina tenuirostris*
Collared Sparrowhawk	*Accipiter cirrhocephalus*
Common Myna	*Sturnus tristis*
Dollarbird	*Eurystomus orientalis*
Double-barred Finch	*Taeniopygia bichenovii*
Dusky Moorhen	*Gallinula tenebrosa*
Eastern Koel	*Eudynamys scolopacea*
Eastern Whipbird	*Psophodes olivaceus*
Eastern Yellow Robin	*Eopsaltria australis*
Fan-tailed Cuckoo	*Cacomantis flabelliformis*
Figbird	*Sphecotheres vieilloti*
Forest Kingfisher	*Todiramphus macleayii*
Galah	*Cacatua roseicapilla*
Glossy Black Cockatoo	*Calyptorhynchus lathami*
Golden Whistler	*Pachycephala pectoralis*
Grey Butcherbird	*Cracticus torquatus*
Grey Fantail	*Rhipidura albiscapa*
Grey Shrikethrush	*Colluricincla harmonica*
Indian Peafowl	*Pavo cristatus*
Laughing Kookaburra	*Dacelo novaeguineae*
Leaden Flycatcher	*Myiagra rubecula*
Lewin's Honeyeater	*Meliphaga lewinii*

Lewin's Rail	*Lewinia pectoralis*
Little Bronze Cuckoo	*Chrysococcyx minutillus*
Little Friarbird	*Philemon citreogularis*
Little Lorikeet	*Glossopsitta pusilla*
Little Shrike-thrush	*Colluricincla megarhyncha*
Magpie-lark	*Grallina cyanoleuca*
Masked Lapwing	*Vanellus miles*
Mistletoebird	*Dicaeum hirundinaceum*
Noisy Friarbird	*Philemon corniculatus*
Noisy Miner	*Manorina melanocephala*
Noisy Pitta	*Pitta versicolor*
Olive-backed Oriole	*Oriolus sagittatus*
Pacific Baza	*Aviceda subcristata*
Pacific Black Duck	*Anas superciliosa*
Painted Buttonquail	*Turnix varia*
Pale-headed Rosella	*Platycercus adscitus*
Pale-vented Bush-hen	*Amaurornis moluccana*
Peaceful Dove	*Geopelia striata*
Pheasant Coucal	*Centropus phasianinus*
Pied Butcherbird	*Cracticus nigrogularis*
Pied Currawong	*Strepera graculina*
Plumed Whistling Duck	*Dendrocygna eytoni*
Purple Swamphen	*Porphyrio porphyrio*
Rainbow Bee-eater	*Merops ornatus*
Rainbow Lorikeet	*Trichoglossus haematodus*
Red Junglefowl	*Gallus gallus*
Red-backed Fairywren	*Malurus melanocephalus*
Red-browed Finch	*Neochmia temporalis*
Rufous Fantail	*Rhipidura rufifrons*
Rufous Whistler	*Pachycephala rufiventris*
Sacred Kingfisher	*Todiramphus sanctus*
Scaly-breasted Lorikeet	*Trichoglossus chlorolepidotus*
Scarlet Honeyeater	*Myzomela sanguinolenta*
Shining Bronze Cuckoo	*Chrysococcyx lucidus*
Silvereye	*Zosterops lateralis*
Spangled Drongo	*Dicrurus bracteatus*
Spotted Pardalote	*Pardalotus punctatus*
Striated Pardalote	*Pardalotus striatus*
Striped Honeyeater	*Plectorhyncha lanceolata*
Sulphur-crested Cockatoo	*Cacatua galerita*
Superb Fairywren	*Malurus cyaneus*
Tawny Grassbird	*Megalurus timoriensis*
Torresian Crow	*Corvus orru*
Varied Sittella	*Daphoenositta chrysoptera*
Variegated Fairywren	*Malurus lamberti*
Welcome Swallow	*Hirundo neoxena*

White-bellied Cuckooshrike	*Coracina papuensis*
White-breasted Woodswallow	*Artamus leucorynchus*
White-browed Scrubwren	*Sericornis frontalis*
White-naped Honeyeater	*Melithreptus lunatus*
White-throated Honeyeater	*Melithreptus albogularis*
White-throated Treecreeper	*Cormobates leucophaea*
Willie Wagtail	*Rhipidura leucophrys*
Yellow-faced Honeyeater	*Lichenostomus chrysops*
Yellow-tailed Black Cockatoo	*Calyptorhynchus funereus*

