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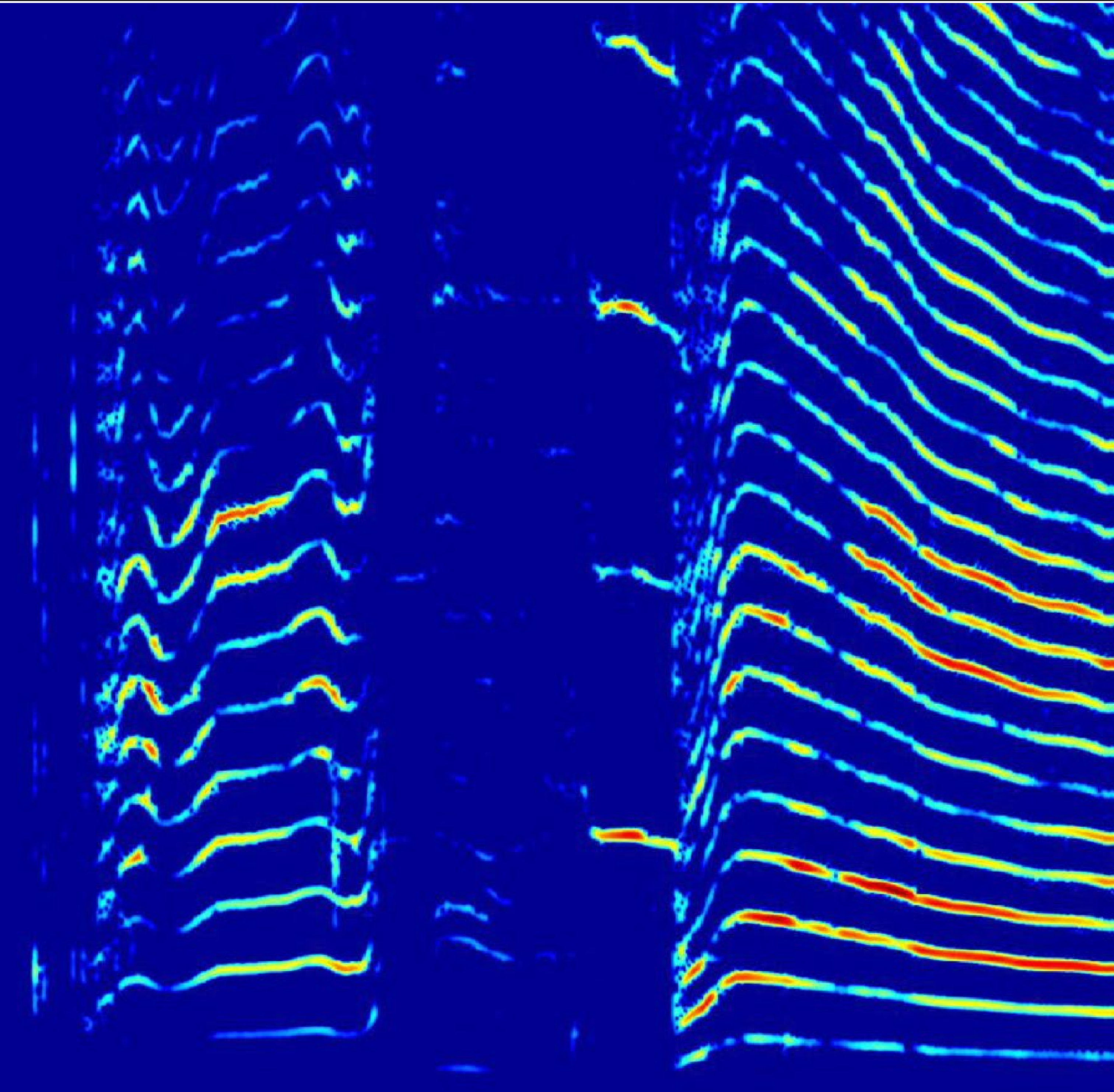
CONSERVATION TECHNOLOGY

ACOUSTIC MONITORING



2 CONSERVATION TECHNOLOGY
ACOUSTIC MONITORING

Passive acoustic monitoring in ecology and conservation

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Cover Image: Transient Orca (*Orcinus orca*) calls recorded in Glacier Bay, Alaska © V. Deecke

ACOUSTIC MONITORING FAQ

What is passive acoustic wildlife monitoring?

Passive acoustic monitoring, or just 'acoustic monitoring', involves surveying and monitoring wildlife and environments using sound recorders (acoustic sensors). These are deployed in the field, often for hours, days or weeks, recording acoustic data on a specified schedule. After collection, these recordings are processed to extract useful ecological data – such as detecting the calls of animal species of interest – which is then analysed similarly to other types of survey data.

Where can passive acoustic monitoring be useful for ecologists and conservationists?

Acoustic sensors are small, increasingly affordable and non-invasive, and can be deployed in the field for extended times to monitor wildlife and their acoustic surroundings. The data can then be used for estimation of species occupancy, abundance, population density and community composition, monitoring spatial and temporal trends in animal behaviour, and calculating acoustic proxies for metrics of biodiversity. Provided the challenges of data analysis are addressed carefully, this can make acoustic sensors valuable tools for cost-effective monitoring of species and ecosystems and their responses to human activities.

What is an acoustic sensor, and what range of sensor types are available?

An acoustic sensor can be any combination of sound recorder, detector, microphone and/or hydrophone, designed to detect and record sound in the environment. Often this is an integrated bioacoustic recorder, designed specifically with ecological monitoring in mind. However, it can also be any custom combination of these components. Commercially available bioacoustic sensors usually record either audible range sound (e.g. birds, most mammals, amphibians) or ultrasound (e.g. bats, many toothed whales), and are designed specifically for either terrestrial or marine deployment. **Find out more in Chapter 3.**

How do acoustic sensors work, and what data do they collect?

Like any sound recording device, acoustic sensors use either a microphone (terrestrially) or hydrophone (underwater) to detect and convert incoming sound waves into an electrical signal, which is recorded and stored for later analysis. Acoustic data are recorded in the form of a time-amplitude signal, at a specified sampling rate. Signal processing methods (such as Fourier analysis) are then used to recover additional information such as the frequency (pitch) of incoming sounds. **Find out more in Chapter 3.2.**

What are the main types of bat detector, and how are they different?

Most bats vocalise in the ultrasonic spectrum, meaning that specialised ultrasonic bat detectors are required to detect and record their calls. The simplest are heterodyne detectors, where incoming echolocation calls are mixed with a signal produced by the detector to produce audible clicks, which can be used to infer species information. Frequency division detectors divide the frequency of the call by a predetermined factor (usually) 10. However these methods lose frequency or amplitude information that can be vital for accurate species ID. Full-spectrum detectors record ultrasound at sufficiently high sampling rates to retain all the calls frequency and amplitude information, meaning that they are usually preferable for surveys and monitoring. These are usually more costly, but are becoming more affordable. **Find out more in Chapter 6.**

How are acoustic monitoring data analysed?

Acoustic analysis is a multi-stage process. Usually frequency information is recovered from the raw waveform through signal processing, often using Fourier transforms, to produce a spectrogram. From there, the calls of animal species of interest can be identified and labelled manually, or with machine learning-based tools that detect and classify sounds automatically. Alternatively, global metrics can be calculated on the entire recording (the 'soundscape') to quantify aspects of the acoustic environment, such as biotic sound power and diversity. **Find out more in Chapter 3.6.**

Is passive acoustic monitoring suitable for my study species or system?

This depends on the biology of your study species and the characteristics of its environment. To be effectively surveyed using acoustics, study animals must produce detectable acoustic signals, and usually these must be identifiable to some useful category (e.g. genus, species, behaviour type). Another important consideration is the acoustic environment: very noisy environments (such as highly biodiverse areas, or urban habitats) can mask the sounds of species of interest, making monitoring individual species more challenging. However, in such instances acoustic sensors may still be useful for measuring global characteristics of the acoustic habitat (e.g. overall biotic sound levels, anthropogenic noise). **Find out more in Chapter 5.**

What's the difference between audible sound, ultrasound and infrasound, and why does it matter?

The human ear optimally detects frequencies between 20 and 20,000Hz, which are described as audible range sounds. Sounds above this frequency range, such as bat echolocation calls, are called ultrasonic, and are usually imperceptible to humans. Sounds below this range, such as elephant rumbles, are called infrasonic, and are also usually imperceptible. Understanding what frequency your study species vocalises at is important, since ultrasound and infrasound often require specialised detectors (such as full-spectrum bat detectors) to detect and record effectively. Find out more in the full guidelines.
Find out more in Chapter 3.2.

How much do acoustic monitoring projects cost?

This depends on the size and time scale of the project. State-of-the-art acoustic sensors are still often costly, although prices are falling and open-source hardware options are increasingly becoming available. However, a major cost is the subsequent analysis of the data; if automated tools are not available for your study system, analysing hundreds or thousands of hours of sound recordings can be extremely time-consuming and labour-intensive. **Find out more in Chapter 5.**

I'm thinking about using acoustic sensors for a monitoring project: what do I need to know before I start?

Consider several key questions before purchasing any equipment. Firstly, these relate to the species and study system: does the species of interest produce audible calls, and is the environment suitable for acoustic monitoring? Secondly, these relate to the challenges of analysis: will automated software tools (either existing software or bespoke tools) be available for processing the data after collection, and if not, how will the data be analysed? Without carefully planning the analysis pipeline in advance, there is a risk of collecting hundreds or thousands of hours of data that are costly to store and very difficult to analyse efficiently. **Find out more in Chapter 5.**

I've used camera traps before, and I'm now thinking about using acoustic sensors: what are the important differences between them?

New acoustic sensors are similar to camera traps in many ways. However, while camera trapping is mostly limited to larger mammals and birds, acoustic monitoring can potentially detect a much broader variety of taxa, regardless of body size (e.g. birds, bats, insects, amphibians, marine mammals, fish). Acoustic data also involves different analysis issues: for example, there is often inadequate reference material for accurately identifying the calls and vocal behaviours of many species. Similarly, it is usually not possible to identify individual animals by their calls alone, making estimation of true detection rates and population sizes more difficult. New methods are addressing these problems, which we discuss in **Chapter 4.1.**

I've collected some acoustic data, and I need to analyse it: what software tools should I use?

There is a broad range of proprietary and open-source software available for bioacoustic data analysis, which range from basic open-source audio processing tools, to species-specific call classifiers, to entire software suites for processing, visualising and quantitative analysis. The correct choice will depend on your study system and previous experience with statistical software. **Find out more in Chapter 8.**

What are spectrograms, and why are they useful for audio analysis?

A spectrogram is a visual representation of a sound recording in the time-frequency domain, with time on the x-axis, frequency on the y-axis, and the amplitude of the signal usually shown as colour density. Spectrograms are calculated from audio waveforms using Fourier analysis or other signal processing methods that recover a signal's frequency information. They are critical tools in the analysis of acoustic wildlife monitoring data, because they allow specific sounds (e.g. animal calls) to be visually recognised and labelled, either manually or using automated classification software. **Find out more in Chapter 3.4.**

Can I estimate animal abundance and population density from acoustic data?

Methods are being developed for estimation of animal density and abundance from acoustic data, however this is often more challenging than with other monitoring data types. Modelling methods must control for variation in acoustic detectability of target animals by species (quieter species have smaller detection distances) and by local environmental factors (e.g. ambient sound levels, land cover), as well as accounting for the non-independence of sequentially detected calls, which may come from the same individual. These parameters are important to consider ahead of data collection. Further information is provided in the full guidelines. **Find out more in Chapter 4.1.**

How far away from a microphone can animals be heard?

This depends on the animal species, environment and sensor type. Detection distances are affected by a sound's amplitude and frequency (how rapidly it attenuates to below a perceptible level): in general, animals calling at higher amplitudes (more loudly) will be detected at greater distances than those calling at lower amplitudes (more quietly), and higher frequencies also attenuate more quickly than lower frequencies. Site-specific environmental factors also have an impact, such as the medium (air/water), temperature, pressure, humidity, ambient sound levels, and habitat structure such as vegetation and buildings. This means that different species are more readily detectable by acoustic sensors than others, and this can vary between habitat types. This is an important consideration during study planning, as it may impact the choice of sensor location, as well as having implications for later analysis. **Find out more Chapter 7.3.1.**

What are acoustic indices, and why are they useful for audio analysis?

An acoustic index is a mathematical function calculated to describe some aspect of the spectral and temporal diversity or complexity of a sound recording. Indices for the study of biotic sound diversity, such as acoustic entropy or diversity, were originally conceived as analogous to traditional community ecology and biodiversity metrics. They are often used to quantify global spectral and temporal characteristics of sound recordings, in order to study their relationships to biodiversity, habitat features and global change (an emerging research field called ecoacoustics). They are useful because they enable quantitative analysis of acoustic monitoring data without the time-intensive process of extracting individual species calls, however they also have drawbacks such as sensitivity to non-biotic noise. **Find out more in Chapter 4.3.**

Animals that use sound to communicate and navigate leak information about themselves into their environment, which for scientists and conservation practitioners can provide useful information on where species are, how big their populations are, and their behaviour.

Image: © Teo Lucas / Gigante Azul / WWF

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1 PREFACE

1.1 The aim of this guide

With biodiversity in rapid global decline, cost-effective and scalable monitoring technologies are urgently needed to understand how global change is affecting wildlife and ecosystems. Sound is an important component of any habitat, and sound recordings made in the field offer potentially rich sources of ecological information about the abundance, distribution and behaviour of vocalising animals in an area. Acoustic sensors are therefore becoming widely used in ecology and conservation settings to monitor animal populations, behaviour, and responses to environmental change. In recent years the burgeoning field of ecoacoustics has also begun providing insights into acoustic community dynamics at larger scales.

With technological improvements making sophisticated off-the-shelf bioacoustic sensors increasingly affordable, it is an exciting and fast-moving time for acoustic wildlife monitoring. Research in this field is now addressing fundamental questions in ecology and animal behaviour, but is also becoming increasingly useful in applied conservation settings, such as monitoring populations of endangered or data-deficient species, or monitoring illegal activities in high-risk areas. However, despite this rapid growth in potential uses, there remains a lack of best-practice guidelines for researchers wishing to deploy acoustic sensors in the field to address particular questions. This guide seeks to address this gap, by providing an introduction to acoustic monitoring technology and its current and emerging uses in ecology and conservation, alongside clear guidelines for acoustic sensor deployment, survey design and data analysis.

1.2 How to use this guide

This guide is written mainly with the requirements of field ecologists and conservation practitioners in mind. It provides sufficient information to assist in selection and deployment of acoustic sensors, and preliminary analysis of the resulting data. It does not need to be read in order, but the information provided in the early chapters provides the necessary conceptual background to understand the guidelines in the second half of the report. A glossary of terms is provided at the back of the guide (**Chapter 10**).

The guide's first half provides a broad primer on the field of acoustic wildlife monitoring, with a brief introductory review of the history of the field (**Chapter 2**) followed by a conceptual and technical background to sound recording and acoustic monitoring technology (**Chapter 3**). These are followed by a review of the emerging applications of acoustic sensors for monitoring species and populations, animal behaviour and acoustic communities, and a discussion of the major challenges and opportunities facing the field now and in the coming years (**Chapter 4**).

The second half of the guide provides best-practice information for selection of acoustic sensors, and acoustic data collection and analysis. This includes guidance on assessing the need for an acoustic survey (**Chapter 5**), criteria for choosing a suitable acoustic sensor **(Chapter 6**), and a multi-part user guide for designing an acoustic monitoring study, including sections on study design, sensor deployment and data analysis (**Chapter 7**). A list of available hardware and software tools for acoustic monitoring (current at the time of publishing) is provided in **Chapter 8**. Since acoustic monitoring methods are developing rapidly, we lastly provide a concise list of recommended reading, which offers further detail on more complex techniques and concepts that are beyond the scope of this guide (**Chapter 9**).

2

THE FIELD OF ACOUSTIC WILDLIFE MONITORING

HIGHLIGHTS

- Animals use sound for communication, echolocation, sexual display, and territorial defence, and bioacoustic monitoring involves the recording of those sounds to infer animal distribution, physiological state, abundance, and behaviour
- Acoustic monitoring can be used to study a broad variety of taxa as long as they emit detectable sounds, and to date has been applied to populations of birds, bats, marine mammals, amphibians, Orthoptera, elephants, and some fish

Animals use acoustic behaviour for many purposes, including communication, echolocation, sexual display and territorial defence, while other sounds may be produced accidentally e.g. through moving or feeding (**Figure 1**) (Bradbury & Vehrencamp 1998). Animals that produce sound thus leak information about themselves into their environment, which can be used to infer whether an animal is present, and often information about its physiological state or behaviour (e.g. socialising, sexual behaviour, warning calls) (Nordeide & Kjellsby 1999; Blumstein *et al.* 2011; Jones *et al.* 2013).

While the field of bioacoustics has historically mainly focused on animal communication and sensory ecology, during the last decade the use of acoustics to monitor wildlife has grown in tandem with new hardware and software innovations that enable the collection and analysis of very large acoustic datasets in field settings. Passive acoustic monitoring, which this guide focuses on, involves the use of acoustic sensors to record sound in the environment, from which ecological information is then inferred (Blumstein *et al.* 2011). It is distinct from active acoustic monitoring, which we do not discuss here, which involves the detection of signals from sound-emitting devices (such as on-animal tags or sonar) (Stein 2011). Throughout this report we use the term 'acoustic monitoring' specifically in reference to passive acoustic monitoring.

Similarly to camera traps, newer acoustic sensors can be deployed in the field for extended periods to monitor wildlife, in order to estimate species occupancy, abundance and population density, to monitor animal behaviour, and to survey and monitor ecological communities (Laiolo 2010; Blumstein *et al.* 2011; Jones *et al.* 2013; Marques *et al.* 2013; Merchant *et al.* 2014). In the emerging field of ecoacoustics, biotic sound levels and acoustic diversity are increasingly being used as proxies for environmental condition more generally (Pijanowski *et al.* 2011b; Sueur *et al.* 2014; Sueur & Farina 2015). These are all discussed in depth in **Chapter 4.**

However, while camera trapping is mostly limited to larger mammals and birds, passive acoustic monitoring can potentially detect a much broader variety of taxa, regardless of body size. This remains limited to species that produce detectable sounds, and in general for monitoring particular animals their calls must be identifiable to a useful category (e.g. species, genus). Studies to date have focused on birds (e.g. (Digby *et al.* 2013; Sanders & Mennill 2014; Towsey *et al.* 2014; Klingbeil & Willig 2015)), bats (e.g. (Jones *et al.* 2013; Bader *et al.* 2015; Barlow *et al.* 2015)), marine mammals (e.g. (Johnson & Tyack 2003; Mellinger *et al.* 2007; Klinck *et al.* 2012b)), elephants (e.g. (Wrege *et al.* 2010; Wrege *et al.* 2017)), amphibians (especially anurans) (e.g. (Weir *et al.* 2009; Stevenson *et al.* 2015)), Orthoptera (e.g. (Chesmore & Ohya 2004; Penone *et al.* 2013)) and commercially important fish (e.g. (Nordeide & Kjellsby 1999; Lobel 2002; Luczkovich *et al.* 2008)).

