

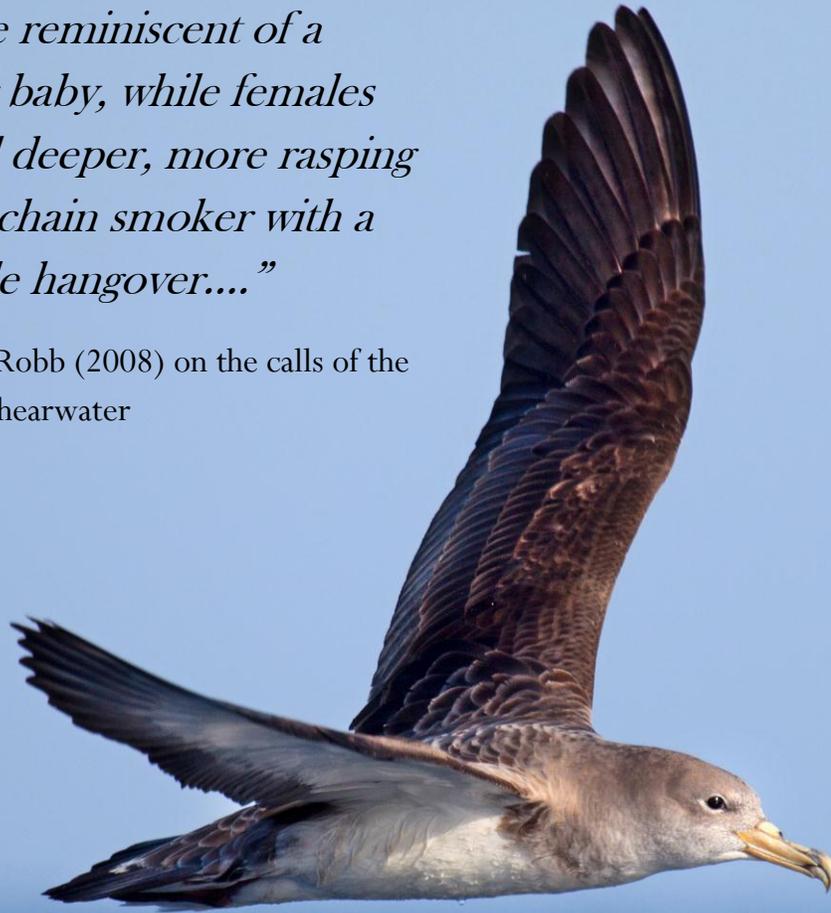
Developing an automated acoustic monitoring system to estimate abundance of Cory's Shearwaters in the Azores

Michelle Goh

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science and the Diploma of Imperial College London

“Across their entire repertoire, males always sound higher pitched, with a timbre reminiscent of a crying baby, while females sound deeper, more rasping like a chain smoker with a terrible hangover....”

Magnus Robb (2008) on the calls of the Cory’s Shearwater



ABSTRACT

Nocturnal burrow-nesting seabirds are often left out of population surveys because censusing them is logistically challenging. Their cryptic behaviour and preference to nest in inaccessible areas on remote oceanic islands make usual seabird monitoring techniques unsuitable for estimating their abundance. However with the rapid advancement of recording technology, automated acoustic monitoring has been suggested as a method to estimate population abundance of nocturnal seabirds. To assess the feasibility and challenges of developing this method, we put our four autonomous recording units on four different Cory's Shearwater (*Calonectris diomedea*) colonies with varying densities in the Azores to measure calling rates over their incubation period to see if we could establish a robust abundance index. We also examined environmental variables that would bias the detected calling rates and tried to correct for them. Although we found that moon light, wind speed and date of recording influenced the calling rate, controlling for those variables did not produce a robust linear relationship between calling rate and nest abundance. We also compared two automatic signal recognition software used to process sound recordings and determined that Song Scope was a more suitable program for detecting shearwater vocalisations.

ACKNOWLEDGEMENTS

First and foremost I would express my gratitude to all my supervisors for their constant support and advice throughout the course of this thesis. To Steffen Oppel, 150 emails, 15 phone calls, 2 train journeys, and 1 apple pie later, you finally won't have to open Gmail in fear anymore! I am indebted to the huge amount of support you have given me throughout the course of this project. To Marcus Rowcliffe, I would not have been able to do this without your patience and guidance, and especially your custom made "Nice" and "Nasty" graphs. To Aurelio Malo, for being the most optimistic and encouraging supervisor whose constant enthusiasm has tided me through this project.

To meus amigos no Corvo, Sandra, Pipa, Luis, Carlos, Pepe, Angel, Sonia and Pedro. Obrigada for all your help with the constantly malfunctioning ARUs, data collection, gorgeous photos and most of all for all the malouco times on the island.

I would like to also thank John Murray for assisting me with XBAT analysis, and Rachel Buxton and Abraham Borker for always being there to answer any bioacoustic questions.

I would also like to thank RSPB and SPEA for giving me this opportunity to work on this project.

To my parents, James and Rita. Thank you so much for always supporting me in my endeavours and adventure. Perhaps one day you will join me in them.

Thank you Stu and Natalia for your constant cheer and support. Stu, thank you especially for kindly lending me your laptop to use in the field and taking care of my Mac.

I could not have done this without the company of the tea club. Rocio, Dareen and Alicky. The countless cups of tea, cheesecakes and your cheerful company were great nourishment during my thesis write up and kept me going.

And finally, thank you Alicky, for always being just one knock away.

Table of Contents

1. Introduction.....	1
1.1 Acoustic monitoring of nocturnal burrow-nesting seabirds.....	1
1.2 Aims, objectives and hypotheses.....	4
1.3 Thesis structure.....	6
2. Background.....	7
2.1 Seabird population decline and its drivers	7
2.2 Invasive mammal eradication	7
2.3 Lack of post eradication monitoring on nocturnal burrowing-seabirds.....	9
2.4 Current methods used to estimate seabird population	8
2.5 Acoustic monitoring in birds	10
2.6 Automated acoustic monitoring.....	10
2.7 Automated sound analysis.....	11
2.8 Automated acoustic monitoring of nocturnal seabirds	13
2.9 Examining bias on calling rates	14
2.10 Factors affecting calling rates of individual shearwaters.....	14
2.10.1 Moonlight.....	14
2.10.2 Changing vocal activity across breeding season	15
2.11 Factors affecting variability of detection rate	16
2.11.1 Wind disturbance	16
2.11.2 Site difference	16
2.12 Determining suitability of automatic signal recognition software	16
2.13 Study site	18
2.14 Study species.....	19
3. Methods.....	21
3.1 Data collection.....	21
3.1.1 Settings for the autonomous recording units	22
3.1.2 Deployment sites.....	22
3.1.2 Estimating nest abundance	22
3.2 Data Analysis	22
3.2.1 Processing sound recordings.....	22
3.2.2 Analysis in XBAT.....	23
3.2.3 Building detection template in XBAT.....	23
3.2.4 Analysis in Song Scope.....	24
3.2.5 Building a recogniser in Song Scope.....	24
3.3 Comparison of sound analysis software	25
3.4 Collection of data for variables in model.....	25
3.4.1 Calling rate as a response variable	25
3.4.2 Predictor variables	27

3.5 Statistical modelling	28
4. Results	29
4.1 Nest Density of deployment sites and recording effort.....	29
4.2 Accuracy of automated signal recognition software	30
4.3 Summary of minimum adequate model.....	31
4.4 Predicted detected calling rate to nest abundance relationship.....	32
4.5 Summary of support for hypotheses.....	34
5. Discussion	35
5.1 Relationship between calling rate and nest abundance	35
5.2 Automated sound recording hardware and software	36
5.1.1 Autonomous recording units	36
5.1.2 Automated signal recognition software comparison.....	37
5.3 Environmental influences on detected calling rates.....	40
5.3.1 Biological bias	40
5.3.2 Detection level bias	41
5.4 Limitations of the study	42
5.4.1 Data collection and experimental design limitations.....	42
5.4.2 Data analysis limitations	43
5.5 Implications for the use of automated acoustic monitoring systems and directions for future research.....	43
Reference List.....	46

List of Tables and Figures

Tables

1. Common seabird survey techniques and problems for nocturnal seabirds.....	9
2. Comparing features and classification methods used by acoustic software.....	12
3. List of predictor variables and their sources	27
4. List of deployment sites, nest found at each site and nights of recording analysed	29
5. Summary of minimum adequate model	5
6. Summary of support for hypotheses	5
7. Comparison of XBAT and Song Scope qualities	5

Figures

1. Spectrogram of discrete sound shapes in bird vocalisations	12
2. Map of the Azores and its islands.....	18
3. Photograph of Cory's Shearwater	19
4. Selection of detection template in XBAT	23
5. Annotating of training data in Song Scope.....	24

6. Scatterplot comparing accuracy of XBAT and Song Scope.....	30
7. Graphs of predicted calling rate obtained from models analysed.....	33

List of acronyms used

ARU: Autonomous Recording Unit

ASRS: Automated Signal Recognition Software

GLM: Generalised Linear Model

Word Count: 10,758

1. INTRODUCTION

1.1 Acoustic Monitoring of Nocturnal Burrow-nesting Seabirds

One of the most devastating threats to seabirds is the introduction of non-native species to islands (Jones et al. 2008; Simberloff 2009; Towns et al. 2006). This has resulted in a considerable amount of effort put into island restoration projects to remove the threat of invasive mammals from endangered seabird colonies (Igual et al. 2006; Pascal et al. 2008; Towns 2009).

Nocturnal and burrow-nesting seabird species such as shearwaters and storm petrels, will spend most of their lives at sea, but they need return annually to land to breed. They often nest on remote oceanic islands and may lay their eggs in burrows or crevices on steep inaccessible cliffs, and only return to their colonies at night (Brooke 2004). These factors make it very difficult to quantitatively assess their density or abundance

Due to the difficulties in monitoring nocturnal burrow-nesting seabirds populations, it is hard to determine the efficiency of conservation effort dedicated to them. For island restoration projects, we often lack the capacity to measure the pre and post eradication population of endangered seabird colonies. Not knowing the community's response will limit the evaluation of the effectiveness of conservation efforts. Therefore there is an urgent need to develop robust monitoring techniques that can accurately measure the relative abundance of nocturnal nest-burrowing seabirds and help to inform future management decisions (Milner-Gulland & Rowcliffe 2007).

Techniques for monitoring most breeding seabirds have improved over the last few decades (Walsh et al. 1995). However the monitoring of nocturnal burrow-nesting seabirds still remains a logistically challenging task.

Acoustic monitoring is a potential method that could be used to monitor nocturnal burrow-nesting seabirds. Recording technology has developed rapidly over recent years, and now battery operated automated autonomous recording units (ARUs) are commercially available and have been used to monitor a diversity of species (Dorcas et al. 2010; Thompson et al. 2010). ARUs can be easily deployed in remote and inaccessible sites and program to record vocal activity over a specified time periods. The recording data collected can then be processed in batches using automatic signal detection software to identify species composition or quantify calling rates.