APPENDIX B: LIST OF TRADITIONAL SURVEY SPECIES DETECTED

Australian White Ibis	*Threskiornis molucca*
Australian Wood Duck	*Chenonetta jubata*
Bar-shouldered Dove	*Geopelia humeralis*
Black-faced Cuckoo-shrike	*Coracina novaehollandiae*
Blue-faced Honeyeater	*Entomyzon cyanotis*
Brown Cuckoo-Dove	*Macropygia amboinensis*
Brown Goshawk	*Accipiter fasciatus*
Brown Thornbill	*Acanthiza pusilla*
Brush Cuckoo	*Cacomantis variolosus*
Cicadabird	*Coracina tenuirostris*
Common Myna	*Sturnus tristis*
Dollarbird	*Eurystomus orientalis*
Double-barred Finch	*Taeniopygia bichenovii*
Eastern Koel	*Eudynamys scolopacea*
Eastern Whipbird	*Psophodes olivaceus*
Eastern Yellow Robin	*Eopsaltria australis*
Figbird	*Sphecotheres vieilloti*
Galah	*Cacatua roseicapilla*
Golden Whistler	*Pachycephala pectoralis*
Grey Fantail	*Rhipidura albiscapa*
Grey Shrikethrush	*Colluricincla harmonica*
Laughing Kookaburra	*Dacelo novaeguineae*
Leaden Flycatcher	*Myiagra rubecula*
Lewin's Honeyeater	*Meliphaga lewinii*
Little Black Cormorant	*Phalacrocorax sulcirostris*
Little Corella	*Cacatua sanguinea*
Little Lorikeet	*Glossopsitta pusilla*
Little Pied Cormorant	*Microcarbo melanoleucos*
Magpie-lark	*Grallina cyanoleuca*
Noisy Miner	*Manorina melanocephala*
Olive-backed Oriole	*Oriolus sagittatus*
Pacific Baza	*Aviceda subcristata*
Pacific Black Duck	*Anas superciliosa*
Pale-headed Rosella	*Platycercus adscitus*
Peaceful Dove	*Geopelia striata*
Rainbow Bee-eater	*Merops ornatus*
Rainbow Lorikeet	*Trichoglossus haematodus*
Red-browed Finch	*Neochmia temporalis*
Rufous Whistler	*Pachycephala rufiventris*
Sacred Kingfisher	*Todiramphus sanctus*
Scaly-breasted Lorikeet	*Trichoglossus chlorolepidotus*
Scarlet Honeyeater	*Myzomela sanguinolenta*
Shining Bronze Cuckoo	*Chrysococcyx lucidus*
Silvereye	*Zosterops lateralis*

Spangled Drongo	*Dicrurus bracteatus*
Spotted Dove	*Streptopelia chinensis*
Spotted Pardalote	*Pardalotus punctatus*
Striated Pardalote	*Pardalotus striatus*
Sulphur-crested Cockatoo	*Cacatua galerita*
Superb Fairywren	*Malurus cyaneus*
Topknot Pigeon	*Lopholaimus antarcticus*
Torresian Crow	*Corvus orru*
Tree Martin	*Petrochelidon nigricans*
Varied Sittella	*Daphoenositta chrysoptera*
Variegated Fairywren	*Malurus lamberti*
Weebill	*Smicrornis brevirostris*
Welcome Swallow	*Hirundo neoxena*
Whistling Kite	*Haliastur sphenurus*
White-breasted Woodswallow	*Artamus leucorynchus*
White-browed Scrubwren	*Sericornis frontalis*
White-naped Honeyeater	*Melithreptus lunatus*
White-throated Honeyeater	*Melithreptus albogularis*
White-throated Treecreeper	*Cormobates leucophaea*
Willie Wagtail	*Rhipidura leucophrys*
Yellow-faced Honeyeater	*Lichenostomus chrysops*
Yellow-spotted Honeyeater	*Meliphaga notata*

APPENDIX C: COPIES OF PUBLISHED MANUSCRIPTS

Ecological Applications, 23(6), 2013, pp. 1419–1428

Sampling environmental acoustic recordings to determine bird species richness

Jason Wimmer,[1] Michael Towsey, Paul Roe, and Ian Williamson

Science and Engineering Faculty, Queensland University of Technology, Brisbane, Australia

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. These 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 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).