Acoustic methods have an especially rich history in the study of free-living animals that are both challenging to survey visually and particularly acoustically active, especially echolocating bats in the terrestrial realm (Russo & Jones 2003; MacSwiney G *et al.* 2008; Walters *et al.* 2012; Barlow *et al.* 2015) and cetaceans in marine environments (Johnson & Tyack 2003; Mellinger *et al.* 2011; Klinck *et al.* 2012b). For example, ultrasonic surveys and monitoring have played an important role in estimating bat species richness and population trends during the last two decades (e.g. (MacSwiney G *et al.* 2008; Barlow *et al.* 2015)).

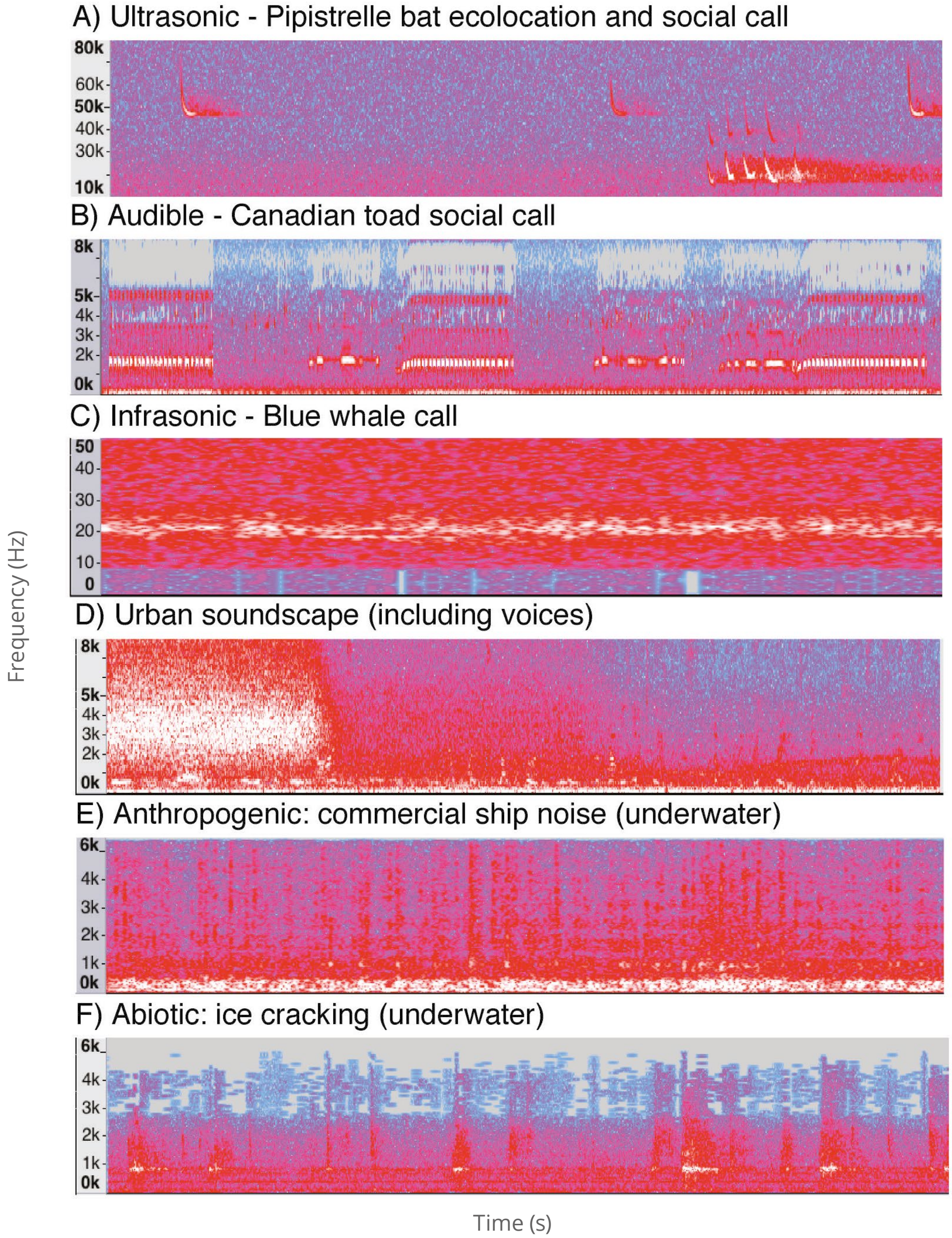
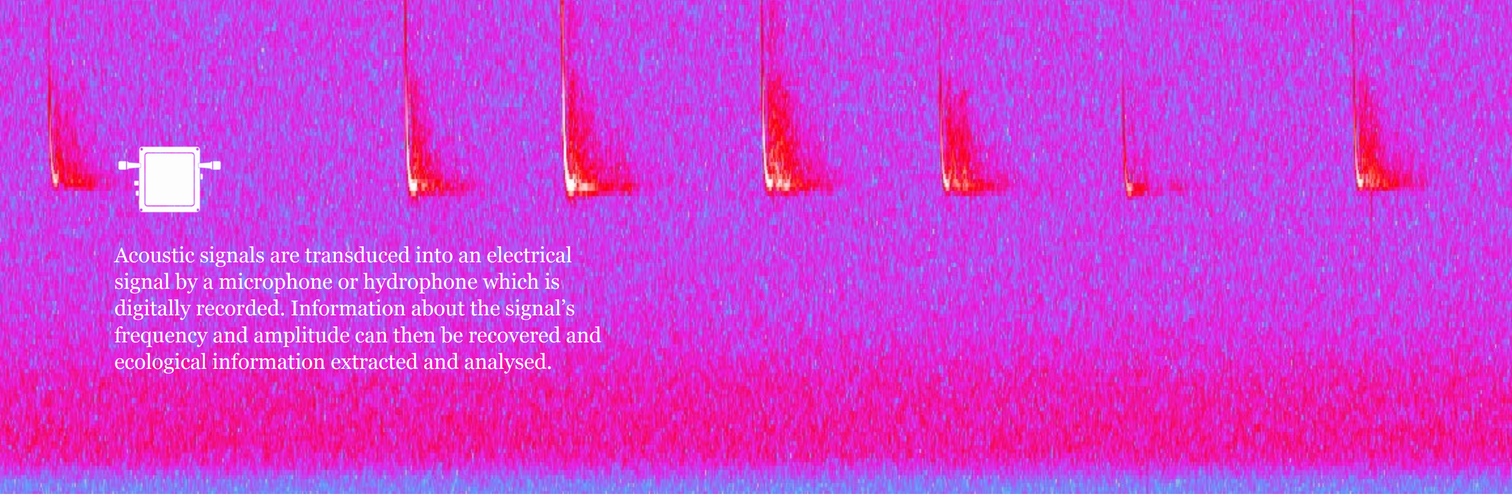
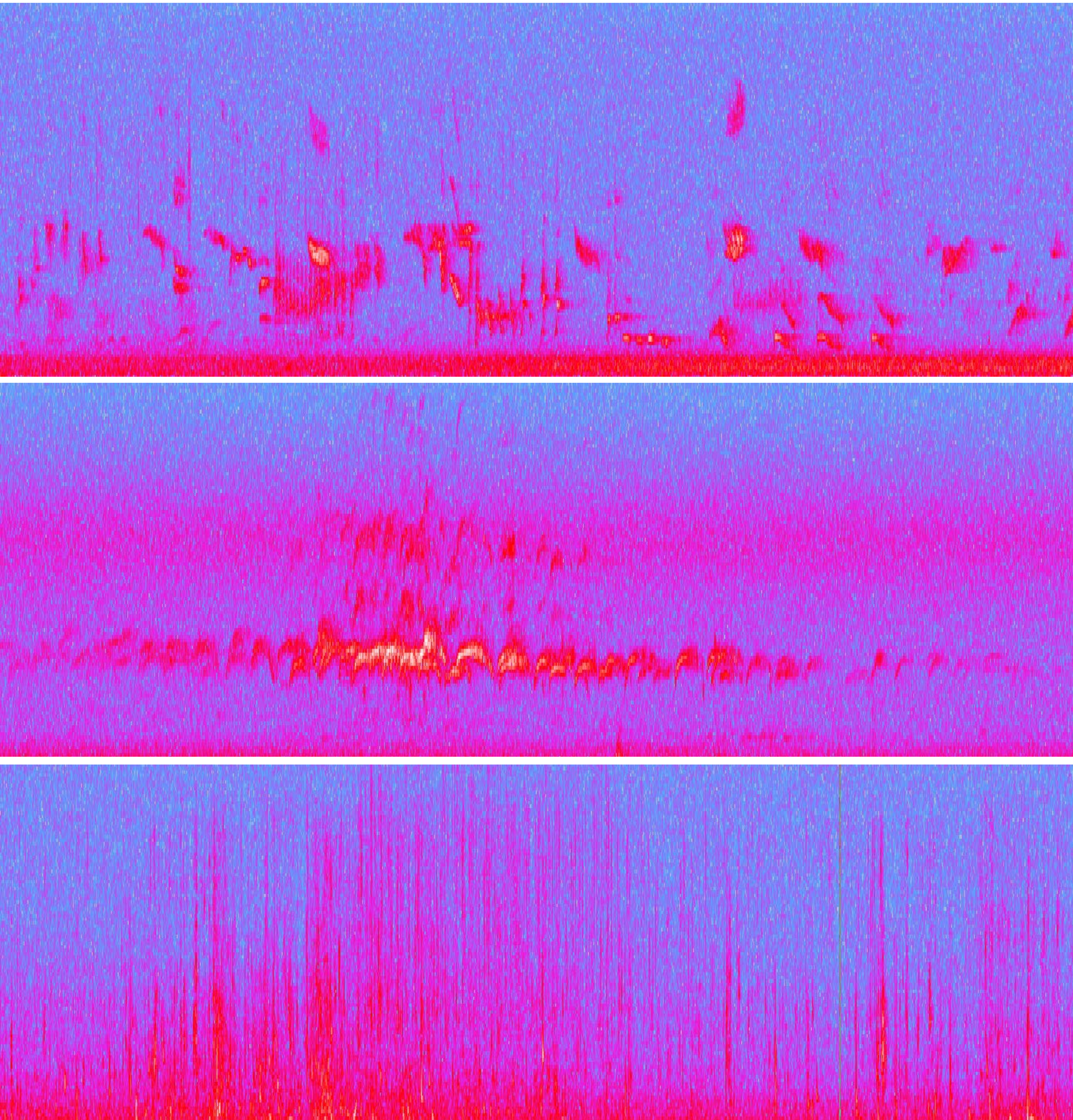


Figure 1: Examples of different biotic and abiotic sounds represented as spectrograms, with amplitude shown on a linear colour scale from blue (low) to yellow (high). Note the different frequency scales.



Acoustic signals are transduced into an electrical signal by a microphone or hydrophone which is digitally recorded. Information about the signal's frequency and amplitude can then be recovered and ecological information extracted and analysed.



3 HOW ACOUSTIC SENSORS WORK: A PRIMER FOR ECOLOGISTS

HIGHLIGHTS

- Acoustic sensors used for passive acoustic monitoring generally consist of a sound recorder/detector and a microphone/hydrophone
- During electronic sound recording, sound produced by an animal propagates through the medium (air or water), and the signals are transduced into an electrical signal by a microphone or hydrophone which is then digitally recorded. Information about the signal's frequency and amplitude can then be recovered and ecological information can be extracted and analysed
- Automated detection and classification of relevant sound using signal processing and machine learning techniques is increasingly required to extract relevant information from even modestly-sized datasets

Throughout this guide we use the term 'acoustic sensor' to refer to any combination of sound recorder, detector, microphone and/or hydrophone, designed to detect and record environmental sound. This could be an integrated bioacoustics sensor specifically intended for environmental or ecological monitoring, or could consist of a custom combination of these components. When planning a survey, it is important to understand how acoustic sensors work and the key technical parameters that affect species detection. This chapter provides a primer on the properties of sound and the principles of sound recording (3.1-3.3), the evolution of hardware for acoustic monitoring (3.5) and principles and tools for acoustic data analysis (3.4, 3.6). These have been written with ecologists and conservation practitioners in mind, and are intended to provide basic information to support the use of acoustic sensors for wildlife monitoring. A list of further reading that provides greater detail on these concepts is provided in **Chapter 9.**

3.1 Sound emission and propagation

Sound is the propagation of waves of pressure through a medium, which may be gaseous (such as air), liquid (such as water) or solid. It is produced when the vibrations of a sound-producing object (such as the larynx of an animal or the cone of a loudspeaker), alternately compress and rarefy the medium, creating waves of alternating high and low pressure that propagate outward from the emitter as a sphere of increasing diameter (Bradbury & Vehrencamp 1998). These can be understood as a wave moving through the medium, with regions of higher pressure alternating with regions of lower pressure. A sound wave has several key properties (**Figure 2**).

As sound waves propagate outward from the emitter, they attenuate, meaning that their amplitude progressively reduces as the sound's energy dissipates into the environment (Russ 2013). Lower frequency sounds experience less attenuation than higher frequency sounds, meaning that they can travel further from the emitter and still be perceived. This has important implications for the detection of signals produced by vocalising animals, since animals calling at higher amplitudes (i.e. more loudly) can be detected at greater distances than those calling at lower amplitudes (i.e. more quietly). Similarly, if two animals are vocalising at the same amplitude but at different frequencies, in general the animal calling at a lower frequency will be detectable at greater distance than the animal calling at a higher frequency.

The properties of the medium also affect signal propagation. Sound waves travel approximately five times faster through water than air due to its higher density. Factors such as temperature, pressure, salinity, water depth and clutter in the environment also all affect the travel distances of a sound wave. These environmental factors therefore also have implications for monitoring wildlife through acoustics, since they affect the likelihood that a calling animal will be detected by a sensor (Darras *et al*. 2016).

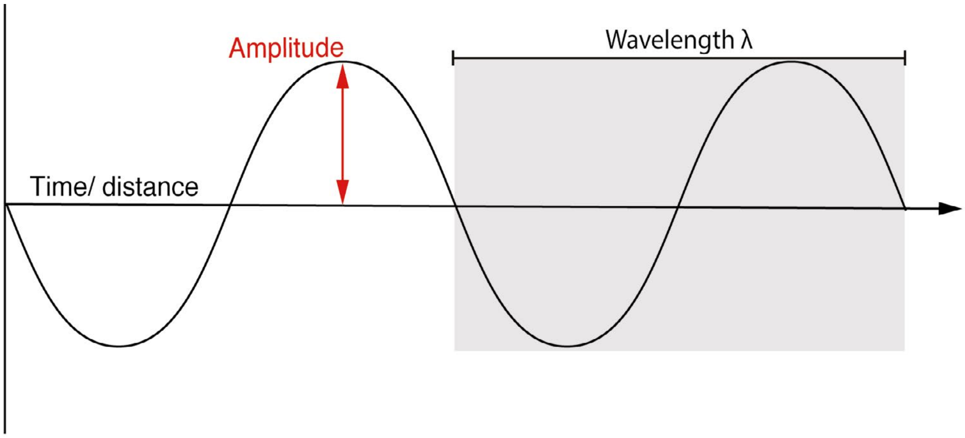


Figure 2: A sinusoidal sound wave, showing characteristics of wavelength (the length of a complete cycle) and amplitude (proportional to energy).

> **Amplitude** is proportional to the amount of energy contained within a sound wave. It is generally perceived by a listener as volume, with higher amplitudes perceived as louder sounds. While amplitude is a relative measure, it is most commonly measured in decibel units (dB).

> **Wavelength** is the length of a complete cycle (the time between successive peaks or troughs of a sound wave).

> **Frequency** is the number of cycles per unit time, and is measured in hertz (Hz, cycles per second) or kilohertz (kHz, thousands of cycles per second). It is generally perceived at a listener as pitch, with higher frequencies corresponding to higher pitches, and vice versa. The frequency of a wave is inversely proportional to its wavelength.

3.2 Sound reception: microphones, hydrophones and frequency sensitivity

Sounds are produced by a sender (a vocalising animal), then propagate through a medium, before arriving at a receiver (**Figure 3a, P17**). In both animal auditory systems and electronic sound recording, the vibrations of a sound wave are **transduced** into an electrical signal whose amplitude is proportional to the amplitude of the sound wave. This typically occurs via the vibration of a membrane or other thin sheet of material. In animal auditory systems this is the function of the tympanic and/or basilar (cochlear – the inner ear) membranes, whereas in sound recording equipment this role is performed by the diaphragm of a **microphone**, or the piezoelectric transducer of a **hydrophone**.

In the mammalian cochlea, sound is transduced when incoming sound causes the basilar membrane to vibrate; this stimulates hair cells which trigger nerve impulses. Analogously, the displacement of a microphone diaphragm when it is hit by a sound wave is used to induce an electric current, although the method used varies depending on the type of microphone. Hydrophones are microphones designed for use underwater and are based on a piezoelectric transducer, a thin sheet of material that produces an electrical current when a mechanical force (such as a sound wave) is applied to it.

Different transducers are sensitive to particular frequency ranges. The human auditory system optimally detects frequencies between 20 and 20,000Hz, which are described as **audible range** sounds. Sounds above this frequency range, such as bat echolocation calls, are called ultrasonic; these are generally imperceptible to humans, and require specialised **ultrasonic** detectors to record. Sounds below this range, such as elephant rumbles, are called **infrasonic**. As with animal auditory systems, any microphone or hydrophone has a particular frequency sensitivity curve, and frequencies outside this range will be detected less optimally.

3.3 Digital sound recording

During sound recording, the transduced electrical signal must then be recorded. In older analogue field recorders this involved directly recording the signal onto analogue cassette tape. However, digital recorders are now almost universally used in bioacoustics research and acoustic wildlife monitoring. These provide practical advantages over analogue equivalents, such as much longer recording times (with digital sound files usually saved to SD cards) and programmable recording schedules, as well as allowing sound recordings to be immediately downloaded to computer for analysis.

During digital recording the amplitude of the electrical signal is sampled at a given **sampling rate** (typically measured in thousands of samples per second, kHz) and **bit-depth** (the number of possible amplitude levels that can be measured, typically 16-bit), from which the sound wave can then be digitally reconstructed and played back (**Figure 3b, P17**). Both of these parameters are important for later analysis. The bit-depth affects the amplitude resolution (and therefore dynamic range) of a sound recording, and the sampling rate affects its frequency resolution.

Critically, in order to fully resolve the frequency information of a sound, the sampling rate must be at least twice as high as the highest frequency of interest (termed the **Nyquist frequency**). The sampling rate for audible range recordings is therefore typically 44.1kHz. However, for devices recording ultrasound, such as bat or cetacean echolocation calls, the sampling rate must be much higher (often between 200 and 400kHz) in order to retain sufficient frequency information (**see Chapter 6**). As a result, full spectrum ultrasonic recordings take up a much greater volume of storage memory.