Nocturnal burrow nesting seabirds such as shearwaters would make good candidates for acoustic monitoring since many species vocalise at night when they return to their colony (Bretagnolle et al. 2000; Brooke 2004). ARUs have already been used to detecting the presence of cryptic seabird species, or providing comparisons across time (Buxton 2010). However up to this point, there has not been conclusive evidence on whether acoustic monitoring could provide a reliable method of obtaining numbers of breeding pairs of seabirds in an area. Therefore before further development of the monitoring system can proceed, several important issues need to be considered.

Firstly, the whole premise of using acoustic monitoring for monitoring seabird abundance relies on the assumption that the frequency of calls increases as density increases. Establishing a positive robust linear relationship between call rates of birds and nest densities surround an ARU is therefore an essential step in determining whether this would be an effective monitoring approach for estimating abundance of nocturnal burrow-nesting seabirds.

Secondly, obtaining calling rates from the sound data recorded by the ARUs would require sophisticated automated signal recognition software that will be able to accurately detect nocturnal-burrowing seabird vocalisations from the recordings and quantify their calling rates. There are currently two commonly used programs used to analyse sound data. It will be necessary to identify the most accurate program, which will then be used constantly across various projects and locations. This will ensure that the software detection rate of

seabird vocalisation remains consistent and reduces the need for training conservation personnel to learn new software.

Thirdly, one of the key processes in increasing the accuracy of an abundance index is to identify sources of bias that might influence the estimates derived from this system.

There are two categories of bias that could potentially arise in an acoustic monitoring system. This system assumes that the calling rate of individual seabirds remain constant under various environments. However, nocturnal burrow-nesting seabirds are known to vocalise at different rates depending on environmental and temporal situations (Bretagnolle 1990).

A second confounding factor arises when we assume that the level of sound detection of the ARUs remain constant throughout their deployment period. However, the transmission of sound may vary under different speeds. High wind speeds as well have been shown to affect recording quality of microphones. The physical differences between the sites of ARU deployment will also have an influence on how propagated sound reaches the ARU's microphone.

Consequently, to improve the precision of an acoustic monitoring system, it is crucial to examine the relationship between these biases with recorded calling rate. Only then can they be controlled for when building an abundance index.

1.2 Aims, Objectives and Hypotheses

The overall aim of this project is to investigate the feasibility and challenges involved in using acoustic monitoring techniques as a means of obtaining accurate estimates of the number of breeding pairs of nocturnal burrow-nesting seabirds in a colony. The results of the project will be used to help the development of this system, which has the potential to be a valuable tool for monitoring conservation efforts of endangered seabird species.

The aim of this project will be achieved through the following objectives and their respective hypotheses:

1. To test for a positive linear relationship between call rate and Cory Shearwater nest density surrounding the automated recording units (ARUs) after controlling for all other nuisance variables.
2. To compare the accuracy of two commonly used automatic signal recognition software programs (XBAT and Song Scope) at detecting Cory's Shearwater vocalisations.
3. To examine the influence of moonlight, weather conditions and site on the calling rates of Cory Shearwater and their effects on the ability of automated recording units to detect calling rates.

Biological Hypotheses:

H1 (Moon): Calling rates will be higher when the moon is out longer during the night and when a higher proportion of it is illuminated.

H2 (Cloud Cover): Calling rates will be higher when there is more cloud cover.

H3 (Cloud Cover *Moon): The relationship between calling rates and cloud cover will depend on the moon intensity because during new moon, cloud cover is not expected to affect calling rate, however cloud cover will affect light intensity during the full moon.

H4 (Visibility): Calling rates will be higher at lower visibility levels.

H5 (Breeding Season): Calling rates will decrease across the incubation period of Cory's Shearwaters.

Detectability Hypotheses:

H6 (Wind): ARUs will detect fewer calls as wind speed increases, obscuring calls and resulting in a lower calling rate

H7 (Site): The number of calls an ARU detects will change depending on which site it is placed on because of the variation in physical site characteristics which will impact the range of the ARU at picking up bird calls.

1.3 Thesis Structure

Chapter 2 provides a background to this study, demonstrating the need for monitoring nocturnal burrow-nesting seabird populations. It then introduces automated acoustic monitoring as a potential census technique and raises the potential biases that might arise from using calling rate to estimate seabird abundance. It ends a short introduction of the study site and species.

Chapter 3 describes the methodology used to collect data in the study and an explanation of the methods used to analyse the data.

Chapter 4 presents the results from this study.

Chapter 5 discusses results of the study and their implications on estimating seabird abundance, the limitations of this study and provides recommendations for future research.

2. BACKGROUND

2.1 Seabird population decline and its drivers

Seabirds are one of the most endangered groups of animals with over 30% of 328 recognised species classified as threatened or endangered by the IUCN. They are also declining at a faster rate globally than any other taxon of birds. Out at sea, seabirds face a range of threats from the global expansion of commercial longline fisheries (Weimerskirch et al. 1997), oilspills (Piatt et al. 1990) and decline in foraging fish (Kitaysky et al. 2006). However on land, predation by invasive mammals is considered one of the largest threats to declining seabird populations (Jones et al. 2008, Simberloff 2009).

Since 1600's, more than 90% of avian extinction on islands has been linked to predation by introduced predators (Steadman 1995). Many seabirds breed on remote oceanic islands. In the absence of terrestrial predators on these islands, they have evolved naive life history traits such as conspicuous ground nesting habits (Ebbert and Byrd 2002) rendering them especially vulnerable to introduced predators. Furthermore, many seabirds are also long-lived with low reproductive rates, making it difficult to replace predated individuals (Owen and Bennett 2002). Introduced rodents for example, are one of the largest drivers of seabird extinction. Rats occur on 90% of island archipelagos where seabirds nest, and will prey readily on seabird eggs, chicks and even adults (Jones 2008).

2.2 Invasive Mammal Eradication

The devastating effects of invasive mammals on seabirds and other endemic island species, have spurred the development of techniques to eradicate them and restore island ecosystems (Howald 2010). Invasive species control professionals employ techniques such as systematically dispensing poisoned bait or trapping and shooting in the case of larger mammals (Courchamp 2003). Since then, many successful mammal eradication projects have been carried out on islands (Campbell and Donlan 2005). Until 2007, rodents have been eradicated from at least 284 islands with more projects underway (Howald 2010).

However mammal eradication campaigns are extremely costly, for example rat eradication on Anacapa Island, small 3km² island off the coast of California cost about US\$2 million (Donlan and Wilcox 2007).

2.3 Lack of post eradication monitoring on nocturnal burrow-nesting seabirds

Despite the amount of large amount of effort and resources invested in invasive mammal eradication, many of these projects suffer from a common problem: the lack of long-term monitoring of native species population recovery after eradication (Davis et al. 2004).

Often, island eradication “successes” are equated to the elimination of the target invasive mammal instead of the initial conservation goal of restoring native ecosystems (Courchamp 2003).

Nocturnal burrow-nesting seabirds are a group of seabirds that are hardest hit by invasive predators and would have benefitted most from invasive mammal eradication (Jones et al 2008). Yet the response of their populations after eradication projects have not been monitored due to the high cost and logistical difficulty involved in censusing nocturnal seabirds (Walsh et al. 1995). The remoteness of their colonies and their secretive behaviour make monitoring programs costly and challenging to implement. Hence there is an urgent need to develop cost-effective, long-term monitoring protocols for priority planning and assessment of conservation initiatives of this highly threatened group of birds (EU-Life 2009).

2.4 Current methods used to estimate seabird populations

Seabird monitoring programs have been well established in many countries where colonies exist. This has enabled wildlife managers to collect data on seabird population numbers and breeding success for effective management and conservation (Steinkamp et al 2003; Walsh et al. 1995). As a result, many different standardised survey techniques have been developed to estimate population size and establish trends.

However, nocturnal burrow-nesting seabirds are a logistically challenging group of birds to monitor (Walsh et al, 1995). This group of seabirds, which include species of shearwaters, auklets and storm petrels, only return to their colonies at night and nest in burrows or crevices which greatly reduces their visibility. Some species may also nest on steep friable cliffs that are inaccessible due to safety concerns. Many species return to breed on remote oceanic islands where setting up a field station or campsite for extended monitoring by humans would incur large expenses. Hence many of the techniques that are currently available for monitoring seabirds are not suitable for surveying nocturnal burrowing seabirds. Table 2.1 below describes several of the commonly employed methods and their problems when used on nocturnal burrowing seabirds.

Table 1. Common seabird surveying techniques and reasons why they are unsuitable for estimating nocturnal burrow-nesting seabirds populations.

Monitoring Method	Problem
Aerial or Boat Surveys	Nocturnal seabirds nest in crevices and only return to colony at night, making it impossible to see from a plane or boat (Walsh et al. 1995).
Direct Burrow Counts	Labour intensive and costly. Burrows located in inaccessible areas making hard to get an accurate estimate (Monteiro 1990, Steincamp 2005).
Radar	Expensive, problems with interference by insects. Cannot survey inland colonies. (Reynolds et al. 1997)
Raft Counts (Seabirds often clock together on the sea surface forming “rafts”. This can counted to provide estimate of numbers)	Raft count numbers show huge variation. Not enough understanding about rafting behaviour (Bolton 2001).

It is clear that more work needs to be done to develop a monitoring system suitable for nocturnal burrowing seabirds. One potential method that is being considered now is using acoustic monitoring systems to estimate their abundance. Vocal signals are important for sexual advertisement in nocturnal seabirds as it aids them to find mates and form pair bonds (Brooke 1978, Storey 1984). Nocturnal seabirds species have an array of distinctive and unique vocalizations, and their colonies producing impressively rich soundscapes

during the night (Robb et al. 2008). These characteristics make them good candidates for acoustic monitoring techniques.

2.5 Acoustic Monitoring in Birds

Birds in particular lend themselves well to acoustic monitoring. Vocalisations are one of their primary means of communication, and it is also an easier way to detect them as human observers will often hear more birds than they can see (Parker 1991). Two of the most efficient monitoring techniques used to assess bird populations (point and transect counts) both require the use of passive acoustics (Angehr 2002). One of the main disadvantage of point and transect counts is that they rely on highly trained observers to use aural clues to identify species. This results in two main problems. Firstly, the ability to sample larger areas is limited by the availability of observers (Hobson 2002). Secondly, data comparisons between observers may be biased as the data collected depends on an individual's skill level at recognising birdcalls.