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

[1] E-mail: j.wimmer@qut.edu.au

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° S, 152.878103° 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° and 13°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 Kbit/s, 22.05 KHz) on high-capacity 32GB Secure Digital memory cards (Sandisk Corporation, Milpitas, California, USA). The units were stored in weatherproof

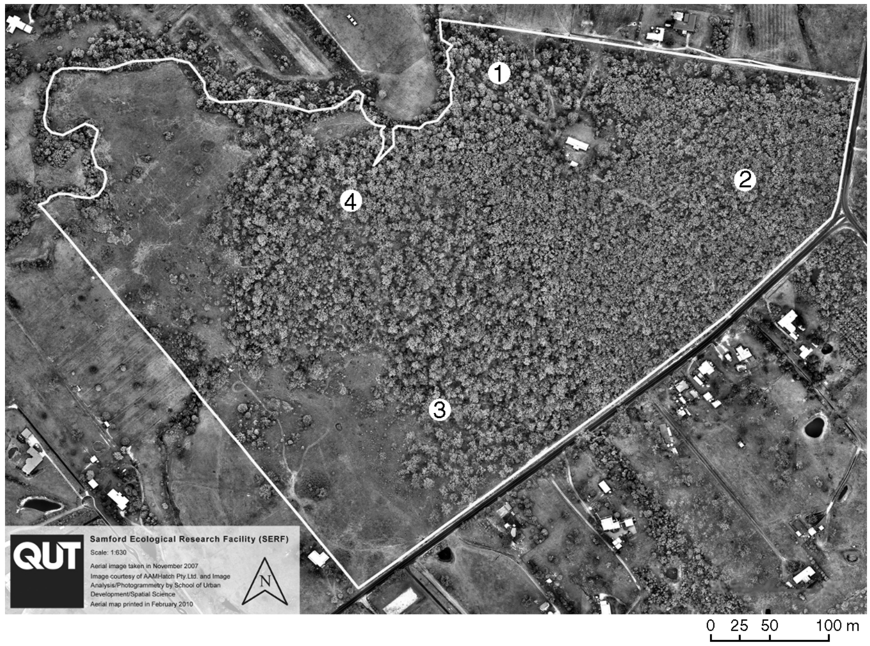

FIG. 1. Samford Ecological Research Facility (SERF) with survey site positions.

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, one-minute 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 one-minute 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 one-minute 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 five-day 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 × 100 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 × 20 minutes) and each day constituted 120 minutes of effort (two surveyors × 20 minutes × 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 28 800 one-minute segments were manually analysed. Fifty-six percent (16 019) of total segments contained calls, and from these, 63 089 birdcalls were identified and annotated (~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).

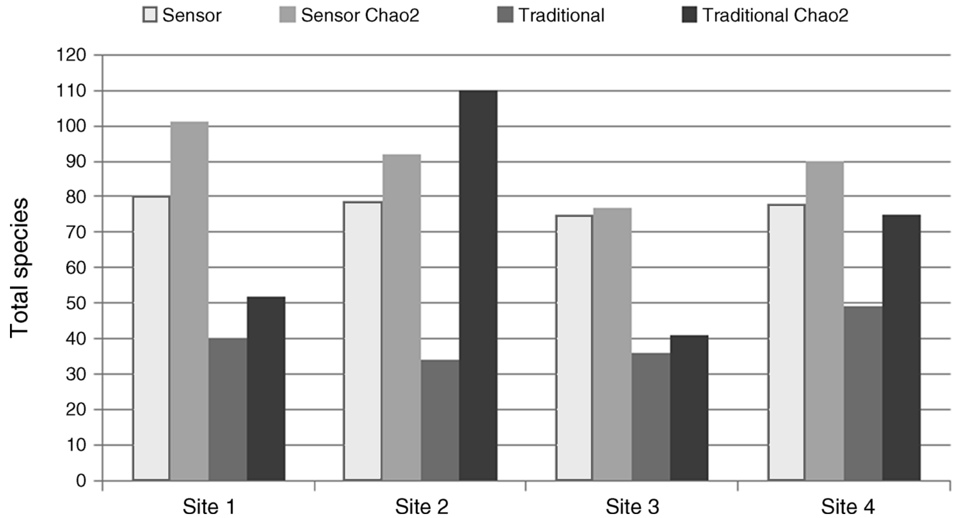

FIG. 2. Total number of unique bird species detected and Chao2 species richness estimates for full acoustic sensor data analysis and traditional survey for each site over the five-day survey period.