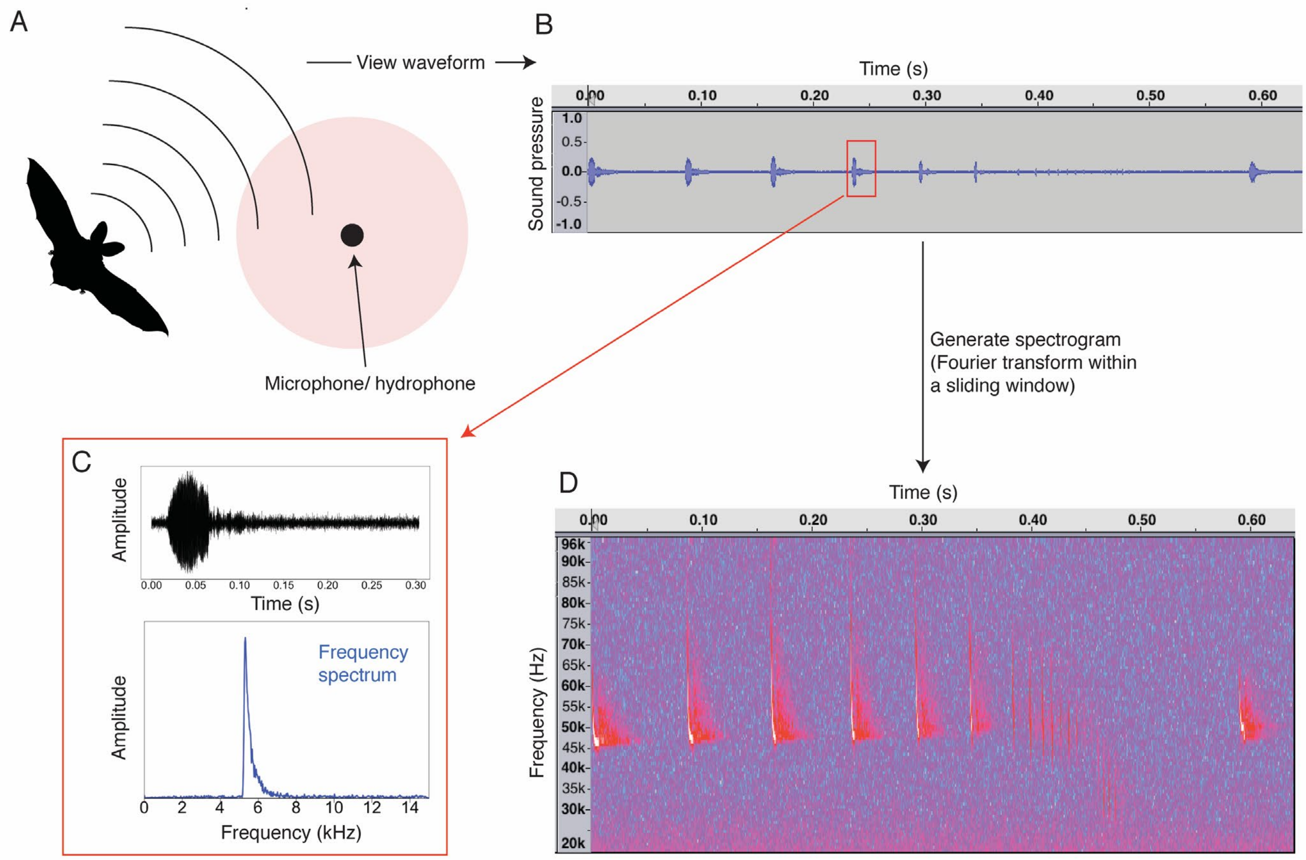


Figure 3: Recording and processing of an acoustic signal. An emitter produces a signal, which if within detectable range is picked up by a microphone or hydrophone (**A**; detection radius shaded in red) and transduced into an electrical signal. In digital recorders the signal is sampled at a specified sampling rate (kHz), enabling the sound to be reconstructed in the time-amplitude domain (**B**). A frequency spectrum can be produced using a fast Fourier transform (FFT), which calculates the signal's frequency components and their relative amplitudes (**C**). Calculating FFT within a sliding window across the recording produces a spectrogram, with time shown on the x-axis, frequency on the y-axis, and with amplitude (energy) shown as colour intensity (blue to yellow) (**D**).

3.4 Signal processing and frequency analysis

Once recorded in the time-amplitude domain (**Figure 3b, P17**), the signal must be processed in order to recover its frequency information. Most commonly this is done using a mathematical process called a fast Fourier transform (FFT), which converts the amplitude data into frequency data. For any given time window of a sound recording, an FFT calculates the frequency components of the signal and their relative amplitudes, producing a frequency spectrum (**Figure 3c, P17**). To visually represent an entire sound recording in the time-frequency domain, a Fourier transform is calculated within an overlapping short sliding window across the recording's length. This produces a spectrogram **(Figure 3d, P17**), with time on the x-axis, frequency on the y-axis, and amplitude shown as colour intensity.

Spectrograms are critical tools in the analysis of acoustic wildlife monitoring data, enabling specific sounds (e.g. animal calls) to be visually recognised and labelled, either manually or using automated classification software (**e.g. Figure 5**). However, many parameters selected during signal processing, such as the Fourier transform window length and window type, can affect the suitability for the resulting data for analysis. For example, one of the major challenges associated with the use of FFT spectrograms in the analysis of audio data is a trade-off between time resolution and frequency resolution; larger sliding window lengths provide improved frequency resolution but reduced time resolution, and vice versa (for a useful discussion of how this relates to bioacoustics analysis see (Russ 2013)). For this reason, a variety of other signal processing approaches are also used in analysis of acoustic monitoring data, including cepstrum-based feature extraction (e.g. (Stowell & Plumbley 2014)) wavelet transforms (Walters *et al.* 2012) and time-domain waveform analysis (Jamarillo-Leforetta *et al.*, 2016); each offers advantages and disadvantages. Further detail is beyond the scope of this guide, but more information can be found in the recommended further reading (**Chapter 9**).

3.5 Hardware for acoustic surveys and monitoring

Passive acoustic sensors were first utilised underwater during World War I (Sousa-Lima *et al.* 2013), and later in the 20th century US Navy acoustic sensors revealed that underwater environments that were previously thought to be silent were in fact very noisy (Kasumyan 2008). Since the 1950s acoustic sensors have been used in fisheries science (Nordeide & Kjellsby 1999; Hawkins & Amorim 2000; Lobel 2002), but it was the development of less expensive and less technically complex fixed autonomous underwater acoustic recorders in the 1990s that significantly opened up this technology for scientific research into marine mammals, particularly cetaceans [e.g. 37,38]. Terrestrial audible range acoustic monitoring for ecological purposes mostly began later than in the marine domain, and early studies mainly used general-purpose field recorders and microphones rather than specialised bioacoustic equipment (e.g. (Riede 1993)). In many early studies, sounds were often recorded on analogue tape, which due to its limited storage space limited the potential to employ acoustic monitoring at larger scales.

However, since the millennium, improvements in processing power and digital recording technology have rapidly improved the utility of acoustic sensors for ecological monitoring. These include reduced size, power and cost of electronic components, and increased battery life and memory storage capacity (via SD cards) (Obrist *et al.* 2010; Merchant *et al.* 2014). There have also been significant developments towards the use of multi-microphone arrays to spatially localise vocalising animals, improving population monitoring and the study of animal behaviour (Blumstein *et al.* 2011; Mennill *et al.* 2012; Andreassen *et al.* 2014; Stevenson *et al.* 2015).

Figure 4: A selection of commercially available bioacoustic sensors, shown for illustrative purposes. These include audible range and ultrasonic sensors for both terrestrial (A: Elekon Batlogger and B: Wildlife Acoustics SM4) and aquatic environments (C: Chelonia Ltd. Deep C-POD and D: High Tech Inc. HTI-99-HF hydrophones).

Acoustic methods have a longer history in bat research due to their nocturnal activity patterns and acoustically active lifestyles. However, since the majority of bats vocalise in the ultrasonic spectrum (at frequencies up to 200kHz), and are thus inaudible to humans, particular technical challenges are associated with detecting bat vocalisations. Early ultrasonic bat detectors used a method called heterodyning, whereby incoming bat echolocation calls are mixed with a signal produced by the detector to produce an audible click;, the species of the calling bat is inferred from the pattern of clicks produced by the detector (Jones *et al.* 2013). Frequency division detectors bring bat calls into audible range by dividing the frequency of the call by a predetermined factor (usually 10) (Jones *et al.* 2013). However, both heterodyne and frequency division significantly reduce the calls information content, making it challenging to distinguish many species (Walters *et al.* 2012; Barlow *et al.* 2015). Newer ultrasonic detectors increasingly record in full-spectrum, often by direct recording at high sampling rates (up to 400kHz). Full-spectrum methods retain the full amplitude and frequency information of the call recording (Walters *et al.* 2012). However, currently these detectors are often very costly.

This has encouraged the development of a broad variety of commercially-available bioacoustics recorders, for both terrestrial and marine environments (**Figure 4; see also Chapter 8**). These are generally designed with the challenges of longer-term monitoring in mind. Most are weatherproof or waterproof to withstand long deployments in variable conditions or underwater at varying depths, most can be programmed to record on a specified schedule over days, weeks or months. Many also come with inbuilt sensors to jointly collect other relevant metadata such as GPS and temperature. Over field seasons these may collect hundreds of hours of acoustic recordings, from which ecological data must then be extracted.

3.6 Analysis tools for acoustic data

Once audio data are collected, relevant ecological information must be extracted from the raw audio recordings. This typically consists of detecting and classifying species calls of interest (often with reference to a spectrogram), for which a variety of open-source and proprietary acoustic analysis software is available (**see Chapter 8)**. **Detection** involves locating where sounds of interest are in a recording, and **classification** then involves assigning them to a category (e.g. species). Doing this manually is labour-intensive for larger datasets, and its accuracy can be biased by the analyst's skill level (Heinicke *et al.* 2015). Automated analysis tools have however rapidly improved in accuracy and efficiency due to innovations in signal processing and machine learning (Digby *et al.* 2013; Stowell & Plumbley 2014), leading to a fast-growing body of work on wildlife signal detection and classification. By facilitating automated or semi-automated analysis with standardised methods, this is rapidly improving the feasibility of large-scale and long-term acoustic surveys and monitoring (**Figure 5**).

Current automated sound detection and classification tools mainly use **supervised machine learning** and related methods, including artificial neural networks (Chesmore & Ohya 2004; Riede *et al.* 2009; Walters *et al.* 2012), random forest (Zamora-gutierrez *et al.* 2016), Hidden Markov Models (Kirschel *et al.* 2009; Wimmer *et al.* 2010; Zilli *et al.* 2014) and support vector machines (Andreassen *et al.* 2014; Heinicke *et al.* 2015). Such methods generally involve using a library of known species calls (e.g. bird or bat calls) to train algorithms to detect and classify unknown sounds in new recordings. Many such classification tools are now available in proprietary bioacoustics software, while others are freely available online (e.g. iBatsID (Walters *et al.* 2012), a number of classifiers in PAMGUARD (Gillespie *et al.* 2008)).

The classification process typically involves extracting features from a sound describing its spectral and temporal characteristics; these include features such as call duration, peak frequency and frequency range (**Figure 5d**). (Walters *et al.* 2012; Potamitis *et al.* 2014). Classification algorithms then match an unknown sound's features to their closest match from a learned sound library, and usually calculate a probability that this match is correct (Reason *et al.* 2016) (**Figure 5e**). Feature extraction methods can be sensitive to factors such as recording quality and ambient noise levels (e.g. (Riede *et al.* 2009; Wimmer *et al.* 2010)), and currently the accuracy of automated classification methods is rarely high enough to enable fully-automated analysis; most studies involve a combination of automated processing and manual validation (e.g. (Kalan *et al.* 2015; Newson *et al.* 2015a)). However, a number of new methods including unsupervised feature extraction (Stowell & Plumbley, 2014), dynamic time warping based feature representations (Stathopoulous et al., 2017) and deep convolutional neural networks (LeCun *et al.*, 2015, Goeau e*t al.*, 2016) can learn discriminating representations directly from spectrogram data, potentially improving their robustness for analysis of noisy, heterogeneous acoustic monitoring datasets (**Figure 5e**). The latter are still emerging as tools for the analysis of acoustic wildlife monitoring data (e.g. Mac Aodha *et al.*, 2017, Goeau *et al.*, 2016), and are likely to become much more widely used in the coming years as the technology continues to improve.

In all cases, developing detection and classification tools requires comprehensive validated call libraries of species of interest, ideally with data recorded in a range of ambient sound situations. Where such libraries exist they are currently generally biased towards temperate regions (Collen 2012; Zamora-Gutierrez *et al.* 2016) and vertebrates (Lehmann *et al.* 2014), and are often small in size, limiting their usefulness as training data for state-of-the-art deep learning methods that require large training datasets. This lack of resources represents a major current gap in the field. Additionally, there is a need for recordings of ambient noise without species of interest present in order to identify major failings in automated signal detection systems, such as the misidentification of marine sediment transport noise as narrow-band high frequency porpoise clicks (Tregenza, pers. comm.).

With these challenges in mind, recent work in the field of ecoacoustics has moved toward more global approaches to extracting ecological information from sound recordings (Pijanowski *et al.* 2011b; Sueur & Farina 2015; Harris *et al.* 2016). Over the last 7-8 years a suite of acoustic indices have been developed to summarise the acoustic characteristics of audio recordings (reviewed in (Sueur *et al.* 2014)). Research using **acoustic indices** to infer ecological trends generally assumes that the amount of biotic sound in a recording (calculated either as sound pressure level within a frequency band corresponding to biotic sound, or as some measure of acoustic complexity (Sueur *et al.* 2014)) is correlated with the diversity of vocalising animals in recording (Pijanowski *et al.* 2011b). However, this relationship is still not well understood (for more detail see **Chapter 4.3**).

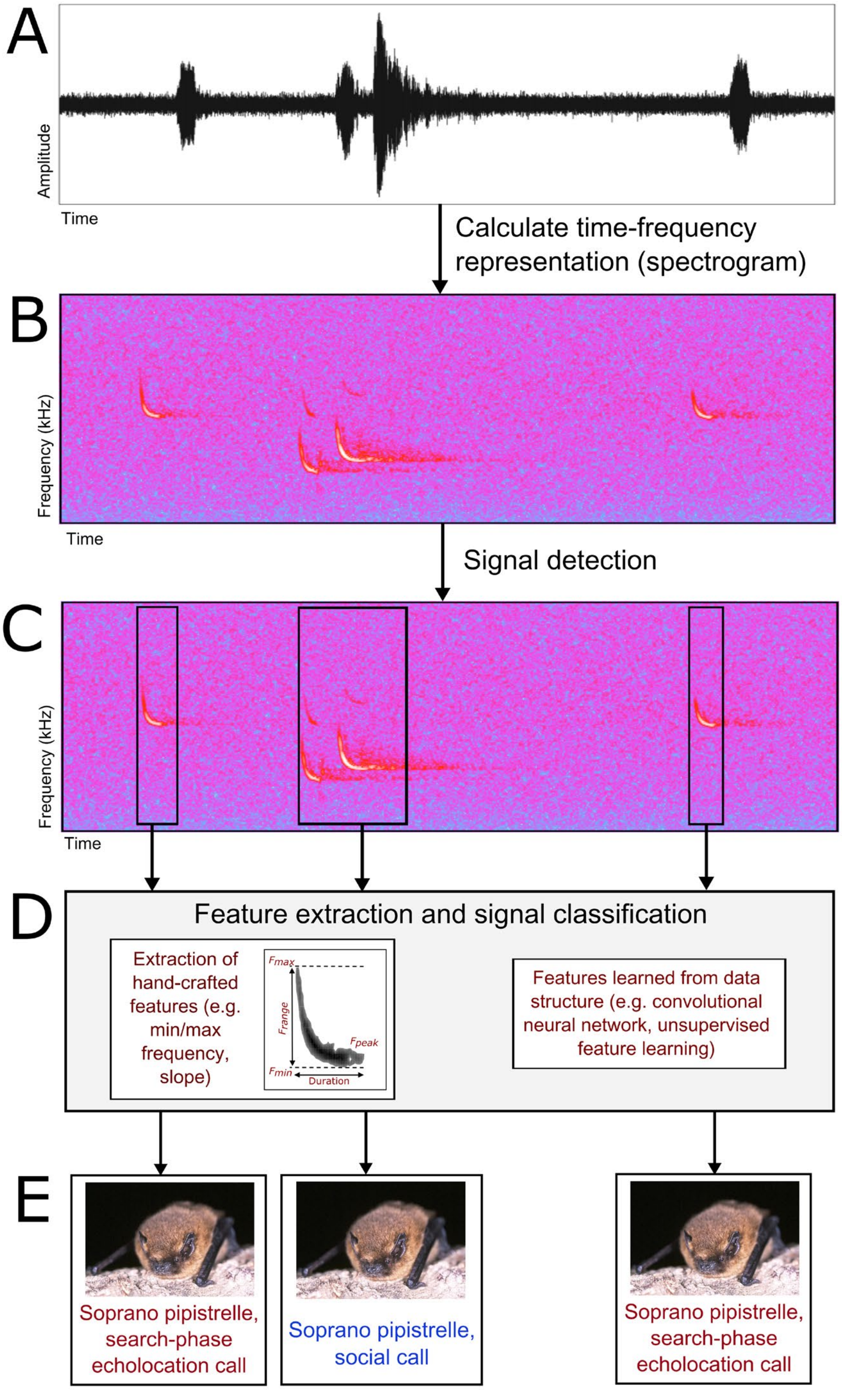


Figure 5: A typical automated analysis workflow for the detection and classification of wildlife sounds from an acoustic recording. Sound recordings are initially displayed in the time-amplitude domain (A), and a time-frequency spectrogram is generated, with amplitude shown as colour intensity (B). Signals are detected within the recording (C), and must classified to species or call type (e.g. echolocation and social calls) using a combination of feature representations extracted from the signal (D-E), which can either be hand-designed (e.g. duration; maximum frequency Fmax; minimum frequency Fmin; peak frequency Fpeak; frequency range Frange) or learned from the data structure (e.g. deep convolutional neural networks). Soprano pipistrelle photograph (c) Evgeniy Yakhontov, reproduced under a CC BY-SA 3.0 license.

Acoustic monitoring can be used to study a broad variety of taxa, including birds, bats, marine mammals, amphibians, Orthoptera, elephants, crustaceans, and some fish

Image: © Jürgen Freund / WWF

4 CURRENT USES, EMERGING TRENDS AND LIMITATIONS OF ACOUSTIC MONITORING

HIGHLIGHTS

- Most current applications of acoustic monitoring endeavour to assess animal population dynamics, behaviour, communities and diversity, or the status of species or populations, often in relation to human activities
- Acoustic monitoring offers advantages over other survey methods, including that it is non-invasive, can survey a broader taxonomic range of species than camera traps, and uses sensors that are relatively easy to deploy and can be left in situ for extended times
- Acoustic monitoring has several disadvantages too, including its inability to detect phenomena that do not emit sound, its dependence on relatively expensive equipment, and high skill level required to analyse what are often massive volumes of data
- In the near future, open-source options for acoustic monitoring hardware and software, sensors integrated with on-board detection and classification capabilities, and networked sensors connected wirelessly will rapidly expand the field of acoustic monitoring

Over the last decade acoustic monitoring has emerged as an increasingly important and widely-used tool for studying wildlife and habitats. This chapter provides a broad background to the current state of the acoustic monitoring field, highlighting both the current and emerging uses of acoustic sensor technology in ecology and conservation, and also discussing the current major challenges and limitations. Its aim is to provide an introduction to how and where acoustic sensors can be applied, and to offer a broad guide to the current scientific literature. The current uses of acoustic monitoring are grouped under three major themes, covering the study of species and populations (**4.1**), animal behaviour (**4.2**), and acoustic communities and biodiversity (**4.3**). The limitations and future trends in acoustic monitoring are then discussed in the context of hardware and data collection (**4.4**) and data analysis (**4.5**). At the end of this chapter, the advantages and limitations of acoustic wildlife monitoring are summarised in **Table 1.**

4.1 Studying species and populations

One of the key current uses of acoustic sensors in ecology is for monitoring particular species and populations, often as a complement to other ecological survey techniques (Figure 6). Such approaches often have the most immediate practical applications in conservation. These include surveying and monitoring endangered or data-deficient species (Laiolo 2010; Thompson *et al.* 2010; Wrege *et al.* 2010; Zilli *et al.* 2014; Borker *et al.* 2015; Jaramillo-Legorreta *et al.* 2016), monitoring indicator taxa such as bats (Jones *et al.* 2013; Barlow *et al.* 2015; Newson *et al.* 2015a) and insects (Penone *et al.* 2013; Lehmann *et al.* 2014, Newson *et al.* 2017), providing baseline data to assess the effectiveness of conservation interventions (Astaras *et al.* 2015), monitoring commercially-important species (e.g. in fisheries, (Rountree *et al.* 2006)), and improving knowledge of species ecology and distributions (Mellinger *et al.* 2011; Klinck *et al.* 2012b; Bader *et al.* 2015; Newson *et al.* 2015a; Campos-Cerqueira & Aide 2016). Rather than detecting animal calls, the same methods can also be used to monitor illegal activity by detecting anthropogenic sounds in the environment, such as gunshots (e.g. (Astaras *et al.* 2015)), logging (e.g. (Rainforest Connection n.d.)) or blast fishing (e.g. (Cagua *et al.* 2014)).