2.6 Automated Acoustic Monitoring

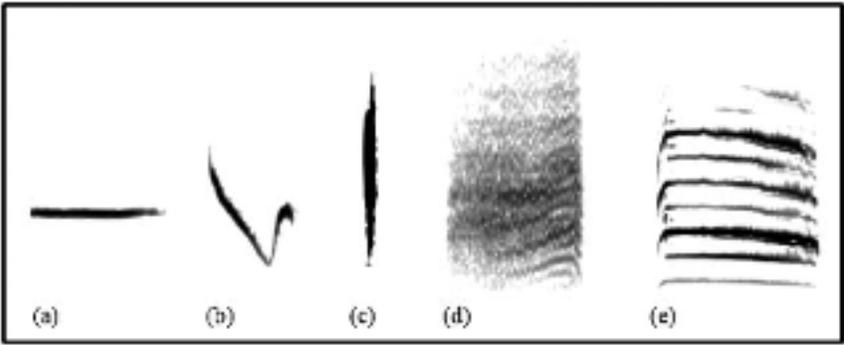
Recording technology however, has been advancing rapidly, and may now provide an alternative to using skilled observers for acoustic bird surveying. Recently the use of autonomous recording units (ARU)s has become commercially available for bioacoustic research. ARUs are self contained recording devices that consists of a microphone, single board computer programmed with software that schedules and records data, and a disk drive to store it in. These new units are powered by batteries and have the capacity to store up to 100GB of data which means they can potentially be deployed for months in remote locations (Wildlife Acoustics). Studies have shown that automated recordings may be a preferable means of acoustically monitoring birds as it minimizes observer biases, creates a permanent record of surveys, and also solves the problem of limited number of observers (Celis-Murillo et al. 2009; Haselmayer & Quinn 2000).

2.7 Automated sound analysis

Although the development of ARUs has made it easier to obtain recording of bird vocalizations, the recordings themselves need to be analysed. Trained analysts may be used to aurally or visually inspect spectrograms to identify and quantify vocalizations. However even though they may be the most reliable method of analysis (Charif and Pitzrick 2008), given the large amount of acoustic data collected by ARUs in the field, this option would require an impractical amount of processing time (Swiston and Mennill 2009). Fortunately, complex automated computer signal recognition software has been developed to aid the processing of large amounts of acoustic data. This has allowed for gains in sampling size, and cost efficiency in bioacoustic research (Agranat 2009).

Automated signal recognition software (ASRS) use a two-step process to conduct analysis of acoustic data. The first part involves call feature extraction, which is a method a program uses to identify the acoustic features of a sound so that it can be distinguished and extracted from other different sounds (i.e. background noise). Some examples of feature extraction include directly measuring of vocal parameters (call duration, highest and lowest frequency etc.) of a target's species call (Farnsworth et al. 2004) or correlating spectrograms of with a template of a target species call (Swiston and Mennill 2009). More examples are given in Table 1.

Depending on what feature extraction methods are employed, a classification technique is then used to sort the sound data into biologically relevant information such as identifying vocalizations of individual animals, species or populations. Different sound analysis tools utilise different feature extraction and classification techniques, and each type fares better at detecting different form of bird calls (Figure 1).



- (a) Constant Frequency
- (b) Frequency Modulated Whistles
- (c) Broadband Pulses
- (d) Broadband with Varying Frequency
- (e) Strong Harmonics

Figure 1 Spectrogram display of five classes of discrete sound shapes that form the basis of most avian vocalizations (Adapted from Brandes 2008).

Table 2. Comparing various feature extraction and classification methods used to detect bird vocalizations, and the type of bird sounds (Figure 2.1) they specialise in detecting. *For detailed description of feature extraction and classification methods, refer to Brandes 2008.

Target Call Type (Based on Figure 2)	Feature Extraction*	Classification Method*
a,b	Direct time and frequency measure from target calls	Bayesian classifier, Euclidian distance
c	Pulse-to-pulse duration	Neural networks
c	Sound template	Minimum cross-correlation threshold, dynamic time warping
e	Multi-spectral estimates with FFT and related functions	Multivariate statistics
a,b,e	Peak frequency contour vector	Bayesian classifier, dynamic time warping, hidden Markov models, neural networks
b,e	Cepstral Coefficients	Dynamic time warping, Gaussian mixture models, hidden Markov modes

2.8 Automated Acoustic Monitoring of Nocturnal Seabirds

Although not widely used as a monitoring technique yet, there have been a few studies that have started to evaluate the use of automated acoustic monitoring systems to monitor seabird populations. Buxton (2010) examined the feasibility of using automated recording and call recognition to monitor the recovery of nocturnal burrowing seabird assemblages after invasive mammal eradication on the western Aleutian Islands. She recorded and analysed vocalizations several species of nocturnal seabirds across several islands and concluded that ARUs had huge potential to be powerful and cost effective tools to census and monitor nocturnal burrow-nesting seabirds. However, this study only assessed relative changes in seabird populations using an index across the different islands. Estimating absolute population abundance from acoustic recording would require the calibration of sound recordings in colonies where the population size is known.

In 2011, we deployed ARUs at colonies with known numbers of nesting shearwaters in the Atlantic and Pacific Oceans. This project is designed to establish a relationship between the number of recorded shearwater vocalisations and the nest density measured in the vicinity of automated recording units. The acoustic data streams collected from the ARUs will be analysed using ASRS, which will pick out species-specific calls and provide a quantitative measurement (number of identified calls per unit time, hereafter 'calling rate'). The objective of the project will be to establish a relationship between call rates recorded and the number of breeding pairs around the ARUs, eventually developing a robust calibration that will be transferable to other nocturnal-burrowing seabird (MOU 2010). Because calling rates of shearwaters are known or expected to vary with a number of environmental conditions, exploratory analyses are needed to determine which variables must be considered if calling rate is to be used to estimate population size of breeding shearwaters. In addition, more in depth evaluation is needed on the automated signal recognition software used to determine calling rate.

2.9 Examining bias on calling rates

Developing a robust and sensitive index for measuring nocturnal burrow-nesting seabirds abundance using calling rates would be require to take into account factors that might bias the estimate (Milner-Gulland and Rowcliffe 2007). Unreliable estimates may adversely influence management decisions, and result in the implementation of unsuitable conservation measures (Brashares and Sam 2005). Therefore it is important to be able to identify sources of bias and correct for them when designing monitoring techniques.

There are three main sources of bias that may arise when using ARU recorded calling rates to determine the abundance of nocturnal burrow-nesting seabirds. These can be categorized into biological variation in call rates of nocturnal seabirds depending on moonlight and temporal conditions, varying levels of detection of vocalisations in ASRS due background noise and finally, changing rates of detection accuracy between different ASRS programs.

2.10 Factors affecting calling rates of individual shearwaters

2.10.1 Moon light

One factor that influences vocal activity in nocturnal seabirds is the level of moonlight intensity. Vocal activity in nocturnal seabirds is reduced during nights when the moon is full (Bourgeois et al. 2008; Bretagnolle et al 2000; Brooke 2004). Mougeot and Bretagnolle (2000) have demonstrated that Blue Petrels (*Halobaena caerulea*) and Thin Billed Prions (*Pachyptila belcheri*) vocalised less on moon light nights, where risks of being predated by Brown Skuas (*Stercorarius antarcticus*) are significantly higher. Nocturnal seabirds are extremely vulnerable to predators when they return to their colonies on land and reduced calling activity has been thought to be an adaptive avoidance strategy to reduce their conspicuousness on moonlit nights (McNeill et al 1993).

Roul (2010) used ARUs to record and Song Scope to analyse Manx Shearwaters vocalisations on islands in Newfoundland to test if vocal activity differed during changing moon phases. She concluded that vocal activity was inversely related to moon phase. However light levels may not only depend on the moon phase of a particular night. The timing of when the moon rises and sets will also affect the level of illumination of a colony. Other studies that investigated the effect of illumination on nocturnal seabird breeding activities used a light intensity meter (Keitt et al. 2004) or included cloud cover as well as moonlight intensity to calculate light levels (Riou & Hamer 2008). Therefore it will be also important to consider both moon phase, moon rise and set times, cloud cover and visibility to determine whether these factors will influence the calling rate of nocturnal nesting seabirds and how much this will bias abundance estimates.

2.10.2 Changing vocal activity across breeding season

One other biologically linked bias that may affect calling rates could be the changing attendance or vocalisation patterns of nocturnal seabirds at their colonies across the course of the breeding season. A study by Harding et al. (2005) noted that attendance at colony for crevice nesting Horned Puffins (*Fratercula corniculata*) changed from lower during mid and late incubation to higher attendance during later chick rearing stages. Cory Shearwaters (*Calonectris diomedea*) on Madeira on the other hand, show a regular oscillating pattern of attendance that does not seem to be explained by weather variables or availability of food (Granadeiro 2009). The work of Bretagnolle et al. (2000) with Audobon Shearwaters (*Puffinus Iherminieri*) on Reunion Island also showed that they displayed a seasonal trend in their vocal activity, with more calls during the beginning of the season where birds return to breed, compared to the end where chicks are fledging.

Although it is biologically important not to confuse vocal activity with attendance rates at colonies, for the purpose of using calling rates to estimate abundance, this confounding factor will not affect our results.

2.11 Factors affecting variability of detection rate

2.11.1 Wind Disturbance

One of the largest challenges that ASRS face when trying to detect bird calls from sound data is the disturbance caused by background noise which may obscure sounds of interest (Agranat 2009). Wind noise in particular has a tendency to create a constant band of noise across a spectrogram. If wind speed is high enough, the noise generated as it blows across the microphone will mask the frequency range of nocturnal seabird vocalisations present in the recordings. The more background noise there is, the harder it is for ASRS to detect calls (Agranat 2009, Buxton 2010). Thus a variation in wind speed may bias the accuracy at which ASRS quantifies the calling rate from the recordings.

2.11.2 Site Difference

The diversity in topography of an ARU may affect sound transmission of calls emitted by NBNS as well. For example, the diffusion of sound reverberation transmitted will vary depending how dense the vegetation is at the site, and whether it is located on a flat surface or a valley (Dawson 2009; Mennill 2006). Background noise between sites also may vary, resulting in varying levels of detectability (Lohr et al. 2003). Hence one must consider difference in deployment sites and their effect on detected call rates.

2.12 Determining suitability of automated recognition signal software (ASRS)

Developing a technique to monitor abundance of nocturnal burrow-nesting seabirds will be globally useful for seabird conservationists. However it would require a standardised protocol that can be easily transferable between species in different locations and personnel conducting the monitoring. Currently Song Scope (Buxton 2010) sold by Wildlife Acoustics and Extensible Bioacoustic Tool (XBAT) (A. Borker pers. comm.) developed by the Bioacoustics Research Program at Cornell University are two programs that have been used to analyse seabird vocalisations.

The two software programs use different feature detection methods and classification methods and there may yield different results depending on a bird's call structure as shown by above in Table 2.2. Using two different programs will result in inconsistent detection rates of calling activity, thus affecting the relationship between calling rate and measured nest density. Monitoring methods should be designed to reduce the amount of training required by personnel conducting the monitoring (Rodriguez 2003). It would be unrealistic to require personnel to learn how to use another ASRS if they were to monitor another species of seabird. ASRS programs themselves are already fairly complex to use (pers. obsv.) but the user interface and analysis protocols between xBAT and Song Scope are also very different. It would be more practical to select one ASRS to be used across the different species. However it is crucial to ensure that the software is accurate enough so that this simplification of methodology will not compromise its ability to accurately estimate population numbers of nocturnal burrow-nesting seabirds.