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 less-pronounced 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 28 800 one-minute segments, these species had a very low probability of detection. In contrast, the most frequently detected species was Rufous Whistler

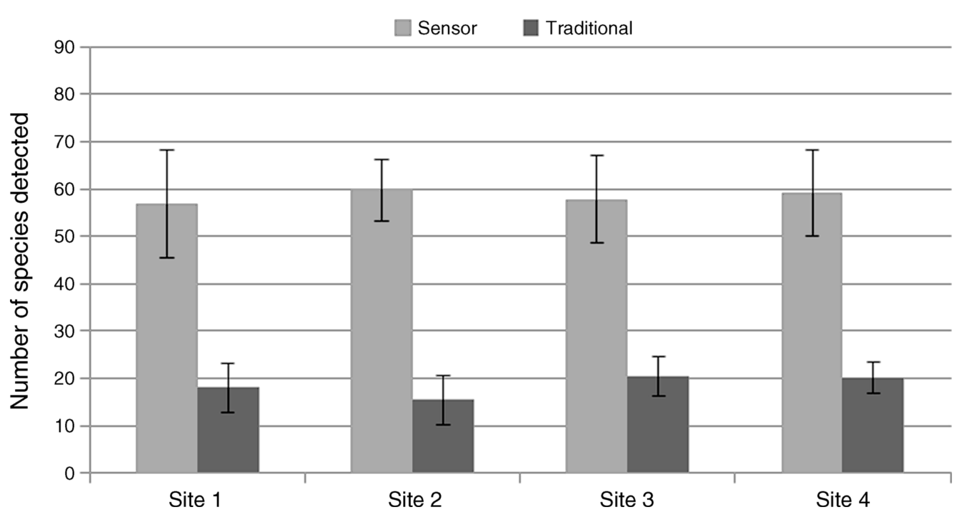

FIG. 3. Number of bird species detected (species richness estimates; mean and 95% CI) daily from full acoustic sensor data analysis and traditional survey for each site over the five-day survey period.

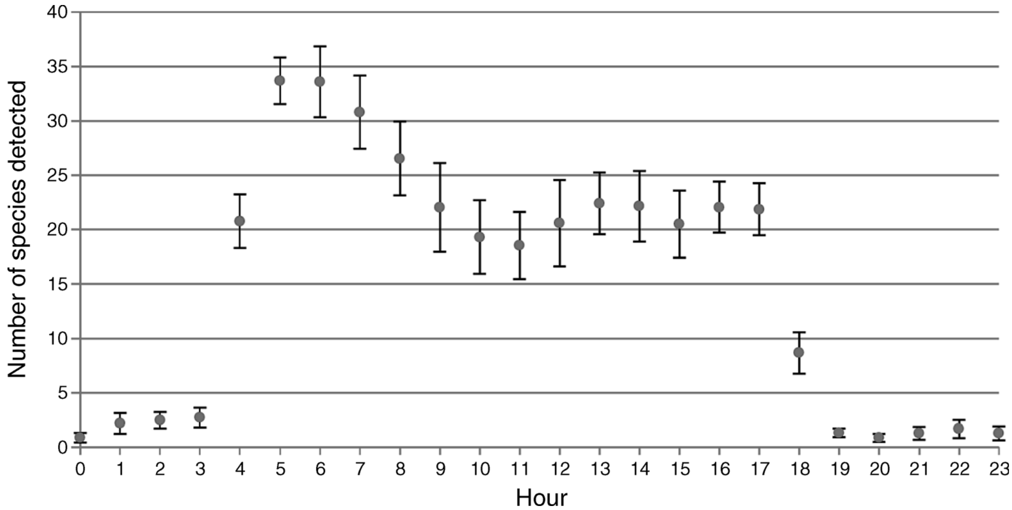

FIG. 4. Number of species detected each hour (species richness estimates; mean and 95% CI) from full analysis of acoustic sensor data across all sites.