Like camera trap data, the record of species detections collected by acoustic sensors can be used in species occupancy and distribution modelling in relation to environmental covariates. However, using acoustic data to infer animal density and abundance, and therefore population size, involves particular challenges. Statistical methods must ideally control for variation in acoustic detectability of target animals by species (quieter species have smaller detection distances) and by local environmental factors (e.g. ambient sound levels, land cover) (Darras *et al.* 2016), and also account for the non-independence of sequentially detected calls, which may come from the same individual (Marques *et al.* 2013; Lucas *et al.* 2015; Stevenson *et al.* 2015).

Newer statistical methods that explicitly incorporate per-species estimates of detectability and/or call rate are providing broadly accurate estimates of population density when validated against other methods, for example in forest elephants (Thompson *et al.* 2010), bats (Bader *et al.* 2015), minke whales (Martin *et al.* 2013) and vaquita (Jaramillo-Legorreta *et al.* 2016) (**see case study 1**). Generalised statistical models that explicitly incorporate parameters related to detectability, such as random encounter models, have also been developed to improve animal density estimates from static sensors (Lucas *et al.* 2015). The use of multi-microphone arrays to spatially localise calling animals also facilitates the use of density estimation methods such as spatially-explicit capture-recapture (Stevenson *et al.* 2015).

Provided surveys are carried out over sufficient timescales, acoustic data enable population trends and species distributions to be estimated over multiple years (Jones *et al.* 2013; Barlow *et al.* 2015; Jeliazkov *et al.* 2016) and correlated to environmental factors (Penone *et al.* 2013; Frommolt & Tauchert 2014) (**Figure 6c**). However, the fast-evolving nature of acoustic sensor technology, and the significant challenges associated with data management and analysis (see 4.2), mean that there are still relatively few long-term acoustic wildlife monitoring programmes. Those that do exist are predominantly for bat monitoring, due to the relatively long history of using acoustic methods to study bats; these include the UK's National Bat Monitoring Programme (Barlow *et al.* 2015) and the global Indicator Bats (iBats) program (see case study 2) (Jones *et al.* 2013).

CASE STUDY 1

MONITORING THE ENDANGERED VAQUITA POPULATION IN THE GULF OF CALIFORNIA, MEXICO, WITH C-PODS

Cetacean PODs: www.chelonia.co.uk

Cetacean PODs (C-PODS) are underwater passive acoustic sensors designed specifically for monitoring odontocetes (toothed whales). The first Porpoise Detector (POD) was developed in the early 1990s by Nick Tregenza in order to investigate the cause of high porpoise bycatch in the Celtic Sea. Using the POD it was found that the porpoises were frequently around the nets without getting caught and do not simply blunder into them and die. The success of this project lead to the development of the Timing-POD (T-POD), which can record the temporal sequence of clicks (click trains) by a two filter analogue system (Tregenza *et al.* 2016). The T-POD requires prior knowledge of the target frequencies, so the C-POD was developed which, as it is digital, is able to store click characteristic summaries for detection and classification (Tregenza *et al.* 2016). Since its development, the C-POD has been used to detect 26 odontocetes species. As porpoises and dolphins vocalise at high frequencies, at least 450 samples per second must be taken, leading to high data volumes and short running times. However, unlike some other sensors C-PODs select which sounds to record, meaning the data volumes are much lower – 8 GB per year as opposed to 30 TB, for example - and can therefore remain in the field for much longer (Trengenza, pers comm).

In response to the increasingly rapid declines in the Vaquita marina (Phocoena sinus) population, endemic to the Gulf of California, Mexico, 44 C-PODs were deployed from 2011 to 2015 to monitor the vaquita refuge set up by the Government of Mexico (Jaramillo-Legorreta *et al.* 2016). Visual surveys had previously been used to monitor the population, however this method of monitoring becomes increasingly expensive with small populations. C-PODs were deployed in a grid of 48 points across the refuge, including 14 buoys around the perimeter, recording continuously for three months per season. Due to loss of sensors, data were collected from 46 points. In order to estimate vaquita density and the population trend, the number of identified clicks in 24 hours was used as a metric. This assumes the detection function stays constant, i.e. that there is no systematic change in the animal's vocalisation. The total duration of click trains is more likely to be proportional to animal density than click rates as they are high in feeding buzzes and low during travelling, causing behaviour to be conflated with density or detection positive minutes, a commonly used measure of animal encounters. Trend analysis of these data revealed a mean annual decline of -34% per year in the vaquita population between 2011 and 2015 (Jaramillo-Legorreta *et al.* 2016). These trends are virtually identical to those from previous visual and acoustic surveys of the vaquita, indicating their validity. A 2-year gillnet ban was enforced by the Mexican Government following preliminary results of the acoustic surveys in 2014.

4.2 Studying animal behaviour

A key challenge of using acoustic sensors to study free-living animal behaviour is that individual vocalising animals are rarely identifiable from acoustic recordings alone, except in particular cases such as some songbirds (Kirschel *et al.* 2009; Petrusková *et al.* 2015) and some odontocetes (Fripp *et al.* 2005; Filatova *et al.* 2012), where individuals have an identifiable acoustic 'signature' or repertoire. However, acoustic data can still provide information about spatiotemporal patterns of acoustic behaviour in wild animals, and how these relate to the environment (Miller *et al.* 2013; Samarra *et al.* 2016). For example, 'hotspots' of particular activities in particular areas can identify important habitats for foraging (Bader *et al.* 2015; Newson *et al.* 2015a; Davies *et al.* 2016) or breeding behaviour (Hawkins & Amorim 2000; Simpson *et al.* 2005; Kennedy *et al.* 2010), which may assist in the siting of protected areas (Rayment *et al.* 2009; Williams *et al.* 2015) (Figure 6d). Microphone arrays are also increasingly used to study communication networks in smaller-scale groups of free-living animals, though most studies currently involve large amounts of manual analysis (Blumstein *et al.* 2011; Petrusková *et al.* 2015).

Acoustic sensor networks are also increasingly providing insights into relationships between human activities and animal behaviour. This includes responses to anthropogenic noise, an area of growing research interest due to rapid rates of urbanisation and industrial expansion in many regions of the world. Acoustic sensors have shown noise-related shifts in calling behaviour in birds (Gil *et al.* 2015) and forest elephants (Wrege *et al.* 2010), as well as behavioural responses to industrial and naval noise in cetaceans (Miller *et al.* 2009, 2013; DeRuiter *et al.* 2013). Static sensors can also track calling behaviour over timescales ranging from hours to years, in order to understand circadian and seasonal trends (e.g. (Amorim *et al.* 2006; Aide *et al.* 2013; Erbe *et al.* 2015) and estimate timings of migration e.g. (Munger *et al.* 2008; Sanders & Mennill 2014; Petrusková *et al.* 2015)).

Another significant trend, at the interface between acoustic wildlife monitoring and movement ecology, is the emergence of multi-sensor on-animal biologgers that combine acoustic recorders with GPS, accelerometers and other movement sensors. These devices record both an animal's own acoustic behaviour and the acoustic properties of its immediate surroundings, as well as its position in space and other movement characteristics. This provides new possibilities to study individual behavioural responses to other vocalising animals and environmental noise field, including anthropogenic noise pollution (e.g. (Isojunno *et al.* 2016)). These tags are widely used to study marine mammal behaviour, including echolocation, social behaviour and responses to noise, using biologgers such as DTAGs (Johnson & Tyack 2003; Tyack *et al.* 2006). As tag sizes decrease they are also increasingly being deployed on terrestrial animals, including deer and large bats (Lynch *et al.* 2013; Cvikel *et al.* 2015), however tag weight often still prevents their ethical deployment on lighter and smaller-bodied animals, including many bats and birds.

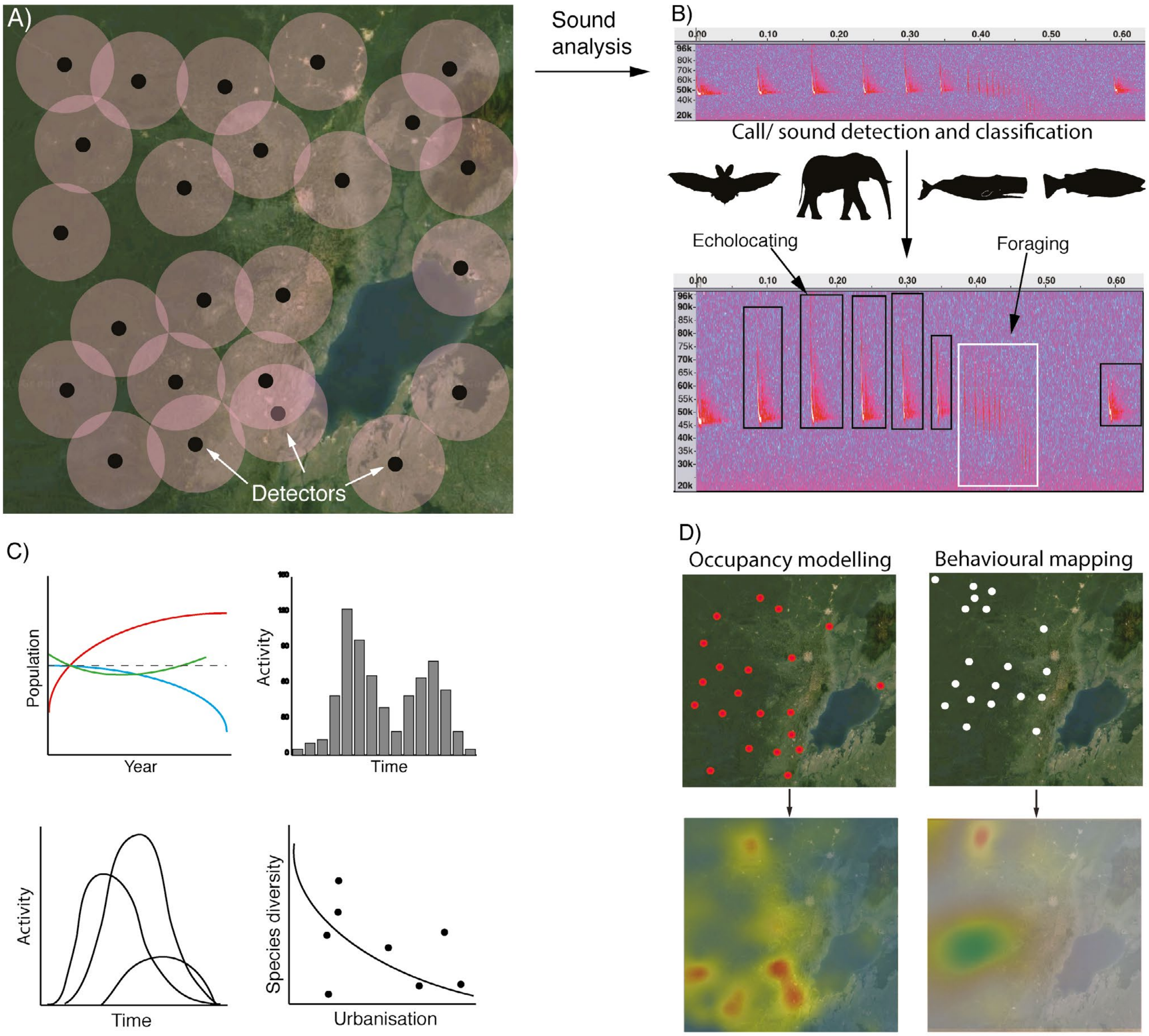


Figure 6: Current uses of acoustic sensors for species or population monitoring. Acoustic data can be collected across an area for a wide range of species or communities (A; black spots are sensors, and shaded areas represent detection radii), and target sounds are then identified within the recordings (B). These data can then be used to model population trends, activity patterns over various temporal and spatial scales (C) and to model spatial distributions of occupancy or behaviour (D).

CASE STUDY 2

INDICATOR BATS (IBATS) - GLOBAL ACOUSTIC BAT POPULATION MONITORING

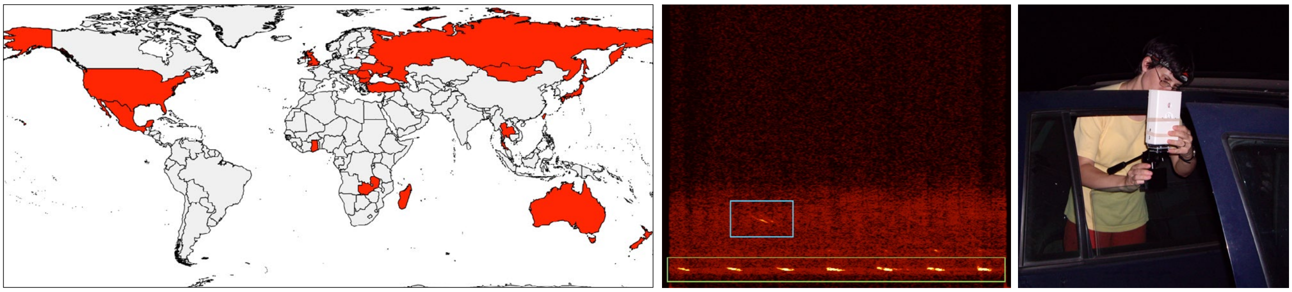


Figure C1: The Indicator Bats Programme. The map shows countries in which iBats data have been collected by volunteers carrying out car transects with a detector mounted on the roof (right). The spectrogram shows annotations on ultrasonic bat survey audio on the Bat Detective citizen science website.

Since acoustic methods have been used to study bats for several decades, sensor technology and analysis tools are relatively more advanced for bats than many other taxonomic groups. Building on these innovations, Indicator Bats (iBats) was founded in 2006 by Kate Jones (University College London, ZSL) and the Bat Conservation Trust (UK), to establish a global citizen science programme for monitoring bat populations [Jones 2013]. It is therefore a useful case study in highlighting many key challenges of larger-scale acoustic monitoring. Volunteers record ultrasonic surveys along car-driven transects, and acoustic recordings and metadata (e.g. GPS, weather) are then submitted to a central database for analysis [Jones 2013]. This citizen science approach facilitates global-scale data collection while reducing data quality biases due to variable volunteer skill levels. Initially focused on Eastern Europe, iBats has expanded to 22 countries worldwide, with volunteers collecting thousands of hours of survey data (**Figure C1**).

For each survey, echolocation calls from every detected bat pass must be classified to species (as shown in **Figure 5**), producing presence data that over multiple years are used to model population trends. Initially this was done in a semi-automated way [Jones 2013], however this is very time-consuming, and automated tools quickly became necessary to process the increasingly large iBats dataset. Many extant bat call classification tools are sensitive to recording noise, reducing their suitability for car transect data, and the limitations of proprietary software are generally inadequately reported. This challenge has continued to delay larger-scale iBats data analyses, although subsets have been published [e.g. Jones 2013, Hawkins 2016].

However, it has also broadened the project's focus to encompass the development of new open-source software tools for acoustic bat monitoring. Drawing on innovations in machine learning, these have included an artificial neural network classifier, iBatsID, for identifying 34 European bat species calls [Walters 2012]. An online citizen science data annotation portal, Bat Detective, has also assisted in developing a general-use detection tool for locating any bat call in full-spectrum ultrasonic audio [Mac Aodha *et al*, in prep]. These new tools are currently being used to analyse the iBats dataset, and will be made freely available to the wider bat research community in future. This case study highlights that, although acoustic monitoring poses significant analytical challenges, problems encountered in the course of a project can often both highlight gaps in knowledge and encourage the development of new tools. More broadly it also emphasises the growing need for transparent, open-source classification tools and sound libraries to facilitate robust ecological research.

Bat Detective
www.batdetective.org

4.3 Studying acoustic communities

Broader community ecology metrics such as species richness and diversity indices can also be inferred from the diversity of vocalising animals in acoustic recordings. Acoustic surveys are already key tools for assessing species richness in bats due to their visually cryptic nature, (MacSwiney G *et al.* 2008; Froidevaux *et al.* 2014; Newson *et al.* 2015a). However, acoustic data offer an increasingly useful means to survey communities of vocalising animals more broadly (Celis-Murillo *et al.* 2009; Blumstein *et al.* 2011; Aide *et al.* 2013; Towsey *et al.* 2014). Although they can only detect acoustically active species, they offer some advantages over traditional surveys: recordings can be analysed with standardised methods post-hoc, reducing observer biases (Aide *et al.* 2013), and they are non-invasive and long-term, increasing the likelihood of detecting more cryptic species (Celis-Murillo *et al.* 2009; Klingbeil & Willig 2015; Darras *et al.* 2016). However, a relative lack of classification tools and call libraries for many regions and taxa currently means that most vocalising species in recordings must be identified manually, making analysis very labour intensive.

As a result, much recent work has favoured whole-spectrogram approaches to quantifying biotic sound levels in acoustic recordings **(Figure 7**). This emerging field is typically referred to as ecoacoustics (Sueur & Farina 2015) or soundscape ecology (Pijanowski *et al.* 2011b; Krause & Farina 2016). Rather than identify individual species, such approaches typically use acoustic indices (see 3.1.3) to summarise the spectral and temporal characteristics of sound recordings, and then study their relationships to biodiversity, landscape characteristics, and anthropogenic change (Pijanowski *et al.* 2011b; Sueur *et al.* 2014; Sueur & Farina 2015). Some indices are intended to quantify relative levels of biotic and anthropogenic sound in recordings (Joo *et al.* 2011; Kasten *et al.* 2012), while others are specifically designed to be analogous to traditional community ecology metrics such as α-diversity and β-diversity (e.g. acoustic entropy H and dissimilarity index D (Sueur *et al.* 2008b)) (**Figure 7b**).