These are all factors that will affect the establishment of a robust abundance index to measure the abundance of nocturnal burrow-nesting seabirds. Thus in the course of developing this acoustic monitoring technique, they must taken into account to increase its accuracy at estimating abundance.

2.13 Study Site

The Azores are a group of nine volcanic islands located in the middle of the Atlantic Ocean. They are located approximately 1500km west of Lisbon and are considered an autonomous region of Portugal. Currently all nine islands are populated with numbers ranging from 150,000 inhabitants on Sao Miguel the largest island to 425 on Corvo, the smallest (INE 2001).



Figure 2: Global location and map of the nine main islands in the Azores

The islands of the Azores are important nesting grounds for many seabird species including 5 species of Procellariiformes, four Charadriiforms and one Pelecaniform (Monteroi et al 1996). Once home to millions of breeding seabirds, their numbers have drastically declined since humans colonised the islands in the late 15th century making them of international conservation concern (De Leon et al. 2006). Threats to the seabird population range from

human disturbance and exploitation, habitat loss, interaction with fisheries and most importantly, predation by introduced mammals (Monteiro et al. 1996).

The recognition of the Azores as an important nesting ground for seabirds has been growing and in 2009 Life EU grant “Safe Island for Seabirds” was awarded to promote seabird conservation on the Azores through habitat management and assessing the impact of native invasive species (EU-LIFE 2009). One of the main objectives of the project was to obtain accurate population numbers of the breeding seabirds of the Azores.

2.14 Study species

Cory’s Shearwater (*Calonectris diomedea*) is a large species of shearwater from the seabird family *Procellariidae*. They nest in the northeast Atlantic and islands in the Mediterranean. At their colonies, they nest in cavities which can include a diversity of locations such caves, crevices on cliff faces, in burrows under thick vegetation (Catry et al. 2006). Like many other seabirds, they are long lived with a life span of over 30 years and have with slow reproductive rates, only reaching sexual maturity after 7-9 years and producing one chick a year (Thibault et al. 1997). Cory’s Shearwaters like other procellariiformes are also highly vocal birds producing loud distinct calls, with extreme sexual differences (Robb et al. 2008).



Figure 3. Photograph of a cute Cory’s Shearwater (*Calonectris diomedea*)

Cory’s Shearwaters are currently considered ‘Vulnerable’ in Europe (Tucker et al. 1994), with several populations facing decline in numbers. Threats they face include long line fisheries (Belda and Sanchez 2001), urban light induced mortality of fledglings (Fontaine et al. 2011) and predation by invasive mammals (Thibault 1995). Despite these threats, the

demographic parameters and dynamics of Cory Shearwaters in the Azores still remain unknown (Fontaine et al. 2011).

3. METHODS

3.1 Data Collection

3.1.1 Settings for the autonomous recording units

Four SongMeters TM2 from Wildlife Acoustics were deployed to record the nocturnal calling activity of shearwaters. These are autonomous recording units (ARU) that can be programmed to record at specified times during the day. For the purpose of this study all four units were scheduled to record 1 minute of sound every 10 minutes during the period 30 minutes prior to sunset to 30 minutes after sunrise to capture all possible times at which Cory's Shearwaters may be vocalising. This setting ensures representative sampling throughout the entire night, while preserving battery power and limiting the memory requirements to store the recorded data and thus forms a useful compromise that has proved beneficial in other projects (A. Borker, M. McKown, pers. comm.). The gain of both microphones was held at factory default +42.0dB, with recordings in stereo, without compression with the sampling rate set at 16kHz as most seabird calls are below 8kHz.

Each ARU was equipped with 32GB of memory in the form of four 8GB SD cards. The ARUs are powered by 4 D size batteries, which on the above recording schedule, should run for 6 weeks based on the manufacturer's estimates. However, we encountered significant problems with rechargeable NiMH batteries, and Alkaline batteries of certain brands which did not provide sufficient power to repeatedly turn the units on and off. The chosen setting requires a minimum power level in the battery to turn the units on every 10 min, which is not accounted for in the manufacturer's estimate of recording time. Hence, the units frequently ceased recording due to power failure after a fraction of the estimated operating time. Data were downloaded from the ARU and batteries changed at least once a month, or as close as possible depending on the accessibility of the site. Only brand new alkaline batteries of very high quality were useful to power the units for > 3 weeks.

3.1.2 Deployment Sites

Four different sites with a range of burrow densities were chosen for ARU deployment. The ARU's were placed on the ground in areas that offered protection from high winds to reduce background noise and away from objects that could obstruct sound waves from reaching the microphones, creating a sound shadow. A wire cage was placed around each ARU to prevent grazing animals or rodents from damaging the recording device.

Four ARUs were deployed on islands around the Azores with two on Corvo (Cancelo do Pico and Pau de Acucar) on the 12th of June. One was deployed on the 3rd of June on Faial and 1st June 2011 on Vila Franca..

3.1.3 Estimating nest abundance

To obtain nest density at a deployment site, we counted all the number of occupied burrows in a 50m radius around the ARU. Given that Cory's Shearwaters do not respond to playback of vocalisations, burrow occupancy was determined using other evidence of occupation (Bolton 2001). If a Cory's Shearwater was not clearly visible in the burrow, signs of occupancy were noted. A burrow was counted as being occupied when two of the following were observed: 1. Absence of vegetation or spider web obstructing the entrance 2. Presence of seabird excrement indicating recent use of burrow 3. Presence of white breast feathers 4. Presence of excavated soil indicating recent burrowing activity.

However, there were inaccessible areas within 50m of the ARU. In this situation, we excluded these areas from the nest density number as did not take up >10% of the 50m radius. On Faial, nest density estimates were largely based on the expert knowledge of a researcher who had been monitoring breeding success of the colony and knew the numbers of occupied burrows in the area at the time of the study.

3.2 Data Analysis

3.2.1 Processing sound recordings

Sound recordings from the ARU were downloaded onto an external hard drive. All the recordings are saved in the .wav file format and were analysed using automated signal recognition software (ASRS) for automatic call detection and spectrogram visualisation of

the sound files. To decide which software program would be more suitable for shearwater acoustic monitoring, we tested the accuracy of two ASRS, XBAT and Song Scope, which are currently being used by researchers.

3.2.2 Analysis in XBAT

XBAT's automatic call recognition system (developed by Cornell Bioacoustics Lab) uses its data template detector tool to extract and classify sounds. The data template detector uses a **detection template** of a target species vocalisation to scan recorded sound streams and then identifies sounds that are similar to the template. The detector quantifies acoustic similarity by cross co-relating it with the spectrogram of the sound streams, and counts the number of positive matches based on whether they exceed a certain correlation threshold, which was left at the default of 0.4 for this study. The number of positive matches and their location on the sound files are saved and presented in an event log (Clark & Fristrup 2009).

3.2.3 Building a detection template in XBAT

Cory's Shearwater calls were recorded by ARUs in the Azores. I visually scanned spectrograms of the recordings and selected a sample of a clear and distinct target call (See Figure 4) with minimal background interference on the spectrogram to be used as a detection template. However we were only able to construct successful templates for the male call. Female calls for Cory's Shearwater are less distinct on a spectrogram and their frequency coincides with the frequency of the background noise that is constantly present in the spectrograms of the recording. This makes difficult to construct an accurate template of their calls.

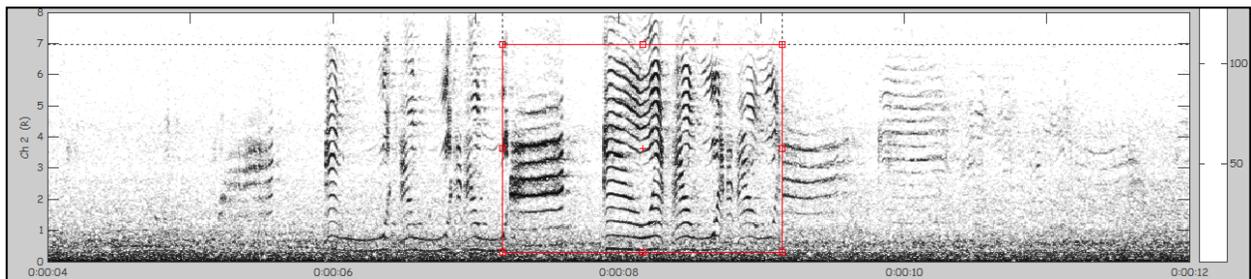


Figure 4. Selecting detection template for a male Cory's Shearwater call in XBAT.

3.3.4 Analysis in Song Scope:

Song Scope automatic detection software relies on the generation of a recogniser model (a type of classifier). Generating a recogniser requires a collection of “*training data*”, which is a sample of known target vocalisations. To generate a recogniser, Songscope automatically runs a signal-detection algorithm based on Hidden Markov Models on the training data under set model parameters. The algorithm considers the spectral and temporal characteristics of the target vocalisation and the variability that is present in them to generate a recogniser (see Agranat 2009 for more details on the algorithm and models used to build recognisers). The generated recogniser can then be used to scan longer and multiple sound recordings in batches to find and count acoustic matches.

3.2.5 Building a recogniser in Song Scope

To build a recogniser in Song scope, I selected training data from field recordings from all the four deployment sites. I visually scanned spectrograms of the recordings to locate and select (“annotate” in Song Scope terminology) (See Figure 5) loud and distinct target species calls with minimum background interference. To ensure that the generated recogniser encompassed the range of variation in call qualities across the different sites, training data was annotated from recordings from all four ARUs. Again, recognisers were only generated for the male calls of the Cory’s Shearwater as the quality of the female calls were not clear enough to build an accurate recogniser. A total of 16 vocalisations were manually annotated from 10 different recordings to be used as training data.

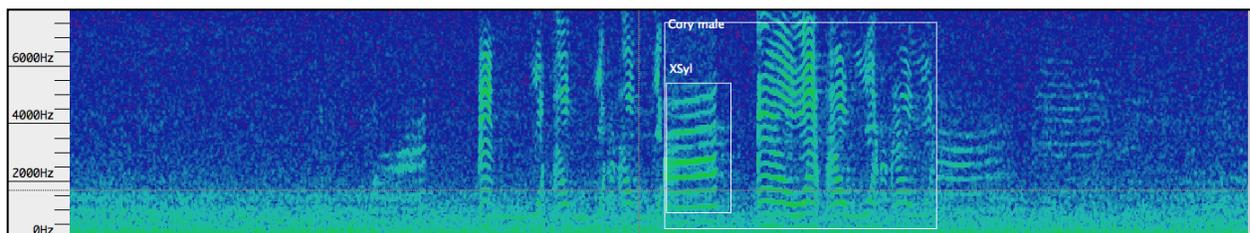


Figure 5. Annotating training data to build a male Cory’s Call recogniser on a spectrogram in Song Scope.