(*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 for 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 person-minutes of effort per day (three 20-minute surveys × 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

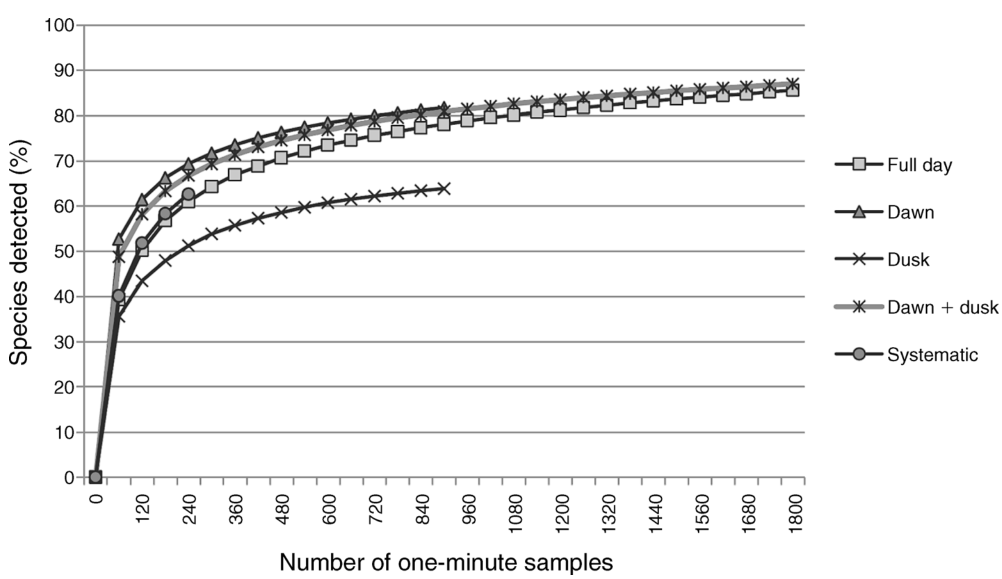

FIG. 5. Percentage of total species detected for each sampling method (species richness estimates; means) for the associated number of minutes sampled (data combined over sites).

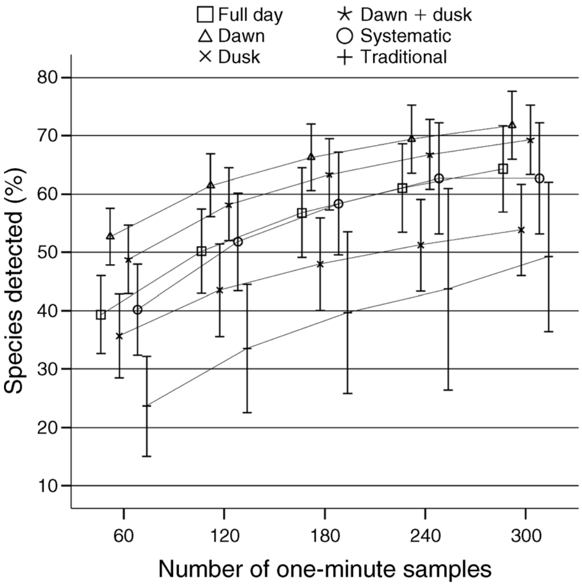

FIG. 6. Percentage of total species detected by each sampling method (species richness estimates; mean and 95% CI) for the associated number of minutes sampled. Error bars for each group of samples have been offset for clarity.

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 one-minute 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, Celis-Murillo 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 efforts, 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 in 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.

Literature Cited

Acevedo, M. A., C. J. Corrada-Bravo, H. Corrada-Bravo, L. J. Villanueva-Rivera, and T. M. Aide. 2009. Automated classification of bird and amphibian calls using machine learning: a comparison of methods. Ecological Informatics 4:206–214.

Acevedo, M. A., and L. J. Villanueva-Rivera. 2006. Using automated digital recording systems as effective tools for the monitoring of birds and amphibians. Wildlife Society Bulletin 34:211–214.