Index-based analyses offer the advantage of extracting quantitative information about environmental sound dynamics from acoustic data while avoiding the time-consuming process of identifying every vocalising species. So far these methods have provided insights into temporal and spatial trends in biotic, abiotic and anthropogenic sound components (Figure 7c) (Halfwerk *et al.* 2011; Tucker *et al.* 2014; Erbe *et al.* 2015; Fuller *et al.* 2015), the vocalising phenology of entire acoustic communities (Farina *et al.* 2011; Desjonquères *et al.* 2015; Nedelec *et al.* 2015; Bittencourt *et al.* 2016), and links between acoustic diversity and habitat characteristics (Pekin *et al.* 2012; Rodriguez *et al.* 2014; Erbe *et al.* 2015; Fuller *et al.* 2015). Until recently ecoacoustics research has been conducted mainly in terrestrial habitats, however indices are increasingly used in aquatic monitoring, such as in coral reefs (McWilliam & Hawkins 2013; Lillis *et al.* 2014; Staaterman *et al.* 2014; Harris *et al.* 2016) and freshwater habitats (Desjonquères *et al.* 2015; Martin & Popper 2016).

However, although acoustic indices provide biogeographical insights into soundscape dynamics (Lomolino *et al.* 2015), their usefulness in long-term ecological monitoring requires rigorous understanding of relationships between indices and ground-truthed measures of biodiversity. Acoustic index values must therefore be calibrated against ecological community data collected by other means (Harris *et al.* 2016). Currently these relationships are typically assessed on a per-study basis by co-collecting acoustic alongside other ecological survey data (e.g. (Sueur *et al.* 2008b; Pekin *et al.* 2012; Fuller *et al.* 2015)), and the general usefulness of ecoacoustics indices for monitoring different habitats and taxonomic groups is still not well understood (Gasc *et al.* 2013; Lellouch *et al.* 2014). Many indices are also sensitive to background noise, including weather conditions such as rain and wind and anthropogenic sounds (Farina *et al.* 2011), which may limit their applicability for biodiversity monitoring in noisier habitats on the frontiers of anthropogenic change, e.g. cities (Fairbrass *et al.* 2017). Understanding whether acoustic indices can be generally used to measure particular ecological characteristics therefore represents a major current challenge in this field.

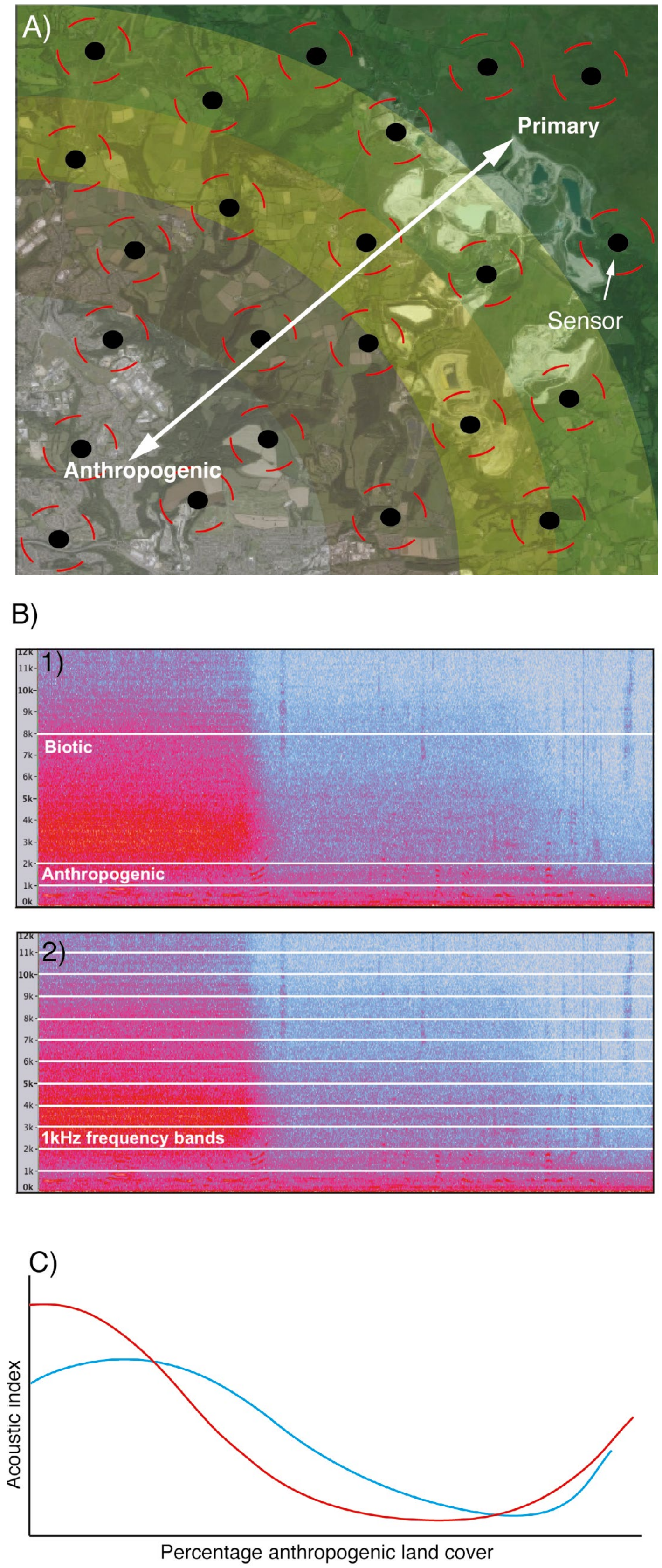


Figure 7: An example of soundscape monitoring using acoustic indices. Sensors are placed along a gradient of land cover (A; anthropogenic to primary), and soundscape indices are calculated from recordings (B). Some indices partition the soundscape into frequency bands corresponding to anthropogenic and biotic sounds (B1), e.g. Normalised Difference Soundscape Index; and others calculate the ratio of power between multiple frequency bands as a measure of acoustic diversity (B2), e.g. Acoustic Diversity Index. These can then be used to model how anthropogenic land use affects these indices (C).

4.4 Limitations and emerging opportunities in hardware and sensor deployment

Although the costs of purpose-designed acoustic sensors have been rapidly decreasing in the last decade, state-of-the-art sensors are still often very costly, meaning there are large initial expenses associated with establishing an acoustic survey programme. This remains a major barrier to the broader uptake of acoustic monitoring for budget-limited conservation programmes and citizen science. However, there are promising trends towards the development of low-cost, and customisable bioacoustic sensors (e.g. AudioMoth, see **case study 3**, and Solo (Whytock & Christie 2016)) and use of smartphones as acoustic sensors for citizen science (e.g. (Jones *et al.* 2013; Stevens *et al.* 2014; Zilli *et al.* 2014; Jepson & Ladle 2015)). Alongside their practical conservation applications, these developments have great potential to involve wider public in standardised ecological data collection, in both developing and developed regions of the world (Vitos *et al.* 2014; Zilli *et al.* 2014; Newson *et al.* 2015a).

Currently, long-term field deployment of sensor networks involves on-going maintenance and regular data retrieval. There is often significant effort and cost associated with maintaining such a network, especially in more logistically-challenging environments such as marine areas or tropical forests. In the future wireless networked arrays, with data automatically transmitted to a central server, have potential to significantly reduce such costs (e.g. ARBIMON I/II (Aide *et al.* 2013)). Some terrestrial studies have had success in using networks powered by solar panels (Ellis *et al.* 2011; Aide *et al.* 2013), while in the marine environment ocean gliders (drones) are being developed to autonomously record cetaceans (Dassatti *et al.* 2011; Klinck *et al.* 2012a; Baumgartner *et al.* 2013).

Similarly, as computational power increases, the quantity of data that must be stored and analysed can be reduced by the use of on-board detection and classification algorithms operating with sensors, as with ocean gliders (Dassatti *et al.* 2011; Baumgartner *et al.* 2013) and citizen science initiatives such as the New Forest Cicada Project (Zilli *et al.* 2014). These would also improve capacity for real-time monitoring and reporting of time-sensitive events such as illegal human activities (Rainforest Connection n.d.; Cagua *et al.* 2014; Astaras *et al.* 2015), Ultimately, the joint development of autonomous sensor networks and improved signal processing tools will improve the potential of acoustic sensors to be used as remote-sensing tools, to monitor environmental change over extended time periods.

More broadly, the long-term and large-scale datasets collected by acoustic sensors have the potential to contribute large volumes of ecological data to global repositories (Villanueva-Rivera & Pijanowski 2012). Firstly, this requires increasingly robust analysis tools (see the next section, **4.5)**. However, ensuring data comparability also requires standardised protocols for acoustic data and metadata collection, which are not currently in place across the acoustic monitoring field. This is a key current topic of discussion, covering microphone calibration (Merchant *et al.* 2014), quantification of sound detectability across species and habitats (Darras *et al.* 2016), standards for appropriate metadata collection (including both technical specifications and environmental variables e.g. temperature and weather) (Roch *et al.* 2016), and the development of database platforms to facilitate data sharing (Villanueva-Rivera & Pijanowski 2012). Improving these standards will make acoustic data as comparable as possible across different survey programmes, improving its potential for use in global-scale monitoring programmes and ecological databases.

4.5. Limitations and opportunities in acoustic data analysis

Another key challenge is the development of robust and transparent automated tools with clearly reported methods and limitations for analysis. This is necessary both to lower the time costs of analysis and to standardise methods in order to reduce manual analysis biases (Aide *et al.* 2013; Heinicke *et al.* 2015). Improvements in automated signal detection and classification are proceeding quickly, and newer machine learning methods hold great promise for analysing even very noisy recordings (LeCun *et al.* 2015). However, currently the accuracy and transparency of such tools is still rarely high enough to allow fully automated analysis. Scientific research requires tools whose methods and limitations are clearly reported, and preferably released within an open-source framework to facilitate access by users across the globe. While some acoustic analysis tools are reported in the scientific literature (e.g. PAMGUARD (Gillespie *et al.* 2008), iBatsID (Walters *et al.* 2012), WarbleR (Araya-Salas & Smith-Vidaurre 2016)), many widely-used classifiers are incorporated within costly proprietary software, and their limitations are often not clearly reported. Most current acoustic monitoring studies therefore necessarily involve semi-automated analysis, with automatic signal detection and classification followed by manual checking of processed data (Wimmer *et al.* 2013; Andreassen *et al.* 2014; Heinicke *et al.* 2015; Newson *et al.* 2015a; Petrusková *et al.* 2015). Moving forward there is a need for robust empirical testing of multiple automated sound identification systems (both commercial and freeware) against expert-labelled gold-standard datasets from a variety of environmental situations. This would improve understanding of the sensitivity (maximising true positives) and specificity (minimising false positives) of different tools in different environments, enabling users to choose the appropriate tool for their study objectives.

There are also major taxonomic and environmental biases in the availability of such tools. Several exist for bats and cetaceans (e.g. C-POD.exe, PAMGUARD, SonoChiro, SonoBat, iBatsID, Kaleidoscope), mainly covering temperate regions although some bat classifiers are now available for the Neotropics. In contrast, far fewer are available for other taxonomic groups such as invertebrates and fish (Lehmann *et al.* 2014), and in general there is a lack of classifiers available for highly biodiverse tropical biomes (Kalan *et al.* 2015; Zamora-gutierrez *et al.* 2016). This is coupled with significant analytical challenges associated with acoustic monitoring in very biodiverse areas, such as high degrees of interspecific call similarity (Zamora-gutierrez *et al.* 2016). With many tropical ecosystems experiencing high rates of environmental change, this is a major limitation. There are also similar biases in the availability of species call libraries with which to train classifiers (Lehmann *et al.* 2014), although publicly-curated online sound libraries such as Xeno-Canto for birds (are potentially rich resources (e.g. (Stowell & Plumbley 2014; Araya-Salas & Smith-Vidaurre 2016)).

Xeno-Canto:
xeno-canto.org

One means of addressing this challenge would be the provision of user-friendly software that enable ecologists and conservation practitioners to develop project-specific tools suited to their own data. Currently, machine learning methods are prohibitively complex for most non-statistically trained researchers, so smart, interactive tools that allow users to train machine learning classifiers on their own datasets, and clearly report their limitations, would further improve the practicality of acoustic monitoring methods in ecology and conservation. There is currently some progress being made towards this goal, such as classifier training tools incorporated in the ARBIMON platform (Aide *et al.* 2013) , the open source software Tadarida (Bas *et al.* 2017) and the bioacoustics work of ENGAGE at University College London.

ENGAGE:
www.engage-project.org

Acoustic indices have great potential for monitoring of biotic sound at the temporal and spatial scales needed for applied ecology and conservation management, such as providing quick assessments of biodiversity in areas of rapid change, or for urban and industrial planning. Their applicability to studies of phenology, such as seasonal patterns of behaviour, also suggests they may in future prove useful as indicators of climate change effects (Pavan *et al*. 2015; Krause & Farina 2016). However, as discussed in Chapter 4.3, current understanding of their applicability for biodiversity monitoring is ad-hoc and tested on a per-study basis. It is often not clear what aspects of the soundscape are being captured by acoustic indices, limiting consensus around which indices are most appropriate for monitoring wildlife. There is a pressing need for improved understanding of the relationships between biodiversity and global acoustic indices across environments and species. This will involve systematic ground-truthing of indices against biodiversity data across multiple habitats and taxonomic groups (Sueur & Farina 2015), and the concurrent development of new analysis techniques that extract ecologically-meaningful information from audio recordings in well-understood ways (Eldridge *et al*. 2016).

Table 1: Summary of the current advantages and limitations of acoustic wildlife monitoring.

Advantages	Limitations
Enable the non-invasive study of wildlife and of animals that are nocturnal or otherwise difficult to survey visually, e.g. bats, many insects, marine mammals. Acoustic data enable species presence, and increasingly population density, to be estimated and correlated to environmental factors; the same methods also enable monitoring of illegal activities (e.g. logging, blast fishing).	Currently acoustic sensors only be used to monitor species that emit recognisable sounds.
Acoustic recorders require relatively little expert knowledge to use or deploy in the field, making them potentially ideal for use by citizen scientists or local conservation groups.	Purpose-designed, programmable acoustic sensors are often expensive, and microphones and electronics are vulnerable to damage from weather, animals and people.
Acoustic data are increasingly useful to infer community ecological information, such as species richness and diversity metrics, using either individual call ID or global acoustic indices (e.g. acoustic entropy, acoustic diversity)	Limited reference call libraries and classification tools mean identifying the diversity of calling species is often difficult, and the usefulness of acoustic indices for monitoring biodiversity is still not well understood.
Acoustic data increasingly enable inference of activity and behaviour patterns in free-living animals.	It is currently difficult to identify individual animals, except in cases where individuals have a recognisable acoustic signature (e.g. singing birds, dolphins).
Sensors can be deployed remotely and programmed to collect data over weeks or months, potentially enabling surveying of environments at much larger temporal and spatial scales than traditional ecological survey methods.	Large-scale acoustic datasets that are often so large that manual analysis is difficult to impossible, making automated tools important. Although many automated tools are currently incorporated in commercial software, their limitations are not always clearly reported. Development of project-specific automated tools for detecting and classifying sounds of interest is mostly prohibitive for non-statistically trained scientists.

CASE STUDY 3 AUDIOMOTH - LOW-COST, OPEN-SOURCE ACOUSTIC SENSORS

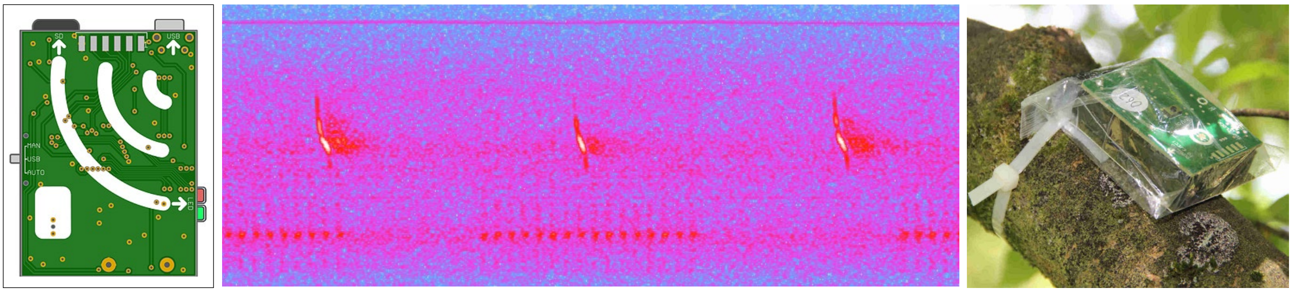


Figure C2: AudioMoth open-source acoustic logger (left) and shown deployed in the New Forest (right). The spectrogram shows bat echolocation calls in an ultrasonic recording from an AudioMoth.

AudioMoth: www.openacousticdevices.info

The high cost of sensors is a major barrier in acoustic monitoring (**see section 4**), since it generally limits the number of sensors deployed and the capacity to involve the public in data collection (although the Norfolk Bat Survey, which loans static ultrasonic detectors to volunteers for data collection, is one example of a project working around these constraints [Newson 2015]). To scale up acoustic monitoring in ecology and conservation, there is a need for inexpensive sensors that are adaptable to a range of applications. In response to this the AudioMoth, an open-source, full-spectrum acoustic/ultrasonic logger based on a small processor board (similar to an Arduino or Raspberry Pi), has recently been developed by Alex Rogers' group at Oxford University and University of Southampton.

The AudioMoth was first developed for the New Forest Cicada Project, an ongoing citizen science programme to detect the UK's only cicada species. Initially the project focused on an app that enables volunteers to record and upload audio if a cicada-like sound is detected by their smartphone's microphone [Zilli *et al* 2014]. However, it became clear that there was a need for additional remote loggers to expand the spatial and temporal coverage of monitoring. The AudioMoth logger was prototyped in 2015 and tested in the New Forest in 2016. During deployment the devices are sealed in a plastic bag for waterproofing and zip-tied to features in the environment, and audio is recorded to a microSD card for retrieval.

Following prototyping, the key challenges have been to make the logger's capabilities as flexible as possible for a variety of possible uses; to minimise power consumption to facilitate long-term deployment; and to minimise component costs (the device currently costs under UK£40 to produce). This includes developing on-board algorithms so that the loggers only record audio when sounds within particular frequency bands are detected, preserving battery life; these features are being developed by Andrew Hill and Peter Prince at the University of Southampton to enable monitoring of logging and poaching in rainforests. The latest version is also suitable for full-spectrum ultrasonic bat surveys: its analogue microphone is sensitive to frequencies exceeding 100kHz, while the processor can record at sampling rates of 250kHz (Figure C2). These are currently being tested on a range of ecological use-cases, including dawn and dusk bird chorus surveys in Kenya and gunshot detection in Belize. The group are also exploring the potential to use them for large-scale citizen science biodiversity monitoring. At the time of writing, they are preparing the devices for open-source release: their specifications will be made available online in the near future, enabling users to use and adapt the hardware and firmware for their own applications.

Like camera traps, remote acoustic sensors can now be deployed in the field for extended periods - potentially for several weeks or months - and crucially are non-invasive, meaning that there is little interaction with or disturbance of target species.

Image: © Paige Byerly

5 IS ACOUSTIC MONITORING SUITABLE FOR YOUR OBJECTIVES?

Conservation technologies such as acoustic sensors and camera traps are increasingly user-friendly to deploy and maintain, and bioacoustic sensors are gradually becoming more affordable as component costs decrease. However, most commercially-available bioacoustic sensors remain costly, while the huge volumes of data collected by newer-generation sensors present major data analysis challenges, even for short-term deployments (Walters *et al.* 2012). It is therefore important to carefully assess in advance whether acoustic monitoring is the most appropriate technology for your research objectives.

This chapter highlights key considerations that affect the suitability of acoustic sensors for ecological and conservation research. These are intended as complementary to **Chapter 4**, which outlines the breath of current uses and the major limitations associated with acoustic monitoring technology.