3.3 Comparison of Sound Analysis Software

To evaluate whether Xbat or Song Scope was more suitable for analysing Cory Shearwaters' calls, a comparison of their accuracy at detecting call frequencies was conducted. Accuracy was tested using both programs to count the call frequencies of a small subsample of 20 one-minute recordings. These recordings, obtained from the ARU field recordings, were selected to represent a range of calling frequencies to test the software's accuracy of detection over a wide range of call rates. They were also selected from different days, weather conditions and sites to examine the software program's accuracy across a variety of conditions.

An analyst reviewed the twenty recordings to obtain a count of the call rates that would be closer to the actual call rate of the Cory's Shearwaters, since manual human observation currently still tends to be more accurate than software processing (Charif and Pritznick 2008). I visually examined the spectrogram of the recording and listened to the recordings if visual inspection was not clear, to count the number of calls present in each one-minute sample. The number of calls counted by each program was then compared against the number I detected using a Pearson's correlation test to determine which software had a better relationship to the actual 'true' figure.

3.4 Collection of data for variables in model

3.4.1 Calling rate as a response variable:

Calling Rate is defined as number of calls per minute for each night.

To obtain calling rate, I analysed the sound recordings we had obtained from the four ARUs we deployed on the Azores. The more accurate sound analysis software (as determined from the first part of this study) was used to batch process the recordings. The program scanned all the one-minute files that were recorded and downloaded from the ARUs in

batches at a time. It then matched the recogniser against each of the recordings, and listed all the positive matches it found in an output table, giving us the total number of calls matched in each one-minute file.

Calling Rate per minute was obtained by using the total number of calls recorded per night, with the log of the number of minutes sampled each night as an offset.

3.4.2 Predictor variables

Table 3. List of predictor variables used in our model and how they were obtained

Predictor Variables	Source
<u>Site (number of nests at site)</u>	The individual sites on which the ARUs were deployed.
<u>Moonshine</u> The intensity of moonlight during the night.	This was defined as the amount of time the moon was up during the night calculated using moonrise and set times. The amount of time was then multiplied by the proportion of the moon that was illuminated calculated using moon phase information. Moon Rise, Moon Set and Moon Phase data were obtained from the National Oceanography Portal (http://www.usno.navy.mil/USNO/astronomical-applications/data-services/rs-one-year-world)
<u>Weather Variables</u> <ul style="list-style-type: none"> - Mean Wind Speed (m/s) - Mean Cloud Cover (Eights of the sky) - Minimum Visibility (km) 	Weather Underground (http://www.wunderground.com).
<u>Date</u> The date when the ARU started recording for the night.	

3.5 Statistical Modelling

All statistical analysis was carried out using R 2.13.0 (The R development core team, 2011).

A full model was first fitted to investigate the various factors that would influence the number of calls detected in an automated acoustic monitoring system. This was analysed using a generalised linear model (GLM) with a log link function using Detected Calling Rate (number of calls per minute) as a response variable. Predictor variables (Table 3) were selected to test each of the hypotheses listed in the introduction, which were determined a priori. Using a GLM approach with a Poisson error structure showed the presence of overdispersion (residual deviance: 1813764 on 79df). I therefore used a negative binomial GLM (glm.nb function in R) to correct for overdispersion (residual deviance 203.31 on 79df). The full model was then simplified into a minimum adequate model by removing environmental variables that were not significant in the full model (Crawley 2005).

4. RESULTS

4.1 Nest Density of Deployment Sites and Recording Effort

Table 1 shows the number of nests counted at each different deployment site. It also notes the number of nights of recordings that were downloaded from the ARU units in total. Pau de Acucar only had 5 nights of recording as the unit malfunctioned after 5 days. Cancelo do Pico's downloaded sound data could not be processed by the software programs, hence only five nights were analysed manually by an analyst.

Table 4. Number of nests found at each deployment site, and the number of recorded nights used in our analysis.

Deployment Sites (Island)	Number of Nests counted in a 50m radius around ARU	Total number of nights used in statistical analysis
Faial (Faial)	39	38
Cancela do Pico (Corvo)	11	5
Pau de Acucar (Corvo)	20	5
Vila Franca (Vila Franca)	60	38

4.2 Accuracy of Automated Signal Recognition Software

The relationship between the number of Cory's Shearwater calls Song Scope and XBAT detected and the 'true' number of calls that I manually detected was assessed with a Pearson Correlation Test using a sub sample of 20 one-minute sound recordings.

For Song Scope, there was a strong positive correlation between the number of calls detected by Song Scope and manually ($r=0.956$, $n=20$, $p<<0.0001$; see Figure 6). However, there was no correlation between the number of calls detected by XBAT ($r=-0.22$, $n=20$, $p=0.3531$; see Figure 6).

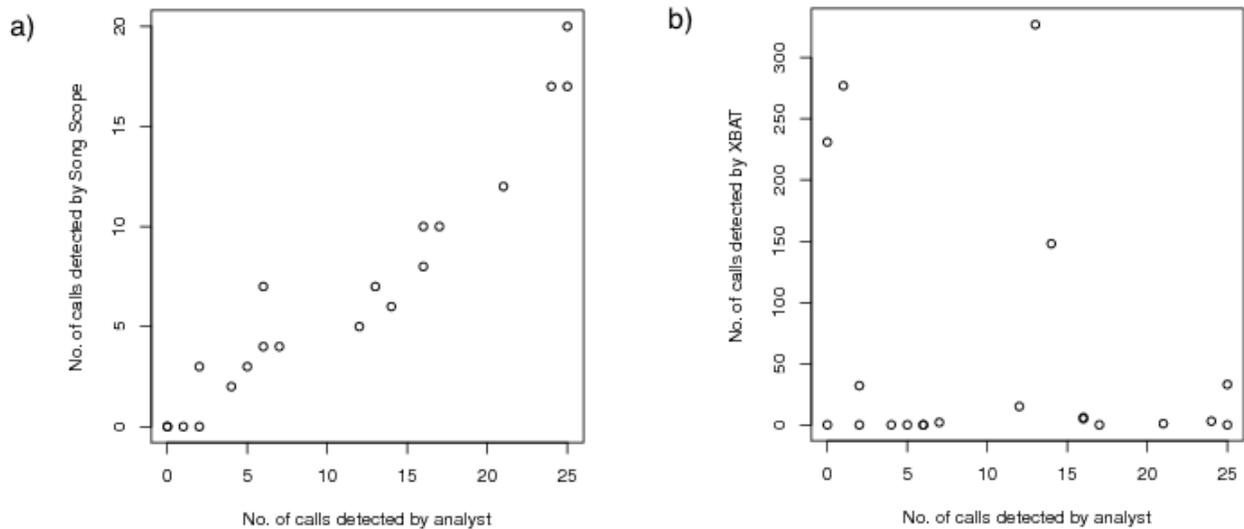


Figure 6. Scatterplots illustrating the relationship between the number of calls detected by Song Scope (a) and XBAT (b) and the number of calls detected by an analyst (n=20).

4.3 Summary of minimum adequate model

Table 5. shows the results of the GLM, demonstrating the relative importance of each of the variables in the minimum adequate model on the calling rate. The ARU deployment sites and date all showed a positive relationship with the calling rate, although date was only comparatively less significant than site. On the other hand, moonshine and mean wind speed had significant negative effects on calling rate.

Table 5. Results of the full GLM (using negative binomial error distribution) conducted to test several predictor variables on calling rate.

Predictor Variable	Estimate	Standard Error	Z value	P value
(Intercept)	-2.62600	1.21246	-2.166	0.0030323*
Site(20)	2.10003	0.43964	4.777	1.78e-06***
Site(39)	2.02194	0.36096	5.602	2.12e-08***
Site(60)	2.83288	0.37368	7.581	3.43e-14***
Moonshine	-0.009772	0.02914	-3.354	0.000797***
Mean Wind Speed	-0.04104	0.01431	-2.868	0.004125**
Date	0.01227	0.00628	1.955	0.050641 .

. P<0.1, *P<0.05, **P<0.01, ***P<0.001

4.4 Predicted Detected Calling Rate to Nest Abundance Relationship

To determine if there was a positive linear relationship with detected calling rate and nest abundance, I plotted the predicted call rates from the minimum adequate model against known abundance with all the significant environmental variables controlled (Figure). To provide a comparison, the predicted rates of a site model (only fitted with site as a predictor variable) were plotted as well (Figure 7).

Although the predicted values from the minimum adequate model show a positive trend between detected calling rates and nest number (Figure 7a), the relationship is only a general overall trend with nest number increasing as call rates increase. The diverging trend lines indicate that there is no direct proportional relationship between detected calling rate and nest number. The trend lines of the predicted values from the site model (Figure 7b) on the other hand, converge more than those of nest number (Figure 7a), demonstrating a more proportional relationship between detected calling rate and nest number. For example, a doubling in of detected calling rates from lowest density site, results close to doubling in nest number Figure 7b. This indicates that when we used the minimum adequate model to control for environmental variables, the residual variation does not produce an accurate index between detected call rates and nest number. In fact, it makes the trend less robust than just looking at site differences.

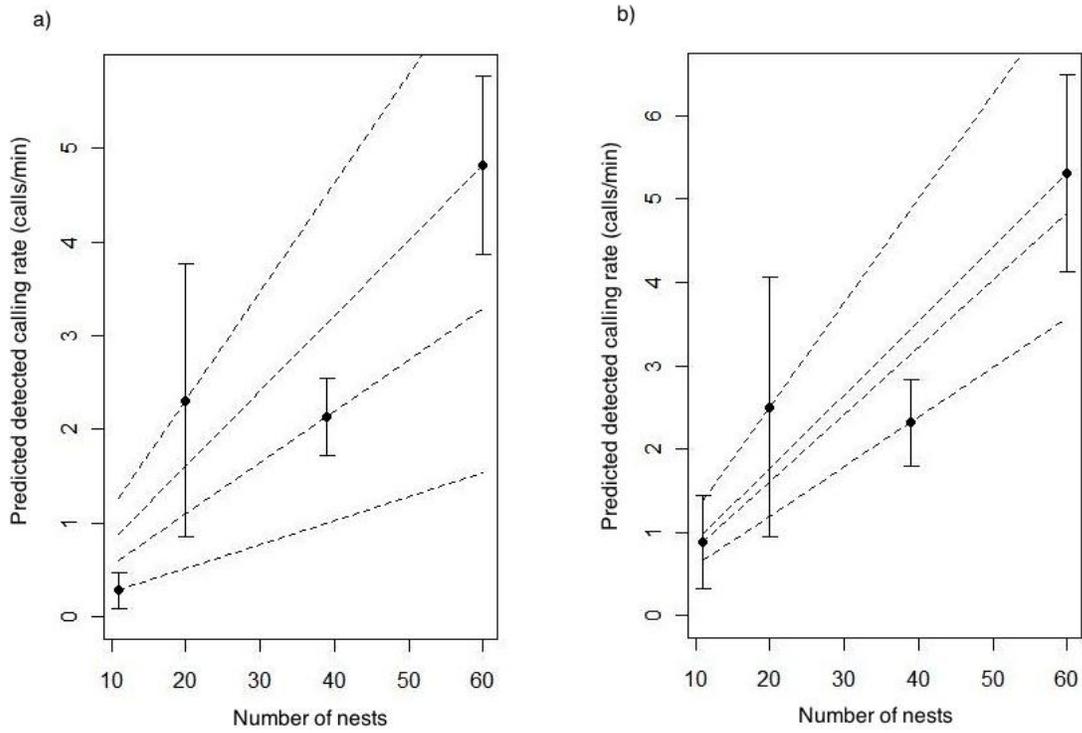


Figure 7. Graphs of predicted detected calling rate from the minimum adequate model (a) and site model (b) plotted against known values of calling rate at each site. Confidence intervals were set at 95%

4.5 Summary of support for hypotheses

Table 6: Support for a priori hypothesis based on results from our model.