Anderson, S., A. Dave, and D. Margoliash. 1996. Template-based automatic recognition of birdsong syllables from continuous recordings. Journal of the Acoustical Society of America 100:1209–1219.

Australian Government Bureau of Meterology. 2012. Climate Statistics for Samford CSIRO. Australian Government Bureau of Meterology, Brisbane, Queensland, Australia.

Baker, M. C., and D. M. Logue. 2003. Population differentiation in a complex bird sound: a comparison of three bioacoustical analysis procedures. Ethology 109:223–242.

Bardeli, R., D. Wolff, F. Kurth, M. Koch, K. H. Tauchert, and K. H. Frommolt. 2010. Detecting bird sounds in a complex acoustic environment and application to bioacoustic monitoring. Pattern Recognition Letters 31:1524–1534.

Brandes, S. T. 2008. Automated sound recording and analysis techniques for bird surveys and conservation. Bird Conservation International 18:S163–S173.

Cai, J., D. Ee, P. Binh, P. Roe, and Z. Jinglan. 2007. Sensor network for the monitoring of ecosystem: bird species recognition. Pages 293–298 *in* 3rd International Conference on Intelligent Sensors, Sensor Networks and Information, 2007. IEEE, New York New York, USA.

Carignan, V., and M. Villard. 2002. Selecting indicator species to monitor ecological integrity: a review. Environmental Monitoring and Assessment 78:45–61.

Celis-Murillo, A., J. Deppe, and M. Allen. 2009. Using soundscape recordings to estimate bird species abundance, richness, and composition. Journal of Field Ornithology 80:64–78.

Chao, A. 1987. Estimating the population size for capture–recapture data with unequal catchability. Biometrics 43:783–791.

Charif, R., D. Ponirakis, and T. Krein. 2006. Raven Lite 1.0 user's guide. Cornell Laboratory of Ornithology, Ithaca, New York, USA.

Chen, Z., and R. Maher. 2006. Semi-automatic classification of bird vocalizations using spectral peak tracks. Journal of the Acoustical Society of America 120:2974.

Collins, S. L., et al. 2006. New opportunities in ecological sensing using wireless sensor networks. Frontiers in Ecology and the Environment 4:402–407.

Colwell, R. K. 2009. EstimateS: statistical estimation of species richness and shared species from samples. Version 8.2. http://purl.oclc.org/estimates

Cormen, T. H., C. E. Leiserson, R. L. Rivest, and C. Stein. 2009. Introduction to algorithms. Third edition. MIT Press, Cambridge, Massachusetts, USA.

Corn, P. S., E. Muths, and W. M. Iko. 2000. A comparison in Colorado of three methods to monitor breeding amphibians. Northwestern Naturalist 81:22–30.

Ellis, W., F. Bercovitch, S. FitzGibbon, P. Roe, J. Wimmer, A. Melzer, and R. Wilson. 2011. Koala bellows and their association with the spatial dynamics of free-ranging koalas. Behavioral Ecology.

Ellis, W. A., S. I. Fitzgibbon, P. Roe, F. B. Bercovitch, and R. Wilson. 2010. Unraveling the mystery of koala vocalisations: acoustic sensor network and GPS technology reveals males bellow to serenade females. Integrative and Comparative Biology 50:E49–E49.

Farnsworth, A., J. S. A. Gauthreaux, and D. v. Blaricom. 2004. A comparison of nocturnal call counts of migrating birds and reflectivity measurements on Doppler radar. Journal of Avian Biology 35:365–369.

Grigg, G., A. Taylor, H. McCallum, and L. Fletcher. 2006. Monitoring the impact of cane toads (*Bufo marinus*) on Northern Territory frogs—a progress report. Pages 47–54 *in* K. L. Molloy and W. R. Henderson, editors. Science of cane toad invasion and control. Proceedings of the invasive animals CRC/CSIRO/Qld NRM&W cane toad workshop, Brisbane, June 2006. Invasive Animals Cooperative Research Centre, Canberra, Australia.

Haselmayer, J., and J. S. Quinn. 2000. A comparison of point counts and sound recording as bird survey methods in Amazonian southeast Peru. Condor 102:887–893.