- Can the species, sounds or environments of interest be effectively surveyed using acoustic sensors? This includes whether animals of interest make identifiable sounds (**see Chapter 7, Table 3**) and whether ambient sound levels in the habitat may impact recordings (for example high levels of anthropogenic noise in urban or industrial environments).
- Would other methods (e.g. traditional ecological field surveys, camera traps) be more effective? For example, identifying individual vocalising animals via acoustics is currently not possible for the majority of taxa, and visual surveys or camera traps may be more effective for larger species that rarely vocalise. However, if the innovative use of acoustic monitoring in the context can assist in answering broader technical or methodological questions, this may justify its use over other methods.
- What environmental factors might limit the effectiveness of acoustic surveys? Technology is vulnerable to damage from factors such as weather, humidity, theft or wildlife damage, which may affect whether and for how long sensors can be deployed (**see Chapter 7, Table 4)**. High ambient noise levels in a habitat (often from human activity) may impact recording quality. Safety issues, due to both human (e.g. conflict, illegal activity) and wildlife activity are also priority concerns.
- How will the data be analysed? Manual analysis of large datasets is time-consuming, costly in terms of labour and can introduce biases. Automated methods are currently taxonomically and geographically biased, and are often error prone. It is critical to design data analysis workflows in advance, to avoid collecting large volumes of data that are prohibitive to analyse and expensive to store.
- Monetary budget of project. Providing comprehensive costings is beyond the scope of this guide, however both commercial sensors and proprietary analysis software for bioacoustics are costly. A variety of free and open-source analysis software is available online (**see Chapter 8**). State-of-the-art bioacoustic sensors typically range in price from around UK£500 to UK£2000 (for terrestrial sensors), but sensors for marine environments are much more expensive, ranging from around UK£2000 to costs exceeding UK£5000. Budgets should also factor in costs of replacement components (e.g. microphones, hydrophones) to replace damaged elements, and also costs of securely storing, managing and backing-up audio databases. Further costs are associated with the labour and logistics involved in deploying and retrieving sensors, as well as the time involved in data analysis.

- Timescale of project. Funding and resource requirements will be proportionately higher for long-term monitoring programmes than short-term surveys; this will include the costs of replacement components, sensor maintenance, and long-term data storage and analysis.
- Important additional considerations for marine acoustic monitoring: There are major safety issues associated with the marine realm and you should not attempt to deploy sensors at sea without proper training and experience. The sea can be very unpredictable, with extreme weather and dangerous currents. Use of boats to deploy acoustic sensors should only be undertaken if you have experience of sailing and navigating or have engaged someone with the expertise to do so for you. Deploying sensors from boats usually requires the use of ropes, moorings and weights. Inexperience of using these be extremely hazardous, as individuals may become trapped by the rope on deck, and can even lead to the boat tipping over, endangering the lives of all on board. Using acoustic releases avoids the need for surface markers, removing the risks to users and animals that may become entangled in the mooring lines. If deploying sensors by scuba diving ensure that divers have the necessary training and certifications for the depths, underwater environment and any equipment required (from PADI or other authorised training bodies).

  The financial cost of monitoring in the marine environment is also very high. Alongside the cost of sensors, you also will require moorings, transport via boats, the use of scuba equipment and additional personnel for these activities. Additionally, local regulations may require you to use particular moorings, which can vastly exceed the cost of the sensor. Ensure you are fully aware

In the near future, open-source options for acoustic monitoring hardware and software, sensors integrated with on-board detection and classification capabilities, and networked sensors connected wirelessly will rapidly expand the field of acoustic monitoring

Image: © Roger Leguen / WWF

6 CHOOSING AN ACOUSTIC SENSOR

Selecting appropriate equipment for any given research question is crucial, since this choice will affect the quality of the resulting data, its suitability for analysis, and the equipment's longevity in the field. This chapter therefore provides supporting information to assist in selecting an appropriate acoustic sensor for any given research objective.

However, both well-defined research questions and robust analysis frameworks are equally important when planning an acoustic monitoring study, and these will inform the best choice of technology. These are discussed in greater detail in **Chapter 7**, which should be also consulted in advance of choosing an acoustic sensor.

Bioacoustics technology is evolving quickly, so rather than offering a comprehensive list of hardware for particular objectives, we instead provide key technical and design criteria to consider when selecting a model of sensor. These are listed in **Table 2**. Your requirements for meeting these criteria will vary depending on the nature and length of sensor deployments. Be aware of how the characteristics of any acoustic sensor equipment (e.g. frequency sensitivity ranges, sampling rate, audio compression, frequency division) may affect or bias the data they collect. These factors are discussed in **Chapter 3**.

To support equipment choice, a reference list of current manufacturers and models of bioacoustics sensors for both terrestrial and aquatic environments is provided in **Chapter 8**. Many commercially-available sensors are designed for deployment in all weather, have custom programmable recording schedules and integrated units for metadata collection (e.g. geographic coordinates). However, they may be costlier than custom or open-source alternatives. We recommend thoroughly researching the available options and making a decision primarily based on the key criteria in **Table 2.** If budg*et al*lows, trying out several different sensors may assist in making the best choice for your project.

- **An important note on data quality.** While the cost of sensors will contribute substantially to a project's set-up and maintenance costs, we strongly recommend always collecting the best possible quality of data for your available budget. Minimising information loss during data collection (e.g. by recording ultrasonic data in full-spectrum rather using frequency division) will future-proof your data by improving their potential for further analysis with new tools. This may also allow the same data to be used to answer other questions; for example, Orthoptera population studies have been conducted using data originally recorded for bat surveys (Penone *et al.* 2013; Jeliazkov *et al.* 2016, Newson *et al.* 2017). Collecting data of best possible quality is especially important to ensure data comparability throughout long-term monitoring programmes over years or decades, during which time the hardware and software state-of-the-art will change drastically.

Type of device	Feature	Key considerations
Recorder / detector	Digital/analogue	Use a digital recorder, to enable longer recording times (onto SD card) and facilitate data analysis. Most new acoustic recorders record digitally, however analogue recorders (e.g. using tape) may be available; these have limited storage space, and analogue recordings must be digitised prior to analysis.
	Sampling rate	Sampling rate determines the maximum frequency that can be accurately reconstructed from a digital sound recording. This is important in wildlife monitoring because the sampling rate must be over twice the highest frequency in the recorded sounds of interest (Nyquist frequency). For recordings within human audible range the standard is 44.1kHz. If recording animals that produce ultrasonic calls (e.g. bats/ odontocetes), ensure recorder is able to record at the appropriate sampling rate (e.g. 250kHz, or up to 400kHz for some bat species).
	Full-spectrum or frequency division (bat detectors only)	Bat detectors record ultrasound using two major methods, full-spectrum recording and frequency division (e.g. Anabat). Frequency division significantly reduces memory demands which is useful for long-term monitoring, but loses a lot of information from recordings, which can present problems during later analysis. If possible we recommend the use of full-spectrum recorders to preserve as much useful information as possible.
	Bit-depth	Determines the amplitude resolution of recorded audio; files should be recorded at minimum 16bit to ensure appropriate quality.
	Audio compression	Ensure audio is stored either as uncompressed .wav or another lossless format (e.g. flac), to prevent loss of valuable information from sound recording. Avoid storing as mp3 or other lossy format except in exceptional circumstances, and assess the impact of resulting information loss beforehand.
	Storage capacity	Most digital acoustic recorders store data onto one or more SD cards; if recording for long periods, and/or recording ultrasound (which takes up more memory due to the high sampling rate), consider selecting a model that can hold multiple SD cards to extend recording time.
	Battery life	Average battery life should be taken into consideration ahead of purchase of equipment, according to needs of the study: if sensors are to be deployed for extended periods consider purchasing a recorder with excellent battery life or the capacity to attach an external battery pack or solar panel. Recording at high sampling rates (e.g. ultrasound) consumes more battery power.
	Programmable schedule	If deploying static sensors in the field for days or weeks, the ability to programme a recording schedule (e.g. dusk until dawn; 5 minutes per hour) is essential to conserve battery life and storage space. Most purpose-built bioacoustics sensors have this function inbuilt, but check beforehand to ensure it meets your requirements.
	Durability	Consider durability of recorder with regard to planned deployment, including environmental conditions, study duration, and potential biotic hazards (e.g. wildlife/ human interference). If intending to deploy for extended periods in challenging conditions, ensure that recorder is designed for this purpose, and/or consider costs of protecting and maintaining the device. Key considerations include biofouling; damage to recorder or external attachments (e.g. microphones) by wildlife or people; resistance to humidity and temperature (both hot and cold); resistance to water turbulence (aquatic environments).
	Weatherproofing	Many purpose-designed acoustic wildlife sensors are designed to be weatherproof or come in weatherproof casings. Ensure that your selected model is suitable for the intended deployment environment, and be aware of requirements for maintenance.
	Theft/tamper proofing	If deployed in habitats with high human activity, consider choosing a model with protective casing that allows sensor to be secured to a tree or post; or ensure that recorder can be protected in some way. In marine deployments consider using acoustic releases to avoid theft.
	Cost	Carefully consider costs in project budget when deciding on model of sensor to use, including both cost of sensor purchase and also labour cost of maintenance and data retrieval. Key considerations: number of sensors to be deployed (area to be monitored); durability; length of monitoring project; ease of data retrieval. Ensure that quality of recorded data is as high as possible for your available budget.

Type of device	Feature	Key considerations
	Cost of accessories	Consider cost of any additional accessories (e.g. external microphones/hydrophones) required to use the recorder.
	Designed for terrestrial/ aquatic deployment	Ensure recorder is designed for deployment in intended environment of use.
	Pre-amplification	Most acoustic recorders will contain an internal pre-amplifier, however some models may require additional pre-amplification; check before buying.
	Portability	Sensors designed for remote deployment may be too cumbersome for transects, and handheld recorders may not be robust enough for remote deployment; consider portability of device in relation to proposed study methods.
	Ease of use	Consider how user-friendly the recorder is (e.g. intuitive interface, easily programmable, how easy to assemble and deploy); this is especially important if equipment is to be used by multiple users, e.g. conservation workers, citizen scientists, etc.
Microphone / hydrophone	Frequency sensitivity (frequency response)	Microphones/hydrophones are designed to be sensitive across a particular range of frequencies. Ensure that the microphone/hydrophone is designed for sensitivity to audible sound (if recording in audible range), ultrasound (if recording in ultrasonic range). Similarly, recording infrasound (e.g. elephant rumbles) requires highly sensitive, specialised microphone/hydrophne models. Variation in frequency response across different microphones/hydrophones can affect the detectability of certain animal species, if the frequency of their vocalisations falls outside of the optimum sensitivity range. Ensure that sounds of interest are within correct sensitivity range before purchase.
	Directional sensitivity / directionality (microphones only	Microphones can be directional (sensitivity concentrated in an area) or omnidirectional (sensitivity in all directions). The best choice depends on study requirements. Directional microphones may be appropriate if using a single acoustic sensor to record sounds from a specified direction. However, the majority of bioacoustic sensors use omnidirectional microphones, which have an equal detection radius in all directions, and can be used to localise sound sources if deployed in arrays. Many omnidirectional microphones can be fitted with reflectors to increase directionality.
	Durability / weatherproofing	Even if recorder is protected in strong casing, microphones are usually more exposed to the elements and vulnerable to damage from water, temperature, humidity, biofouling and interference by wildlife. Ensure that microphone is suitable for use in intended environment, and consider additional protection if humidity/ precipitation exceptionally high.
	Compatibility with recorder	Some purpose-built recorders are designed for use with specific microphones/ hydrophones; check compatibility before purchasing additional microphones/ hydrophones.
	Cost	Consider cost of replacement microphones/hydrophones when purchasing any recorder.
	Maximum operating depth (hydrophones and marine sensors only)	Hydrophones are designed for use in depths up to a specified maximum; ensure that you select the correct model according to needs of study (i.e. choose a greater depth for deeper-water deployments).
	Pre-amplification	Certain recorders require that hydrophones/microphones include an integrated preamplifier; check these requirements before purchase.

Acoustic sensors are increasingly being used to monitor illegal human activities such as the poaching of wildlife and illegal logging

Image: © naturepl.com / Bruce Davidson / WWF

7 BEST PRACTICES IN PASSIVE ACOUSTIC MONITORING

This chapter provides guidelines for acoustic monitoring survey design, sensor deployment, and subsequent analysis. Its main aim is to provide conservation and ecology researchers and practitioners with information to support the selection and deployment of appropriate equipment, and to carry out initial acoustic signal processing and analysis. It has been developed from a combination of practical experience, a comprehensive review of the acoustic monitoring literature, and the results of a purpose-developed WWF-UK survey of users of acoustic sensors from across the scientific, NGO and consulting sectors (for details see acknowledgements). These guidelines are applicable to research in both terrestrial and aquatic environments, although each has its own technological and analysis challenges, which are highlighted when necessary.

The survey design information in this chapter is complementary to earlier chapters covering current uses and limitations of technology (**Chapter 4**), assessing the need for an acoustic survey **(Chapter 5)** and choosing a sensor (**Chapter 6**). However, it is not intended as a substitute for experience of either acoustics or biodiversity monitoring more generally, and there are many cases where departures from these guidelines will be appropriate depending on the context. Prior knowledge and experience of good practice in ecological surveying and monitoring is essential to ensure robust study design and data collection protocols. Best-practice for acoustic surveys involves many complex considerations whose details are beyond the scope of this guide, so **Chapter 9** provides a complementary list of further reading.

This chapter's guidelines follow a series of steps for planning and conducting an acoustic monitoring survey, which are listed below. They are discussed in broadly chronological order, from early study design to implementation and analysis, with references and examples provided for clarity. However, they are not independent from one another. Good study design is an iterative process, and will be influenced at all stages by the combination of overall objectives, species or taxonomic groups of interest, environmental factors and resource budgets. In order to design rigorous and effective ecological surveys it is important to understand how these elements interact with one another.

1. Defining clear objectives
2. Planning data management and analysis
3. Designing survey and data collection protocols
4. Testing equipment
5. Pilot surveys
6. Sensor deployment: practical considerations
7. Signal processing and acoustic analysis
8. Conducting further statistical analyses

7.1. Defining clear objectives

As with any ecological research, clear objectives must be defined prior to beginning data collection (Bat Conservation Trust 2016). Information on the current uses and limitations of acoustic monitoring, which can be used to assist in this stage, is available in Chapters 3, 4 and 9 (further reading). Consider both short and long-term questions and objectives. These will inform all aspects of study design, which will then affect the suitability of your data for appropriate statistical analysis.

- Short-term objectives can include estimating species richness, occupancy or distribution, activity patterns or abundance (**see Section 4**). These could be for a single animal species (e.g. the abundance of a particular bird species), taxonomic group (e.g. bat species richness), or entire acoustic community (e.g. species richness of vocalising birds, bats and insects).

Longer-term monitoring objectives involve estimating changes to measured ecological parameter(s) over time, and often in response to environmental change. These could include estimating multi-year population trends of a particular species or taxonomic group (e.g. bat population trends (Jones *et al.* 2013; Barlow *et al.* 2015)), estimating changes to species abundance in response to anthropogenic activity (e.g. urbanisation, poaching), or monitoring the effectiveness of conservation interventions (e.g. the effects of anti-poaching initiatives on gunshot activity and primate abundance (Astaras *et al.* 2015). If planning a monitoring programme, it is critical to design data collection regimes that ensure the data are appropriate for robust trend analysis (Jones *et al.* 2013; Frommolt & Tauchert 2014) (**for more detail see Section 7.6**).

Be prepared to communicate and collaborate with other people who work with acoustic monitoring in similar settings. This will allow you to share practical knowledge about the use of acoustic monitoring technology, and to learn from challenges others have experienced ahead of commencing surveying.

7.2. Planning data management and analysis

Plan in advance how the data will be analysed. Conservation technologies such as acoustic sensors are becoming increasingly user-friendly to deploy and maintain, however without understanding in advance how the data you collect will be used to answer your questions, there is a risk of generating large volumes of data that are challenging to analyse and expensive to store (Walters *et al.* 2012) (**see also Chapter 5**). Design a clear workflow for managing, processing and analysing data, and test it on representative data (**see Chapter 7.5)** in advance of commencing larger-scale surveying.

During this stage, consider what later statistical analyses you intend to carry out using the data (e.g. occupancy or distribution modelling, density or abundance estimates, population trend modelling). We recommend consulting ecologists with statistical expertise in advance, to ensure your intended data collection regime will be suitable to answer your intended questions.

7.2.1. Data storage and management

Be prepared to manage a large number of files. Design a relational database (e.g. SQL, MS Access) to link each audio file with associated metadata (e.g geographic co-ordinates, temperature). Each survey should have a unique identifier as its primary key and a unique filename; this is vital to avoid losing or confusing files (**see Chapter 7.9**). Increasingly the field of acoustic monitoring is moving towards data collection and storage standards to facilitate comparison across studies, and some existing frameworks are available e.g. Pumilio, ARBIMON (Villanueva-Rivera & Pijanowski 2012; Aide *et al.* 2013; Roch *et al.* 2016).

7.2.2. Call detection and classification

If identifying individual sounds from recordings, develop a workflow to process raw sound files and metadata to produce meaningfully annotated data for use in subsequent analyses. For example, in an acoustic bat monitoring study this will involve tools to detect any bat calls within sound recordings and classify them to species. This process can be conducted manually or using automated tools where available (**Figure 5**). This may involve proprietary software (e.g. SonoChiro, SonoBat) and/or open-source tools (e.g BatScope, iBatsID), and must also include manual validation (**see Chapter 7.10**).

Developing bespoke analysis tools and resources, such as automated sound classifiers or species call libraries, may be most appropriate. Although time and budget-intensive to develop, these can help to make a monitoring project viable in the long-term and may also be useful for other researchers in future (**for example, see Case Study 1: Indicator Bats**). Funding for research is increasingly contingent on making data publicly available, however there are still large taxonomic and geographical biases in available sound libraries and classifiers (**see Chapter 4.5**). Consider making any hardware/software tools or call libraries you develop during your research available as public resources to the acoustic monitoring community. Improving availability of these resources is critical to advancing the field more broadly (**see Section 4.5**).

- A note on selecting acoustic analysis software. A wide range of commercial and open-source software programs are currently available for acoustic signal processing and analysis. At minimum you will require software to visualise and annotate spectrograms (**e.g. Figure 3**) but most offer additional features. Choosing a program that facilitates fast processing of multiple audio files will save a great deal of time. **See Chapter 8** for examples of currently available programs.

7.2.3. Defining a 'detection'

Establishing a fully independent animal detection in acoustic data is inherently difficult, since multiple calls recorded by a sensor during a sampling period may have come from the same individual. There is therefore not a simple relationship between the number of detected calls and the number of animals in a location (Marques *et al.* 2013) (**see Chapter 4.1**).

When making inferences about activity or animal density from acoustic data, it is therefore critical to define what constitutes a single detection. This should be defined in advance and kept consistent throughout the project (Reason *et al.* 2016). It should take into account biological knowledge of species of interest, such as species-specific call rate, and may need to be ground-truthed. For example, in animals that call more infrequently, a single recorded call may be considered a detection. In contrast, echolocating bats emit ultrasonic calls at very regular, sub-second intervals, and a single detection is typically defined as a 'bat pass', which consists of a discrete series of echolocation calls separated from all other calls by a given time interval (usually at least one second) (**Figure 8**).