Hypothesis	Supported
Moonlight Intensity	Yes
Cloud Cover	No
Cloud Cover Interaction with Moon Intensity	No
Visibility	No
Breeding Season	Yes
Wind	Yes
Site	Yes

5. DISCUSSION

5.1 The Relationship between Calling Rate and Nest Abundance

The basis behind using an acoustic monitoring system to estimate abundance relies on the assumption that detected calling rates are positively related to nest density (Bart et al. 1998). Although this study does show a crude positive trend between call rates and nest number, I was unable to establish a sensitive and robust relationship between them. The predicted relationship that was obtained from the minimum adequate model (Figure 7) did not show a linear correlation that would have demonstrated a proportionality between calling rate and nest number. This may have been a result of our small and unbalanced sample size, with Cancelo do Pico and Pau de Acucar only contributing five days of data to the analysis. However, confidence levels indicate that imprecision is also relatively high from the Vila Franca site, where 38 days of data were collected.

Examining the graphs plotted from our models, the site model by chance demonstrated a better relationship than when the confounding variables were statistically controlled for. This suggests that there were underlying differences between the sites that were not accounted for as predicted with the site hypothesis. Examples of site related factors that could have affected detected call rates include background noise and topographical difference between sites (Dawson 2009; Mennill 2006). Influence of background noise, such as wave noise, could be corrected by measuring background noise ratios (in terms of frequency range affected in spectrograms) between sites (Thompson et al. 2009). Topographical differences however will be harder to quantify. Ideally, the ARUs should have been deployed in a place where there were no sound shadows. However, it was not easy to find an obstruction-free area near the colonies, which would have contributed to site differences.

One potential method to control for site difference would be to have four of the ARUs placed on one island instead at different colonies with varying densities. However, this

does not address the issue of the differences present between sites and islands, and will question the potential of using this device in a variety of locations.

At this point, it is also important to highlight the problem of using nest density as a measure of abundance. This assumes that only breeding birds are returning to the colonies at night and vocalising. However, prior studies on Manx Shearwaters (*Puffinus puffinus*) show that non-breeders may actually call more than breeders (James 1985). The vocal activity pattern of breeders and non-breeders of Cory's Shearwaters should be investigated to determine the difference in rates and controlled for if possible.

Although a robust proportional relationship between call rates and nest number has been shown on tern colonies using automated acoustic monitoring systems (Borker pers. comm.), only relative abundance indices have been constructed for nocturnal burrow-nesting seabirds until now (Buxton 2011). Whereas terns are diurnal and nest conspicuously on flat ground (Brunton 1997), nocturnal burrow-nesting seabirds colonies are more cryptic and located in a variety of habitats (Catry et al. 2006). This makes it easier for researchers to collect information about nesting density at tern colonies. The flatness of the colonies also reduces the difference in topography between sites allowing for comparison of calling rates less influenced by site related factors.

5.2 Automated Sound Recording Hardware and Software

5.2.1 Autonomous Recording Units

One of the main issues faced in this study was the small sample size of the recordings used for analysis (Table 4). This can be explained by a combination of several factors, including the high costs of ARUs (US\$500), which limited the total number that could be deployed at different study sites. Despite their high costs, the devices malfunction or were easily damaged on several occasions. Regular weekly checks had to be made to ensure they were recording according to schedule, and even then, one had a microphone damaged by a sheep and the other broke down and had to be return to the company for repair. This resulted in the reduced amount of data obtained from Pau de Acucar and Cancelo do Pico (Table 4).

Considering the environmental factors such that influence the calling rate detected by these

units, a much larger sample would be needed to account for all of them. This would allow more precise and accurate relationship to be drawn between calling rate and nest abundance.

The Royal Society for the Protection of Birds (RSPB) is currently exploring the possibility constructing similar version of ARUs on their own, which would drive down their cost and allow for a larger sampling size. Before we get to that stage, our experience with using ARUs for this study has provided us with several insights into simple guidelines that could extend their reliability and lifespan:

- A cage should always be put on the ARU unit to prevent damage from animals such as goats and rats.
- Ensure that the type of battery used is compatible with the unit, i.e. High quality alkaline batteries should be used instead of rechargeable batteries, as they are less reliable.
- Check for loose battery circuit connections before deployment.
- Insulate the device from humidity and rain, using silicon packets and wrapping up the unit with cling film.

5.2.2 Automated signal recognition software comparison

A comparison of Song Scope and XBAT's accuracy clearly indicates that Song Scope is a more suitable program for analysing Cory's Shearwater vocalizations.

XBAT was selected initially because it had been used successfully to detect calls in other animals with similar harmonic structure to shearwaters in their vocalizations, such as elephants (Dugal et al. 2010; Thompson et al. 2009). However, it did not perform well. XBAT's low accuracy levels could be attributed to the method the software uses to detect calls. Spectrogram cross-correlation feature techniques have been shown to work best with broadband pulses in birds (See table 2), whereas Cory's Shearwater calls are more a combination of varying broadband frequencies, with strong harmonics (Robb et al. 2008). It is more likely that XBAT's poor performance in accuracy in this study was a result of the complications that we faced while trying to use the software. For instance, although XBAT'S website comes with simple instructions on how to utilise the basic tools of the program, it does not go into other more complex analytical functions of the software which may have

increased its accuracy. For example, there exists the possibility of running multiple templates simultaneously. This would have given the detector a higher probability of detecting Cory's Shearwater vocalisations as most birdcalls tend to vary between individuals (Brooks and Falls 1975). However, since instructions on how to use this function were not readily available, we were only able to compare the sound data to one detection template, preventing us from realising its full potential.

We were also unable to explain why XBAT detected unusually high calling rates compared to Song Scope (Figure 6). Further examination of the data revealed all the high calling rates detected come from the Faial deployment site. This suggests the problem might lie with factors that affected the recording quality at that site, such as the interference from background noise of other birds, wind or waves which may have closely matched the Cory's Shearwater detector template.

Song Scope on the other hand, uses Cepstral coefficients and Hidden Markov Models to build recognisers for call detection (Agranat 2009). This is a more suitable method to identify strong harmonics (Brandes 2008), which is one of the characteristics of Cory's Shearwater calls. Song Scope also relies on a series of training templates to build its recognisers, allowing for a more flexible recogniser to account for call variation when detecting target calls. The increased complexity of detection technology in Song Scope makes it more accurate at detecting Cory's Shearwater and the number of automatically detected calls is therefore closer to the actual number found by a human analyst as shown by the results. Despite its sophistication, Song Scope still has a simple and user-friendly interface. It also comes with a detailed instruction booklet, explaining how all the functions on Song Scope work.

Based on the greatly increased accuracy of Song Scope for detecting Cory's Shearwater calls from the sound recordings downloaded from the ARU, we would recommend Song Scope be used for future analysis of calling rates to ensure consistency when processing recorded seabird vocalisations across different studies.

This study primarily focused on evaluating of Song Scope and XBAT's accuracy at detecting calls when used by an inexperienced first-time user. Users more experienced with the

functions of each programs may derive different results than our study. For example, Charif and Pritzrick (2008) developed their own algorithm in XBAT for selecting a series of templates that would increase chances of detection. Provided with a similar algorithm XBAT could have performed substantially better at detecting Cory's Shearwater calls. Communication with other seabird researchers who use XBAT for bioacoustics analysis revealed a high level of proficiency with the software. Even though they required substantial amount of training and practice, has allowed them to construct sensitive and accurate templates (Borker, pers comm).

Apart from the accuracy, other aspects of automated signal recognition software programs also need to be considered before the software can be employed as routinely as part of species monitoring system. The table below summarises our experience working with both

Table 7. Comparison of qualities of XBAT and Song Scope that will be important for use as in a monitoring system.

	XBAT	Song Scope
Cost	Free but requires Matlab Platform which costs about\$400-\$1000	\$600 per installation
Installation and Compatibility	Complicated installation process for latest version of software. Computability issues of Matlab Versions and MacOS.	Simple click to install. Works well on both MacOS and Windows.
User Experience	Simple interface, fairly easy to understand basic tools. More documentation needed for complicated tools.	Simple but professional looking user interface, all features explained in user manual.
Support	Active user group, but responses to answers tend to be erratic.	Active user forum, with quick responses from Wildlife Acoustics Staff. Help line also available Mon-Friday in the US. Provided one to one assistance with building recognisers.
Extensibility	Open source programs allow for added features using Matlab code. But this requires prior knowledge of Matlab programming language.	Closed source. Any changes to program will only appear in new version.

5.3 Environmental influences on detected calling rates

5.3.1 Biological Bias

Moonlight Intensity

Moonshine showed a significant negative relationship on detected calling rates, as was predicted by our moon hypotheses. However, visibility, cloud cover and the interaction between cloud cover and moonlight were not significant and were removed from the original full model. This may indicate that the strong influence of the moonlight overrides any other influencing factors. These results are biologically significant, confirming the prevailing view that moonlight does affect vocal activity of nocturnal burrow nesting

seabirds (Bourgeois et al. 2008; Bretagnolle et al. 2000; Brooke 2004). As a result, they should be controlled for when estimating detected call. Depending on how variable the other confounding factors are, one way to control for moonshine is may be to only record on new moon nights and a few days before or after, when moonlight is at a minimum to reduce the moonlight bias.

Date

Although significant, date seemed to only have a minor effect on the call rate over the sampling period. However, the 38-day range only encompassed the incubation period of the Cory's Shearwater (Granadeiro 1991). The slight increase as the incubation period approached the hatching date may suggest that rates could potentially change as the breeding cycle progresses. This has implications for selecting which period of the cycle an ARU should be deployed at a site. It is crucial that future experimental designs on calling rates include the whole breeding period to control for any bias in changing calling rates as the breeding season changes.