Juang, C., and T. Chen. 2007. Birdsong recognition using prediction-based recurrent neural fuzzy networks. Neurocomputing 71:121–130.

Kasten, E. P., S. H. Gage, J. Fox, and W. Joo. 2012. The remote environmental assessment laboratory's acoustic library: an archive for studying soundscape ecology. Ecological Informatics 12:50–67.

Kasten, E. P., P. K. McKinley, and S. H. Gage. 2007. Automated ensemble extraction and analysis of acoustic data streams. Pages 66–66 *in* 27th International conference on distributed computing systems workshops, 2007. IEEE, New York, New York, USA.

Krebs, C. J. 1999. Ecological methodology. Second edition. Addison-Wesley Educational, Menlo Park, California, USA.

Kwan, C., G. Mei, X. Zhao, Z. Ren, R. Xu, V. Stanford, C. Rochet, J. Aube, and K. C. Ho. 2004. Bird classification algorithms: theory and experimental results. Pages V-289–292 *in* IEEE International Conference on Acoustics, Speech, and Signal Processing, 2004. IEEE, New York, New York, USA.

Loyn, R. H. 1985. The 20-minute search: a simple method for counting forest birds. Corella 10:58–60.

Mason, R., P. Roe, M. Towsey, J. Zhang, J. Gibson, and S. Gage. 2008. Towards an acoustic environmental observatory. Pages 135–142 *in* Fourth IEEE international conference on eScience. IEEE, New York, New York, USA.

McIlraith, A. L., and H. C. Card. 1997. Birdsong recognition using backpropagation and multivariate statistics. IEEE Transactions on Signal Processing 45:2740–2748.

Morcombe, M. 2004. Field guide to Australian birds. Steve Parish Publishing, Archerfield, Queensland, Australia.

Mundinger, P. 1982. Microgeographic and macrogeographic variation in acquired vocalizations in birds. Pages 147–208 *in* D. E. Kroodsma and E. H. Miller, editors. Acoustic communication in birds. Academic Press, New York, New York, USA.

Parker, T. A., III. 1991. On the use of tape recorders in avifaunal surveys. Auk 108:443–444.

Penman, T., F. Lemckert, and M. Mahony. 2005. A cost-benefit analysis of automated call recorders. Applied Herpetology 2:389–400.

Rempel, R. S., K. A. Hobson, G. Holborn, S. L. v. Wilgenburg, and J. Elliott. 2005. Bioacoustic monitoring of forest songbirds: interpreter variability and effects of configuration and digital processing methods in the laboratory. Journal of Field Ornithology 76:1–11.

Schrama, T., M. Poot, M. Robb, and H. Slabbekoorn. 2008. Automated monitoring of avian flight calls during nocturnal migration. Pages 132–134 *in* K. Frommolt, R. Bardeli, and M. Clausen, editors. Proceedings of the International Expert meeting on IT-based detection of bioacoustical patterns. International Academy for Nature Conservation, Isle of Vilme, Germany.

Somervuo, P., A. Harma, and S. Fagerlund. 2006. Parametric representations of bird sounds for automatic species recognition. IEEE Transactions on Audio, Speech, and Language Processing 14:2252–2263.

Sueur, J., S. Pavoine, O. Hamerlynck, and S. Duvail. 2008. Rapid acoustic survey for biodiversity appraisal. PLoS One 3:e4065.

Swiston, K. A., and D. J. Mennill. 2009. Comparison of manual and automated methods for identifying target sounds in audio recordings of Pileated, Pale-billed, and putative Ivory-billed Woodpeckers. Journal of Field Ornithology 80:42–50.

Thompson, M., S. Schwager, and K. Payne. 2009. Heard but not seen: an acoustic survey of the African forest elephant population at Kakum Conservation Area, Ghana. African Journal of Ecology 48:224–231.

Towsey, M., B. Planitz, A. Nantes, J. Wimmer, and P. Roe. 2012. A toolbox for animal call recognition. Bioacoustics 21(2):107–125.

Wimmer, J., M. Towsey, B. Planitz, I. Williamson, and P. Roe. 2013. Analysing environmental acoustic data through collaboration and automation. Future Generation Computer Systems 29:560–568.