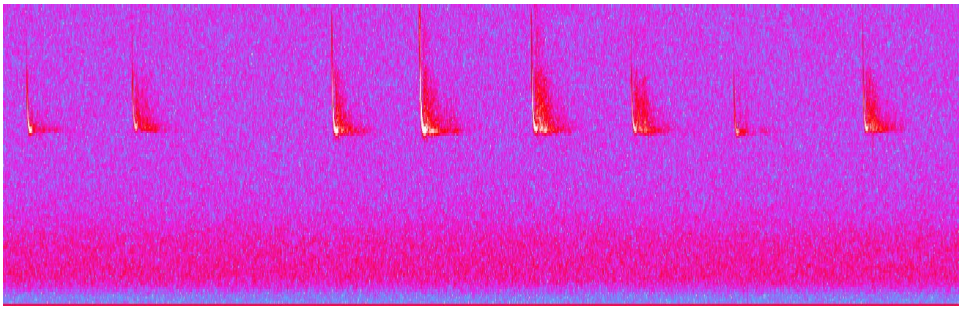


Figure 8: A single 'bat pass', consisting of a discrete sequence of calls coming from the same echolocating species, separated from all other calls by a specified time window. For bats this constitutes a single detection, however for many other animals that call less frequency a single call may constitute a detection. This should be informed by biological knowledge of the animal(s) being studied.

7.2.4. Soundscape indices

Soundscape indices enable global metrics of acoustic complexity and diversity to be calculated from recordings without identifying individual vocalising species (reviewed in [9]). Functions to calculate many indices are included in the R packages seewave (Sueur *et al.* 2008a) and soundecology (Villanueva-Rivera & Pijanowski 2016). In many studies these have been successfully applied as proxies for a range of biodiversity metrics such as along habitat gradients (**see Section 4.3**). For example, acoustic entropy indices (proposed as analogous to alpha-diversity) have been shown to correlate to forest habitat intactness metrics (Sueur *et al.* 2008a), and trends in acoustic richness index values have been shown to correlate to observed species richness between woodland sites (Depraetere *et al.* 2012).

However, there is still little scientific consensus about whether these relationships between indices and other biodiversity metrics are generalisable, and it is important to be critical of results (**see 3.2.3**). If making ecological inferences using indices, you should collect ground-truth biodiversity data, ideally with other survey methods, across a representative subsample of sites.

7.2.5. Sound localisation using microphone/hydrophone arrays

Deployment of multi-sensor arrays enables calling individuals to be spatially localised using the differences in time of call arrival at each sensor, e.g. (Blumstein *et al.* 2011; Wilson *et al.* 2014; Stevenson *et al.* 2015) (**see also Chapters 3 and 4**). Alongside facilitating behavioural studies, these can also improve species density and abundance estimates via methods such as spatially-explicit capture-recapture [Stevenson 2015]. Such analysis methods are beyond the scope of this guide, but a useful primer on microphone arrays is provided in (Blumstein *et al.* 2011) and see **Chapter 9** for recommended references that cover these in more depth.

7.3. Designing survey and data collection protocols

Rigorous survey and sampling design is critical in order to collect good ecological data, and the decisions made at this stage will affect analysis and interpretation of your data. However, best-practice in ecological survey design is a broad subject, and offering comprehensive advice is beyond the scope of this guide. In this section we instead highlight a number of key considerations that are particularly relevant to designing an acoustic monitoring study.

7.3.1 Important sampling parameters Sampling rate.

The required sampling rate (kHz) for recording will depend on whether animals of interest vocalise in audible, ultrasonic or infrasonic range. The sampling rate must be at least twice the highest call frequency of interest (Nyquist frequency) to resolve all frequency information. For example, for a bat species whose highest call frequency is 100kHz, sampling rate must be a minimum of 200kHz; in contrast, animals vocalising within audible range (such as birds and most mammals) can be successfully recorded at 44.1kHz. Table 3 provides information on minimum sampling rates for different taxonomic groups.

Detection distance. Detection distance (or detection space) is the effective three-dimensional volume around an acoustic sensor within which a given sound can be detected (**Figure 9a**). This is not an intrinsic property of the acoustic sensor itself, although more sensitive microphones/hydrophones can detect sounds from a greater distance. It is instead affected by the sound's volume and frequency (i.e. how rapidly it attenuates to below a perceptible level, **see Section 3.1**). In general, animals calling at higher amplitudes (more loudly) will be detected at greater distances than those calling at lower amplitudes (more quietly), and higher frequencies also attenuate more quickly than lower frequencies.

Detection distances are also affected by site-specific environmental factors such as the type of medium (air/water), temperature, pressure, humidity, ambient sound levels, and habitat structure such as vegetation and buildings. Different species are thus more readily detectable by acoustic sensors than others, and this can vary between habitat types (**Figure 9b**)

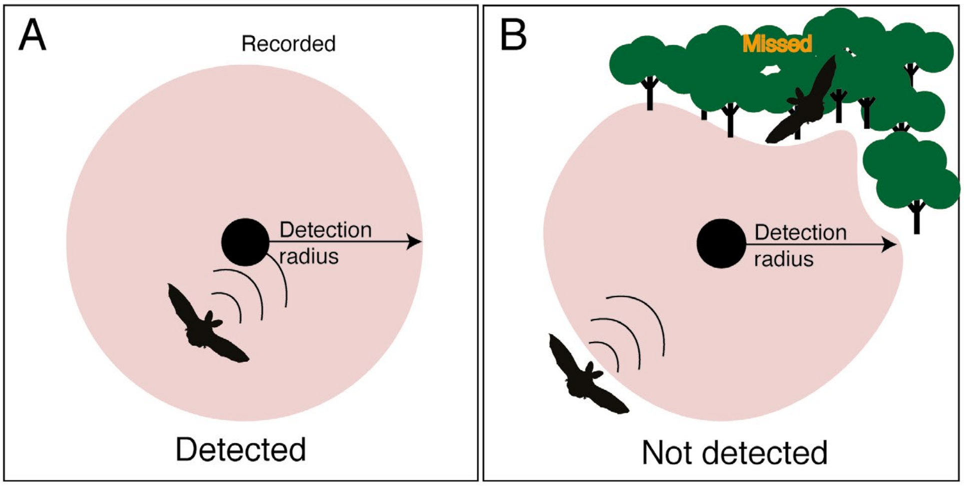


Figure 9: The effects of call volume, distance and clutter on detectability of animal calls. Sounds emitted within a microphone/hydrophone's effective detection radius will be detected (A), while animals calling outside this radius will be missed (B). A sound's detection distance is affected by the volume and frequency of a sound, and by environmental factors such as habitat clutter (B).

Detection distance is an important parameter in acoustic wildlife monitoring, since it affects the effective spatial area coverage of an acoustic sensor network, and thus has implications for estimating animal density (Lucas *et al.* 2015). Since animals vocalising at higher volumes have larger effective detection distances, biodiversity metrics (e.g. Species richness) estimated from acoustic data alone can also be biased towards more detectable species (Darras *et al.* 2016). It is therefore important to test acoustic sensors during study planning, in order to estimate detection distances of sounds at a range of frequencies and distances from the microphone (see (Darras *et al.* 2016), and also Section 7.8). For more detailed discussion and methods see (Merchant *et al.* 2014; Kalan *et al.* 2015; Darras *et al.* 2016)

7.3.2 Spatial sampling regime

The optimal spatial arrangement of sensors in the landscape will be affected by a range of factors, including survey objectives and the vocalising behaviour and detectability of animals of interest. Comprehensive guidelines on spatial sampling in ecological surveys are beyond the scope of this guide, but this section discusses several important factors to consider when designing a spatial sampling regime with acoustic sensors.

Static autonomous detectors or transects. Transects (e.g. walked, cycled, driven, boat-towed) can cover larger areas for less effort (e.g. (Jones *et al.* 2013)). However, data collected with static detectors are generally considered more suitable for estimating animal density and activity (Marques *et al.* 2013; Lucas *et al.* 2015; Newson *et al.* 2015a), and are more commonly used in current acoustic monitoring studies.

Spatial arrangement of static sensors. A schematic of the spatial layout of a static acoustic sensor network is shown in **Figure 10**, with the detection radius each sensor shaded in red. The size of detection radius varies depending on the volume and frequency of sounds of interest (for example, low frequency elephant calls (Lehmann *et al.* 2014) travel for much longer distances than insect calls or ultrasonic bat calls) and habitat characteristics such as vegetation clutter (Darras *et al.* 2016)(**Figure 9**).

The arrangement of sensors and the required coverage of an area will therefore depend on survey requirements. For example, to investigate animal species distribution and/or activity patterns across a large geographical area, a random stratified sampling approach is likely to be most appropriate, with sensors placed across a representative sample of habitat types (for example the large-scale deployment of detectors in the Norfolk Bat Survey (Newson *et al.* 2015b)). Investigating species presence or richness trends across a habitat gradient will require sensors to be placed in appropriate locations across the area of interest (e.g. in a range of habitats ranging from rural to urban). It is also important to take sound-specific detection distances and required survey area coverage into accountwhen choosing a spatial arrangement of sensors (see 7.5.1). For example, louder and lower-frequency sounds such as elephant calls and gunshots travel much greater distances than high-frequency or low-amplitude sounds (e.g. bats, invertebrates), so a much sparser network of sensors may be needed to achieve even coverage of the complete study area.

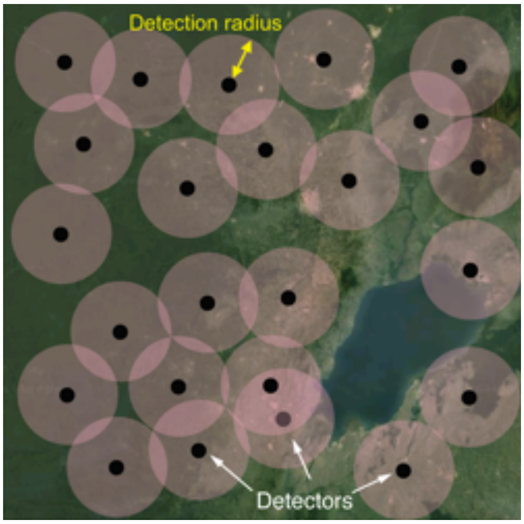


Figure 10: An example schematic of the spatial arrangement of an acoustic sensor network. Each sensor is shown as a black dot, with its detection radius shaded in red. The size of a detection radius varies according to sound volume, frequency and habitat characteristics; for example, louder bird calls will be detectable at greater distances than quieter insect calls.

- **A note on the number of sensors.** The number of acoustic sensors available for deployment will be constrained by the project budget. More sensors will be required for finer scale, temporally synchronised sampling of a given geographical area during a discrete time period (e.g. if monitoring a forest for illegal activity, or investigating phenology of an animal population). However, a small number of sensors can suffice for studies investigating trends such as species abundance and activity levels, occupancy, habitat associations and community ecology metrics. In such cases, each sensor can be used to sample at multiple locations, although each location should be sampled for multiple units of sampling time (e.g. over several days/weeks) to enable calculation of detection means and error estimates (**see 7.5.3**).

7.3.3 Temporal sampling regime and survey replication

Temporal sampling regime incorporates a range of factors. This includes defining a single sampling period for data analysis (in minutes/hours/days depending on survey objectives), and for longer-term static sensor deployments it includes daily programmed recording schedules and the total length of deployment. It also includes replication of sampling to calculate averages and error estimates.

Daily programmed recording schedules should account for the time of day that animals of interest vocalise (e.g. dawn, dusk, night). Many ultrasonic detectors use triggers that only record when ultrasonic sound exceeds a specified amplitude threshold; these should be tested to ensure they record species of interest. If estimating species richness of vocalising animals in an area, it may be necessary to sample over several days to ensure less vocally active species are detected (Froidevaux *et al.* 2014; Klingbeil & Willig 2015; Bat Conservation Trust 2016).

Table 3: Key taxonomic considerations for acoustic monitoring, including typical frequency range of animal vocalisations and minimum sampling rates for successful recording.

Study subject	Frequency range	Example sound sources	Typical frequency range of sounds	Minimum sampling rate	References
Mammals	Audible	Primates, cetaceans, seals	20Hz – 20kHz	44.1kHz	(Klinck *et al*. 2012b; Heinicke *et al*. 2015)
	Ultrasonic	Bats, dolphins, echolocating whales	20kHz – 200kHz	192kHz, but often higher (e.g. up to 1000 kHz for small cetaceans) depending on call frequency	(King *et al*. 2013; Newson *et al*. 2015a)
	Infrasonic	Elephants, many baleen whales	10Hz – 35Hz	44.1kHz, but can be lower if only interested in infrasound (e.g. 1-2kHz)	(Stafford *et al*. 1998; Thompson *et al*. 2010)
Birds	Audible	Most vocalising birds, e.g. passeriformes	20Hz – 20kHz	44.1kHz	(Frommolt & Tauchert 2014; Sanders & Mennill 2014; Petrusková *et al*. 2015)
Amphibians	Audible	Anurans (calling frogs/toads)	20Hz – 20kHz	44.1kHz	(Weir *et al*. 2009; Stevenson *et al*. 2015)
Invertebrates	Audible	Orthoptera, snapping shrimp	20Hz – 20kHz	44.1kHz	(Hugel 2012; Lehmann *et al*. 2014; Rossi *et al*. 2016)
	Ultrasonic	Orthoptera (crickets/ grasshoppers), cicadas	>20kHz	192kHz, but possibly higher depending on call frequency	(Penone *et al*. 2013; Zilli *et al*. 2014, Newson *et al*. 2017)
Fishes	Audible	Teleost fish	20Hz – 20kHz	44.1kHz	(Nordeide & Kjellsby 1999; Lobel 2002; Parsons *et al*. 2016)
Anthropogenic sound	Audible	Gunshots, chainsaws, traffic, mechanical or electrical noise	20Hz – >20kHz	44.1kHz	(Astaras *et al*. 2015; Gil *et al*. 2015)
	Ultrasonic	Boat sonars	20kHz – 200kHz	50kHz	
	Infrasonic	Traffic, city infrastructure, mining or seismic activity	10Hz – 20kHz	44.1kHz, but can be lower if only interested in infrasound (e.g. 1-2kHz)	(Wrege *et al*. 2010; Merchant *et al*. 2014)
Soundscapes	Audible	Whole soundscape indices calculated on entire spectrograms		44.1 kHz, but higher if ultrasonic included	(Sueur *et al*. 2008b, 2014; Pijanowski *et al*. 2011b; Harris *et al*. 2016)

The probability of detecting a species during any time period is affected by behavioural factors such as daily or seasonal patterns in vocalising behaviour (e.g. [15,67]), and whether these are affected by environmental covariates (Kalan *et al.* 2015). This variation means that sampling should be repeated multiple times within any field season to allow for calculating averages and error estimates. For static autonomous sensors, this may simply involve deploying the sensor for sufficient time to cover multiple sampling periods. For example, if surveying birds at the dawn chorus, the sensor could be deployed for two weeks, programmed to record for the appropriate hours in each day.

During longer-term monitoring, sites must be repeatedly sampled over seasons and years in order to calculate trends (Heinicke *et al.* 2015; Campos-Cerqueira & Aide 2016). Methods should be kept consistent between sites and years.

- Example temporal sampling regime. A researcher wants to investigate abundance trends of a particular bat species over several years, using static ultrasonic detectors. In this investigation, a sampling period is one night of recording (from which the number of bat detections can be estimated). The sensor is programmed to record from dusk until dawn each night, and is deployed in each location for two weeks. The data are retrieved and processed to calculate the number of bat species detections per night of recording, enabling averages and estimates of error to be calculated. The same sites are sampled repeatedly over multiple years, using the same regime, producing data that can be used to model abundance trends.

7.3.4 Metadata

Appropriate metadata must be systematically recorded alongside each audio recording, since these must be accounted for in any statistical analysis. These include any salient environmental and ecological data collected in addition to acoustic recordings, and are likely to include geographic co-ordinates (e.g. latitude-longitude); recording time/date; temperature, precipitation, humidity and other climate variables; land cover and other variables relating to habitat structure. They should also include technical specifications of the sensor such as sampling rate and microphone model (Roch *et al.* 2016).

7.4. Testing equipment

Test your equipment regularly, ideally prior to each survey deployment, or at the very least at the beginning of each field season. As well as familiarising yourself with the technology, these will ensure sensors are recording data correctly and enable the testing of key parameters related to deployment and analysis, helping refine study design (**5.6**) and intended data analysis protocols (**5.5**). Key considerations while testing equipment may include the following.

- Ensure sensor is recording correctly. This includes checking audio recording quality (are there high levels of environmental or electronic noise which could interfere with data analysis; if recorded signals are clipping the sensitivity or gain levels may be set too high), checking that trigger thresholds for ultrasonic detectors are set at an appropriate level, and ensuring that the sensor is successfully recording calls from the animal(s) of interest.
- Test detection distances. Test and record detection distances of sound playbacks at a range of frequencies and distances from the microphone (see discussion of ‘detectability’ in 7.3, and for more information and methods see (Merchant *et al.* 2014; Darras *et al.* 2016)). This improves the comparability of recordings collected with multiple sensors or across different time periods, and is important for statistical estimates of parameters such as population density.

- Test microphone sensitivity. Microphone and hydrophone sensitivity may change over time due to natural wear. Set performance benchmarks for microphone/hydrophone sensitivity, such as minimum acceptable detection distances across a range of frequencies. Prior to each deployment microphones/hydrophones should be tested to ensure they reach this standard, and replaced if they fall below the threshold level. This improves the statistical comparability of recordings made using separate microphones/hydrophones (Merchant *et al.* 2014).
- Check parameters related to sensor deployment. These may include approximate battery life, storage capacity (how many hours/days of recording can be stored on an SD card), and ensuring that programmed recording schedules are working correctly prior to deployment.

7.5. Pilot surveys

In addition to testing your equipment it may be appropriate to conduct smaller-scale pilot surveys, for example at a subsample of planned sites. This will be especially useful when planning large-scale surveys or long-term monitoring programmes, since it will help refine survey and analysis methods in advance, as well as highlighting any potential problems early in the project timeline. Considerations during pilot studies may include the following.

- Ensure sensors are working correctly in the field. This may include testing how environmental conditions (e.g. humidity, precipitation, water depth) affect sensor function, and adjusting deployment methods accordingly. It may also include ensuring that the spatial arrangement of sensors in the habitat (e.g. deployment height and position relative to vegetation) is not preventing sounds of interest from being recorded (see also 7.3.1). For longer-term deployments, it is also useful to regularly test whether microphone sensitivity is diminishing over the course of a deployment, for example due to factors such as exposure to moisture and diminishing battery life.
- Training field staff involved in equipment maintenance and data collection. Maintaining an acoustic sensor network can be labour intensive if the environment is challenging, if multiple sensors are deployed or if deployments are over extended time-frames (e.g. months, years). Pilot studies provide an opportunity to train staff to regularly check sensor function and download data from SD cards, as well as any protocols related to preliminary data management, metadata collection and analysis.
- Test signal processing and analysis methods on representative data. A small pilot dataset will highlight many problems or unresolved issues with the analysis workflow, and ensure that the data collected are suitable for subsequent analysis before larger-scale surveys are conducted at greater cost.

7.6. Sensor deployment: practical considerations

This section specifically covers practical considerations for deploying sensors. This includes spatial placement in the habitat, environmental factors that might impact sensors or data collection, and collection of additional relevant data.