5.3.2 Detection level bias

Wind

Regarding the question of how the detection rate the ARUs and Song Scope is influenced by wind speed, our model provides evidence that increased wind speed negatively affected the calling rate detected. This corresponds to prior work investigating the negative effects wind speed had on call quality (Agranat 2009; Buxton 2010). A more detailed analysis of wind speed's effect on the detectability of Song Scope could be conducted by looking at how the ratio of 'true' calls to calls detected by Song Scope changes as wind speed increases. This can be achieved with a simple experiment of playing recordings of Cory's Shearwater vocalisations at fixed distances from the ARU under different wind speeds. The change in recognition rate across varying wind speeds can then be factored into abundance estimates.

5.4 Limitations of the Study

5.4.1 Data Collection and Experimental Design Limitations

The methodology used in this study to count the number of burrows in a 50m radius around an ARU is imprecise, and as a result may have affected the accuracy of our data. Instead of using occupancy signs to determine if a burrow had been occupied, accuracy would have been improved through the use of a burrowscope (video camera on a flexible tube) if funding had been available (Lyver et al 1998). Inaccuracies also occurred when we did not include nests in our count when they were located in inaccessible areas around the 50m radius of the ARU. Future test deployment sites should be completely accessible if possible. If not, employing systematic sampling techniques on inaccessible areas (Steinkamp et al. 2005, Wolfaard and Philips 2011) or using density values instead of total abundance to exclude them entirely will be preferable.

One other limitation in our methodology was the decision to use 50m as a radius to measure nest density around the ARU, where we assumed that 50m was the effective detection radius of the unit. However, this needs to be tested by a calibration exercise using playbacks of Cory's Shearwater vocalisations from speakers at various intervals surround the ARU, and under different wind conditions, to determine its effective detection radius. Following this, nests that fall outside the detection radius, could be excluded, providing a more accurate estimation in nest numbers.

One of the issues that plagues the use of acoustic monitoring to estimate abundance is that there might be social facilitation of calling rates, where an increased number of seabirds may result in increased instances of aggressive interaction causing them to call more (Mackin 2005). Behavioural studies could be used to identify if this applies to shearwaters. Although this it was not apparent in our results, one could test a wider range of nest abundance numbers and their detected calling rates to determine if the relationship accelerates as numbers increase. If an increase in the interaction rates between Cory's Shearwaters did generate louder and higher number of actual calling rates this may result in an overestimation of abundance of populations if not accounted for.

5.4.2 Data Analysis Limitations

Analysing calling rates on a nightly scale may simply not be a fine enough temporal resolution for the purpose of this study since many different variables, especially weather conditions and even calling frequency of the shearwaters can vary throughout the night (Bretagnolle 1990; Granadeiro 2000). It would create more meaningful predictor variables as well. For example using daily cloud cover or wind speed may not be representative of the actual weather conditions during the recording periods since these weather variables can vary extensively during the day and it would reduce accuracy if we used their mean values. The ARUs recorded sound data consistently one minute out of every ten throughout the night, giving us enough resolution if we intend to sample by an hourly instead of nightly rate. The limiting factor however, is the availability of weather data on a finer time scale. For this study, we were only able to get detailed hourly weather through the day for the site on Vila Franca. This also poses a potential limitation for using acoustic monitoring techniques on remote islands without weather stations where it may be impossible to obtain detailed weather data.

5.5 Implications for the use of Automated Acoustic Monitoring Systems for Nocturnal Seabirds and directions for Future Research

Despite not establishing a clear linear robust index of detected calling rate to abundance, this study still demonstrates a positive relationship between calling rates and nest numbers. Even if the eventual index developed does not have high levels of precision, automated acoustic monitoring may still be the most cost effective technique to detect abundance changes and provide information on population parameters in nocturnal seabird populations. The last acoustic survey conducted on petrels and shearwaters in the Azores required 300 man-hours of listening (Monteiro et al. 1999), which could have been more effectively achieved with setting out ARUs. Current methods are similarly imprecise or require large inputs of manpower and resources (Table 1). Hence we should invest more effort to increase testing on larger range of densities, and investigating whether site differences can be accounted for and improving the accuracy of the index in the future.

With regards to the hardware and software used for this monitoring system, decreased cost and increased reliability would help to greatly accelerate the process of developing a robust acoustic monitoring technique. More work is also needed to investigate the procedures used to create recognisers or data templates in this software. There is no fixed protocol for their construction, and the manner that a recogniser is built will greatly affect its detection rate. There should also be consideration to construct a global library of sample vocalisations from nocturnal nesting seabirds with clear and distinct vocalisations that would aid the recogniser building process (Agranat 2009).

The results of the nest abundance and calling rate relationships obtained from the ARU units deployed in the Pacific on other species of shearwaters (MOU 2010) will also provide a relevant comparison to this study. This will determine if the techniques developed are not just limited to Cory's Shearwaters but transferable to other shearwater species as well. Eventually, expansion to other threatened nocturnal burrowing seabird species such as petrels and alcid in different locations may be possible. These results will allow for adjustments in monitoring protocols to account for the variance of vocalisation patterns in different species under different weather conditions ensuring that it will be globally applicable.

Ultimately if the accuracy and precision of automated acoustic monitoring systems can further be developed, it would be a novel powerful and cost-effective monitoring tool that in conjunction with other traditional methods will strengthen our monitoring efforts of nocturnal burrow-nesting seabirds on remote oceanic islands. This will drive down the costs of long term monitoring of seabird populations on oceanic islands and play an important role in facilitating long-term assessment of seabird community response to mammal eradications from islands. This in turn will inform future management decisions on seabird conservation.

The use of this automated acoustic monitoring system may also have an added benefit for conservation in the form of a rare species detection program that can be integrated within it. The large amount of data collected throughout the course of getting reliable detected call rates provides an opportunity for the detection of rarer species that may also be present in

the colony. For example, although Cory's Shearwater was the study species in this study, I managed to occasionally detect calls of the less common Manx Shearwater when manually listening to the sound streams. If recognisers can be developed for rarer species, the sound data can easily be batch processed to detect their calls. This will be useful for detecting the post-eradication recolonisation of islands by rarer species (Buxton 2010).

In terms of other possible directions that automated acoustic monitoring could pursue, it may be useful to assess the feasibility of censusing nocturnal burrow-nesting seabirds based on their vocal signature. This has been demonstrated by Delpont (2002), who managed to use the unique characteristics of African Wood Owls calls to estimate adult turnover rates. Nocturnal seabirds have also been shown to have individually distinct calls (Brooke 1978), hence making them suitable candidates for this level of identification. Acoustic data processing has become more efficient and accurate over time so it may soon be possible to build an abundance estimate at the individual level.

REFERENCE LIST

- Agranat, I. (2009) Automatically identifying animal species from their vocalisations. *Wildlife Acoustics Inc. Concord, MA*, .
- Bart, J., Fligner, M. A., Notz, W. & Notz, W. I. (1998) *Sampling and statistical methods for behavioral ecologists*. , Cambridge Univ Pr.
- Belda, EJ & Sanchez, A. (2001) Seabird mortality on longline fisheries in the western Mediterranean: factors affecting bycatch and proposed mitigating measures. *Biological Conservation*, 98 (3), 357-363.
- Bennett, P. M. & Owens, I. P. F. (2002) *Evolutionary ecology of birds: life histories, mating systems, and extinction*. , Oxford University Press, USA.
- Blackburn, T. M., Cassey, P., Duncan, R. P., Evans, K. L. & Gaston, K. J. (2004) Avian extinction and mammalian introductions on oceanic islands. *Science*, 305 (5692), 1955.
- Bolton, M. Interviewed by: Anonymous Development and evaluation of techniques for monitoring threatened procellariiform species in the Azores archipelago. .
- Bourgeois, K., Dromzée, S., Vidal, É. & Legrand, J. (2008) Yelkouan shearwater *Puffinus yelkouan* presence and behaviour at colonies: not only a moonlight question. *Comptes Rendus Biologies*, 331 (1), 88-97.
- Brandes, T. S. (2008) Automated sound recording and analysis techniques for bird surveys and conservation. *Bird Conservation International*, 18 (S1), S163-S173.
- Brashares, J. S. & Sam, M. K. (2005) How much is enough? Estimating the minimum sampling required for effective monitoring of African reserves. *Biodiversity and Conservation*, 14 (11), 2709-2722.
- Bretagnolle, V., Attie, C. & Mougeot, F. (2000) Audubon's shearwaters *Puffinus iherminieri* on Reunion Island, Indian Ocean: behaviour, census, distribution, biometrics and breeding biology. *Ibis*, 142 (3), 399-412.
- Brooke, M. (2004) *Albatrosses and petrels across the world*. , Oxford University Press, USA.
- Brooke, M. L. (1978) Sexual differences in the voice and individual vocal recognition in the Manx Shearwater (*Puffinus puffinus*). *Anim.Behav*, 26, 622-629.
- Brooks, R. J. & Falls, J. B. (1975) Individual recognition by song in white-throated sparrows. I. Discrimination of songs of neighbors and strangers. *Canadian Journal of Zoology*, 53 (7),

879-888.

Brunton, D. H. (1997) Impacts of predators: center nests are less successful than edge nests in a large nesting colony of Least Terns. *Condor*, , 372-380.

Buxton, R. T. (2011) *Monitoring and Managing Recovery of Nocturnal Burrow-Nesting Seabird Populations on Recently Predator-Eradicated Aleutian Islands*, , .

Catry, P., Granadeiro, J. P. & Oliveira, P. (2006) Do Cory's shearwaters *Calonectris diomedea* synchronize laying among close neighborhoods? A reappraisal using data from artificial nest sites. *Acta Ethologica*, 9 (2), 87-90.

Celis-Murillo, A., Deppe, J. L. & Allen, M. F. (2009) Using soundscape recordings to estimate bird species abundance, richness, and composition. *Journal of Field Ornithology*, 80 (1), 64-78.

Charif, R. A. & Pitzrick, M. (2008) Automated detection of Cerulean Warbler songs using XBAT data template detector software. *Preliminary Report. Bioacoustics Research Program Cornell Laboratory of Ornithology Technical Report*, , 08-02.

Courchamp, F., Chapuis, J. L. & Pascal, M. (2003) Mammal invaders on islands: impact, control and control impact. *Biological Reviews*, 78 (3), 347-383.

Crawley, M. J. (2005) *Statistics: an introduction using R*, , Wiley.

Davis, T. J., Klinkenberg, B. & Keller, C. P. (2004) Evaluating restoration success on Lyell Island, British Columbia using oblique videogrammetry. *Restoration Ecology*, 12 (3), 447-455.

Dawson, D. K. & Efford, M. G. (2009) Bird population density estimated from acoustic signals. *Journal of Applied Ecology*, 46 (6), 1201-1209.

de León, A., Mínguez, E., Harvey, P., Meek, E., Crane, J. E. & Furness, R. W. (2006) Factors affecting breeding distribution of Storm-petrels *Hydrobates pelagicus* in Orkney and Shetland: Capsule The main factors are past and present human activities, especially the introduction of rats to islands. *Bird Study*, 53 (1), 64-72.

De León, A., Mínguez, E., Neves, VR & Furness, RW. (2006) Factors affecting breeding distribution and seabird richness in the Azores archipelago. *Atlantic Seabirds*, 7 (1), 15-22.

Donlan, C. J. & Wilcox, C. (2007) Complexities of costing eradications. *Animal Conservation*, 10 (2), 154-156.

Dorcas, M. E., Price, S. J., Walls, S. C., Barichivich, W. J. & Dodd, KC. (2010) Auditory monitoring of anuran populations. *Amphibian Ecology and Conservation: A Handbook of Techniques. Oxford University Press, Oxford, UK*, , 281-298.

Dugan, P. J., Rice, A. N., Urazghildiiev, I. R. & Clark, C. W. (2010) North Atlantic right whale

acoustic signal processing: Part I. Comparison of machine learning recognition algorithms. *Applications and Technology Conference (LISAT), 2010 Long Island Systems*, IEEE. pp. 1-6.

EU-Life 2009. *Ilhas Santuário para as Aves Marinhas - LIFE07 NAT/P/000649*. [Online] Available from: <http://life-corvo.spea.pt/en/>.

Farnsworth, A., Gauthreaux Jr, S. A. & Blaricom, D. (2004) A comparison of nocturnal call counts of migrating birds and reflectivity measurements on Doppler radar. *Journal of Avian Biology*, 35 (4), 365-369.

Fontaine, R., Gimenez, O. & Bried, J. Í. (2011) The impact of introduced predators, light-induced mortality of fledglings and poaching on the dynamics of the Cory's shearwater (*Calonectris diomedea*) population from the Azores, northeastern subtropical Atlantic. *Biological Conservation*, , .

Granadeiro, J. P. (1991) The breeding biology of Cory's Shearwater *Calonectris diomedea borealis* on Berlenga Island, Portugal. *Seabird*, 13, 30-39.

Granadeiro, J. P., Bolton, M., Silva, M. C., Nunes, M. & Furness, R. W. (2000) Responses of breeding Cory's shearwater *Calonectris diomedea* to experimental manipulation of chick condition. *Behavioral Ecology*, 11 (3), 274.

Harding, AMA, Piatt, JF, Byrd, GV, Hatch, SA, Konyukhov, NB, Golubova, EU & Williams, JC. (2005) Variability in colony attendance of crevice-nesting Horned Puffins: implications for population monitoring. *Journal of Wildlife Management*, 69 (3), 1279-1296.

Haselmayer, J. & Quinn, J. S. (2000) A comparison of point counts and sound recording as bird survey methods in Amazonian Southeast Peru. *The Condor*, 102 (4), 887-893.

Howald, G., DONLAN, C., Galván, J. P., Russell, J. C., Parkes, J., Samaniego, A., Wang, Y., Veitch, D., Genovesi, P. & Pascal, M. (2007) Invasive rodent eradication on islands. *Conservation Biology*, 21 (5), 1258-1268.

Igual, JM, Forero, MG, Gomez, T., Orueta, JF & Oro, D. (2006) Rat control and breeding performance in Cory's shearwater (*Calonectris diomedea*): effects of poisoning effort and habitat features. *Animal Conservation*, 9 (1), 59-65.

James, P. C. (1985) The vocal behaviour of the Manx shearwater *Puffinus puffinus*. *Zeitschrift Für Tierpsychologie*, 67 (1-4), 269-283.

Jones, H., Tershy, B., Zavaleta, E., Croll, D., Keitt, B., Finkelstein, M. & Howald, G. (2008) Severity of the effects of invasive rats on seabirds: a global review. *Conservation Biology*, 22 (1), 16-26

Keitt, B. S., Tershy, B. R. & Croll, D. A. (2004) Nocturnal behavior reduces predation pressure on black-vented shearwaters *Puffinus opisthomelas*. *Marine Ornithology*, 32 (3), 173-178.

- Kitaysky, A. S., Kitaiskaia, E. V., Piatt, J. F. & Wingfield, J. C. (2006) A mechanistic link between chick diet and decline in seabirds? *Proceedings of the Royal Society B: Biological Sciences*, 273 (1585), 445.
- Lohr, B., Wright, T. F. & Dooling, R. J. (2003) Detection and discrimination of natural calls in masking noise by birds: estimating the active space of a signal. *Animal Behaviour*, 65 (4), 763-777.
- Lyver, P., Hamilton, S., McKenzie, M., Dickson, I., Doohar, T., Broad, T. & Moller, H. (1998) *A burrowscope for examining petrel nests in burrows.* , Dept. of Conservation.
- Mackin, W. A. (2005) Neighbor-stranger discrimination in Audubon's shearwater (*Puffinus l. lherminieri*) explained by a "real enemy" effect. *Behavioral Ecology and Sociobiology*, 59 (2), 326-332.
- Mennill, D. J., Burt, J. M., Fristrup, K. M. & Vehrencamp, S. L. (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, 2832.
- Milner-Gulland, E. J. & Rowcliffe, J. M. (2007) *Conservation and sustainable use: a handbook of techniques.* , Oxford University Press, USA.
- Monteiro, L. R., Ramos, J. A. & Furness, R. W. (1996) Past and present status and conservation of the seabirds breeding in the Azores archipelago. *Biological Conservation*, 78 (3), 319-328.
- Monteiro, LR, Ramos, JA, Furness, RW & Del Nevo, AJ. (1996) Movements, morphology, breeding, molt, diet and feeding of seabirds in the Azores. *Colonial Waterbirds*, , 82-97.
- Monteiro, LR, Ramos, JA, Pereira, JC, Monteiro, PR, Feio, RS, Thompson, DR, Bearhop, S., Furness, RW, Laranjo, M. & Hilton, G. (1999) Status and distribution of Fea's petrel, Bulwer's petrel, Manx shearwater, Little shearwater and Band-rumped storm-petrel in the Azores Archipelago. *Waterbirds*, , 358-366.
- MOU. (2010) Collaborative research project to explore the use of autonomous acoustic recording devices for the quantitative assessment of shearwater nest density ., .
- Mougeot, F. & Bretagnolle, V. (2000) Predation risk and moonlight avoidance in nocturnal seabirds. *Journal of Avian Biology*, , 376-386.
- PARKER III, T. A. (1991) On the use of tape recorders in avifaunal surveys. *Auk*, 108, 443-444.
- Pascal, M., Lorvelec, O., Bretagnolle, V. & Culioli, J. M. (2008) Improving the breeding success of a colonial seabird: a cost-benefit comparison of the eradication and control of its rat predator. *Endangered Species Research*, 4 (3), 267.

Piatt, J. F., Lensink, C. J., Butler, W., Kendziorek, M. & Nysewander, D. R. (1990) Immediate impact of the 'Exxon Valdez' oil spill on marine birds. *The Auk*, , 387-397.

Rayner, M. J., Hauber, M. E., Imber, M. J., Stamp, R. K. & Clout, M. N. (2007) Spatial heterogeneity of mesopredator release within an oceanic island system. *Proceedings of the National Academy of Sciences*, 104 (52), 20862.

Riou, S. & Hamer, K. C. (2008) Predation risk and reproductive effort: impacts of moonlight on food provisioning and chick growth in Manx shearwaters. *Animal Behaviour*, 76 (5), 1743-1748.

Robb, M., Mullarney, K., Van Den Berg, AB & Constantine, M. (2008) Petrels night and day. *Poole: The Sound Approach*, , .

Rodríguez, J. P. (2003) Challenges and opportunities for surveying and monitoring tropical biodiversity—a response to Danielsen et al. *Oryx*, 37 (04), 411-411.

Roul, S. (2010) Distribution and status of the Manx Shearwater (*Puffinus puffinus*) on islands near the Burin Peninsula, Newfoundland. *Master's Thesis, Memorial University*, , .

Simberloff, D. (2009) Rats are not the only introduced rodents producing ecosystem impacts on islands. *Biological Invasions*, 11 (7), 1735-1742.

Steadman, D. W. (1995) Prehistoric extinctions of Pacific island birds: biodiversity meets zooarchaeology. *Science*, 267 (5201), 1123.

Steinkamp, M., Peterjohn, B., Byrd, V., Carter, H. & Lowe, R. (2003) Breeding season survey techniques for seabirds and colonial waterbirds throughout North America. *Laurel, MD: Waterbird Monitoring Partnership, US Geological Survey, Patuxent Wildlife Research Center*. <http://www.Pwrc.USgs.gov/cwb/manual>, , .

Storey, A. E. (1984) Function of Manx shearwater calls in mate attraction. *Behaviour*, , 73-89.

Swiston, K. A. & Mennill, D. J. (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.

Thibault, J. C. (1995) Effect of predation by the black rat *Rattus rattus* on the breeding success of Cory's shearwater *Calonectris diomedea* in Corsica. *Marine Ornithology*, 23 (1), 1-10.

Thibault, J. C., Bretagnolle, V. & Rabouam, C. (1997) *Calonectris diomedea* Cory's shearwater. *BWP Update*, 1 (2), 75-98.

Thompson, M. E., Schwager, S. J., Payne, K. B. & Turkalo, A. K. (2010) Acoustic estimation of wildlife abundance: methodology for vocal mammals in forested habitats. *African Journal of*

Ecology, 48 (3), 654-661.

Towns, D. R. (2009) Eradications as reverse invasions: lessons from Pacific rat (*Rattus exulans*) removals on New Zealand islands. *Biological Invasions*, 11 (7), 1719-1733.

Tucker, G., Heath, M. F. & Tomialojc, L. (1994) Birds in Europe their conservation status. , .

Walsh, P. M., Halley, D. J., Harris, M. P., Del Nevo, A., Sim, I. M. W. & Tasker, M. L. (1995) Seabird monitoring handbook for Britain and Ireland. *JNCC (Joint Nature Conservation Committee)*, *RSPB (Royal Society for the Protection of Birds)*, *ITE (Institute of Terrestrial Ecology)*, and *Seabird Group, Peterborough, UK*, , .

Weimerskirch, H., Brothers, N. & Jouventin, P. (1997) Population dynamics of wandering albatross *Diomedea exulans* and Amsterdam albatross *D. amsterdamensis* in the Indian Ocean and their relationships with long-line fisheries: conservation implications. *Biological Conservation*, 79 (2-3), 257-270.

Wolfaardt, W. & Philips, R. (2011) *Guideline census methodologies for albatrosses and petrels*. Joint Fourth Meeting of Breeding Sites Working Group (BSWG5) and Sixth Meeting of Status and Trends WG (STWG6), Agreement on the Conservation of Albatrosses and Petreles.