7.6.1 Microphone/hydrophone positioning

Microphone. The position of a microphone relative to the ground and to clutter in the environment (e.g. vegetation) affects sound transmission and therefore detectability (**Figure 11; see also section 5.6**). If possible mount microphone(s) on a pole at a suitable height above ground (1m or higher) and at least 1.5m away from trees, shrubs and water bodies to minimise acoustic interference (Newson *et al.* 2015a). If this is not possible, when choosing sites be aware that position of microphones (e.g. attachment to tree trunks) may affect sound transmission and detectability.

Hydrophone. Underwater sound transmission is affected by the position of hydrophones relative to the water surface and bottom substrate, as well as by physical characteristics of aquatic habitats such as clutter (rocks/reefs), substrate (mud/sand/rock), bathymetry and water flow (currents/tides). When acoustic sensors are anchored in marine habitats, hydrophones should be placed at least 5 m below the sea surface to reduce acoustic interference from waves and at least 1-2 m from the bottom, if water depth allows (Figure 12). Sound propagation is particularly affected by depth in shallower water, for example in rivers and shallow lakes (Forrest *et al.* 1993) so if possible deploy hydrophones at a minimum depth below the surface (e.g. 10 cm) to reduce acoustic interference in recordings (Desjonquères *et al.* 2015). In locations with strong water flow, hydrophones should be positioned such that hydrodynamic noise is minimised in recordings (Holt & Johnston 2015). Be aware that small cetacean calls are often highly directional so may not be detected if the hydrophone is positioned close to the bottom or surface.

Three-dimensional sampling. Different animals vocalise at different strata within a habitat (e.g. ground/canopy); this should be taken into account when designing spatial arrangement of sensors, and should be kept consistent between sites (Britzke *et al.* 2013). The full three-dimensional structure of a habitat may need to be sampled (Froidevaux *et al.* 2014). For example, when estimating bird species richness in a forest location, solely deploying a sensor at ground level may fail to detect vocalising birds in the canopy. Deploying microphones at multiple levels in the environment will improve the chance of detecting the full diversity of vocalising birds at the location.

An additional note on aquatic sensor deployment. Underwater deployments, especially in marine areas, are intrinsically more logistically challenging than in the terrestrial realm. Consider logistics well in advance. Deploying underwater recording devices can be very dangerous. Only deploy via scuba diving methods if you are fully trained and qualified. Knowledge and experience of using ropes and moorings is essential before attempting at sea deployments/retrievals from boats. Light moorings with smaller buoys and no heavy weights avoid some of the danger of weights and buoys, as do sonar acoustic releases, although these are expensive. Wave movement can also cause hydrophones to move and change position. Using a secondary sub-surface buoy with a sinking rope which pulls the two buoys together avoids this, as does using two weights, one heavy and one light (**see Figure 12**). Anchor weight should be chosen with reference to local current and wave conditions (Dudzinski *et al.* 2011). For further discussion of static passive acoustic device deployment at sea, see (Dudzinski *et al.* 2011). If hydrophones are being towed by a vessel, the length of tow cable (usually at least 100m), hydrophone depth and vessel speed will affect recording quality, see (Todd *et al.* 2015) for more details.

7.6.2 Key environmental considerations

A variety of environmental factors can cause problems during sensor deployment. These are summarised, and potential solutions discussed, in **Table 4.**

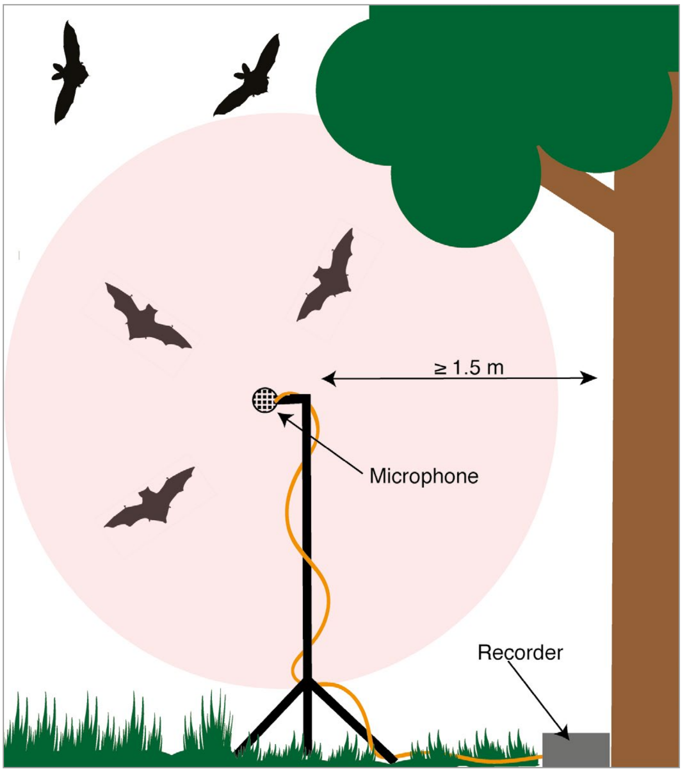


Figure 11: Microphone positioning in the terrestrial environment, in this case for recording bat activity. The microphone should be positioned to ensure the target species will be recorded; here the higher flying species is missed by the detector, but the lower flying species is recorded.

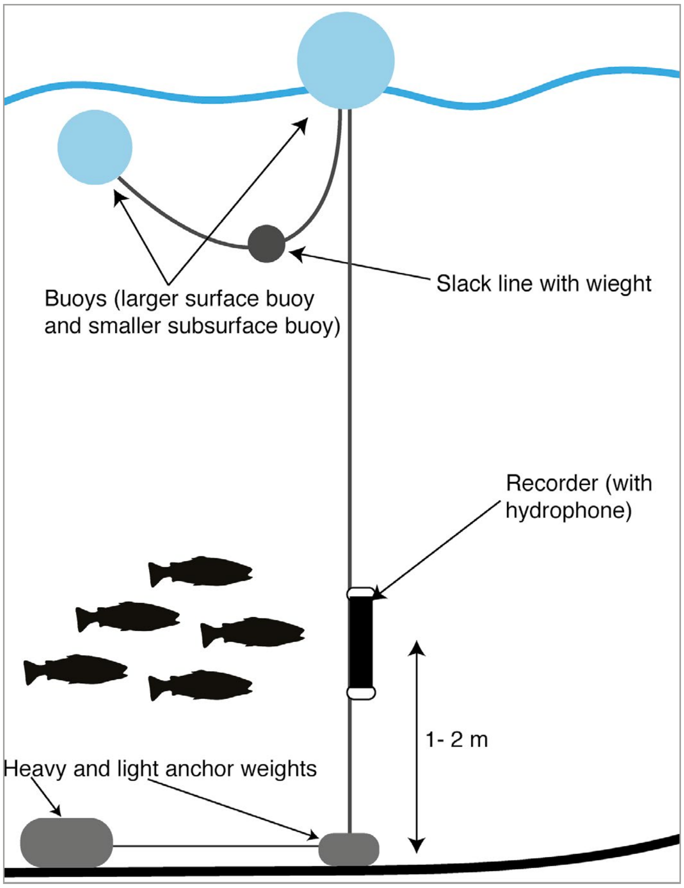


Figure 12: Marine sensor deployment, using a single device with a hydrophone and recorder. The mooring shown here is designed to minimise the drag caused by wave movements, reducing the chance of the detector moving, as is shown here by the smaller buoy diving below as a wave goes past.

7.6.3 Ambient sound levels (including anthropogenic noise)

Ambient environmental sound, whether biotic (other animals), abiotic (landscape/climate/geological) or anthropogenic (e.g. machinery, vehicles, human speech) will affect the quality of sound recordings and therefore can introduce error into analyses (Pieretti *et al.* 2011). Ambient environmental sound is a particular problem underwater, where sound travels much further. Consider the local sound environment when deciding on sensor placement; for example, it may be possible to place sensors in a quieter location within the designated survey area. Be prepared to encounter these challenges if surveys are to be carried out in noisy habitats (e.g. urban or industrial areas).

7.6.4 Maintenance and data retrieval

Batteries should be changed regularly and data retrieved from SD cards before they become full. Regularly check data to ensure sensors are working correctly. This is especially important for long-term deployments (weeks/months). If monitoring is at larger-scale, multiple trained users may be required to maintain sensor networks and regularly download data. It is becoming possible to transmit data from sensors via mobile network to a central hub (e.g. (Baumgartner *et al.* 2013)), however this is currently expensive, technically complex and few off-the-shelf solutions are available.

7.6.5 Additional data collection

Collect appropriate metadata in addition to acoustic recordings (**see 7.3.4**). It may also be appropriate to collect additional ecological data. For example, if using acoustic monitoring to assess biodiversity, consider collecting ground-truth community diversity data by other methods (e.g. traditional field surveys) at a representative subset of deployment sites. This will assist in understanding how acoustically-derived metrics correlate to other metrics of biodiversity in your study system.

7.7. Storing and managing audio data and metadata

Once data are collected from recorders and downloaded to computer, it is important to store and manage them appropriately:

- Record and store audio recordings in highest quality format, preferably .wav, or otherwise a lossless compressed format (e.g. flac). Although MP3s take up markedly less storage space, they also involve a substantial reduction in recording quality; this may not be audible, but will impact statistical analyses of the data.
- If possible check the quality of recordings regularly during a field season (for example to ensure there is not excessive environmental or electronic noise), to allow any problems to be addressed at the time rather than being discovered afterwards. Ideally begin processing data as they are collected rather than waiting until the end of field season, to highlight any problems and reduce the backlog of unprocessed data.

Link audio files to associated metadata in a relational database (**see 7.2**). Each audio file should have a unique filename, which should minimally include date, time and location, as well as project name and any other important information. For example a recording at 10:34pm on 12/08/2016 might be ProjectName_LocationName_20160812_223406.wav. Back-up audio files and databases regularly to avoid losing data.

7.8. Signal processing and acoustic analysis

The first stage of analysis involves signal processing and extracting relevant ecological information from sound recordings. This section discusses the detection and classification of individual sounds of interest (e.g. animal calls) and the calculation of acoustic indices.

Table 4: Key environmental considerations for deployment of acoustic sensors. This includes the potential issues posed by particular environmental factors, and possible resolutions.

Environmental factor	Potential issue	Potential resolutions
Precipitation	Can severely damage recorder and microphones. Heavy rain also causes noise in recordings, which can mask sounds of interest.	Ensure that recorders are adequately sealed in weatherproof housing. Microphones are exposed to the elements, and their membranes will deteriorate through moisture damage, even in models designed to be weatherproof. Always position microphones at the appropriate orientation to reduce water reaching the membrane; this depends on the model, but is often horizontal. Replace foam heads on mics if they become waterlogged.
Humidity	Can severely damage microphone and recorder, including sensitivity of microphone	Ensure that recorders are adequately weatherproofed. Humidity is a major problem in tropical areas, so consider protecting microphones if needed (e.g. by covering the aperture with cellophane). However, be aware of the potential trade-off between protection and maintaining sensitivity, and test sensitivity of protected mics.
Noise levels in environment	Noise can mask target sounds, increases noise in recordings making analysis more challenging, and can interfere with statistical analysis of soundscapes.	Carry out test recordings in advance of full deployment, and choose location for microphone/hydrophone in order to minimise extraneous noise. If possible, seek to minimise overlap in frequency range between environmental noise and animal calls of interest.
Water flow (aquatic only)	Water flow over hydrophone (e.g. freshwater/ ocean environments) can cause noise in recordings and mask sounds of interest. If currents are strong can also cause manual damage to equipment.	Select deployment location in order to minimise water flow across hydrophone, and consider suitability of environment for acoustic monitoring.
Wildlife damage	Wildlife damage to equipment will depend on the study system, and is generally more of a problem in highly biodiverse areas e.g. in the tropics. In marine environments biofouling or attachment of sessile organisms (e.g. barnacles) can be a problem.	Be aware of potential hazards in the intended deployment area. In areas where wildlife damage is expected (e.g. with high primate density) conceal and if possible protect recorder and microphones in tamper-proof casing. Protect microphone cables to reduce chewing by rodents/insects. Regularly check microphones to ensure weatherproofing remains intact.
Damage/theft by humans	This can be a major problem; it is difficult to protect completely against theft or human damage. Some areas are more at risk than others, e.g. in urban /densely populated regions.	Protect valuable detectors in locked boxes and/or padlock to secure elements in the landscape (e.g. tree trunks), however microphones must still be exposed for recording. Insure equipment if possible and select study sites carefully to minimise risk. Consider attaching a note with contact details to equipment, if appropriate.

7.8.1 Signal processing: generate spectrograms

When first imported into audio software, raw sound files will generally be displayed in the time-amplitude domain, and the first step in analysis is usually to generate a spectrogram (**Figure 13**). This displays a sound recording in the time-frequency domain with amplitude shown as colour intensity, and enables sounds of interest to be visually identified. All audio analysis software provide Fourier transform functions to produce spectrograms, and to adjust key parameters such as window function and window length. It is important to understand how these parameters can affect subsequent analyses (**see Chapter 3.4** and recommended further reading, **Chapter 9**), and how this varies across different software tools (see next section).

7.8.2 Sound detection and classification

Detection and classification can be carried out using manual or automated methods, but is likely to involve some combination of both (semi-automated). Detection involves identifying where sounds of interest are present in a recording (spectrogram in **Figure 14**), and classification involves classifying those sounds (e.g. to species level) based on some combination of discriminating features (**Figure 14**). These methods are discussed in detail in Section 3.6, with an example workflow of the entire process (**Figure 5**).

If multiple analysts will be manually classifying data it is important to standardise protocols in advance to minimise errors associated with skill level (Heinicke *et al.* 2015). It is also critical to understand the software you have chosen; for example, particular software may visualise spectrograms with different colour schemes such that certain sounds become more or less visible, which can lead to error in manual annotations. Use high quality reference materials for manual analysis, including books, published scientific literature and published call libraries. Such data are deficient for many taxonomic groups, habitats and regions. It may be possible to contact particular researchers or institutions to request use of unpublished reference material. However, it may also be necessary to collect your own reference recordings prior to commencing large-scale surveys or monitoring.

Many bioacoustics software include automated tools for detection and/or classification of animal vocalisations, in particular bats and cetaceans (**see Chapter 8**). Regardless of the source, all automated call ID tools are subject to error, which is often inadequately reported for proprietary software (**see 5.5**). Always treat results critically. Cross-check their outputs manually and/or with other software tools, either for the entire dataset if possible, or on a sufficiently large representative subset to assess error. Any robust analysis pipeline for processing acoustic data will involve regular cross-checking and reporting of error rates. For a best-practice guide to automatic sound classification, see (Reason *et al.* 2016).

When analysing large datasets, it is often useful to use automated methods as a 'first pass', to identify possible relevant sounds and thus reduce the size of the dataset that must subsequently be manually checked. If this is the case, the sensitivity thresholds of detection/classification tools should usually be set high enough to minimise false negatives, in order to reduce the risk of discarding salient data (Blumstein *et al.* 2011).

More generally, error rates should be considered in the context of study objectives. For example, monitoring endangered species will often require false positive detections to be minimised, to avoid overestimating presence or abundance. However, monitoring illegal activities for example may require false negatives to be minimised, to ensure all possible detections are investigated.

Developing your own project-specific automated tools may be necessary. This offers advantages such as training classifiers on relevant data and better understanding problems associated with their use; however, this requires statistical and computational expertise.

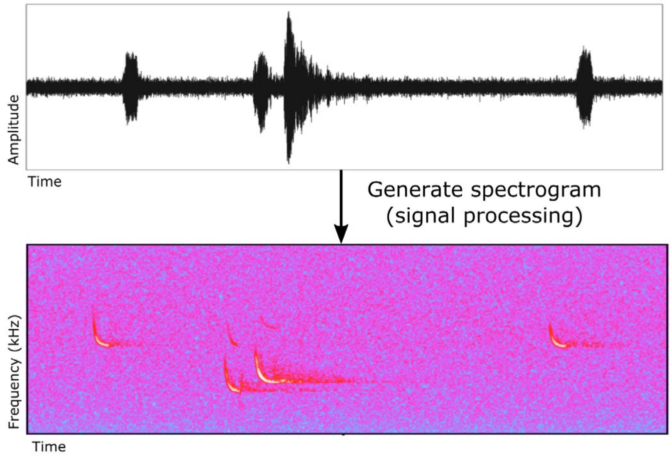


Figure 13: Generating a spectrogram (bottom) from an audio recording in the time-amplitude domain (top). Sounds, in this case pipistrelle bat echolocation calls, are visible as colour density on the spectrogram.

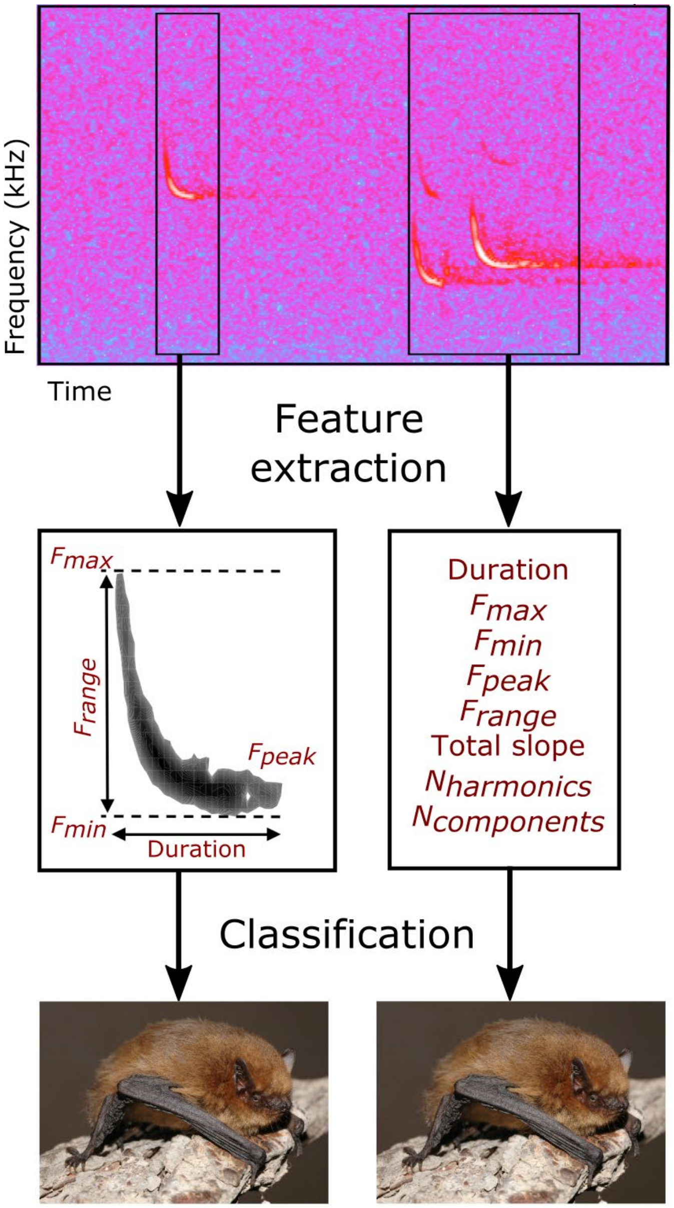


Figure 14: Sound detection and classification schematic. During detection, sounds of interest (in this case pipistrelle bat calls) are located on a spectrogram and annotated, either using manual or automated methods. Features are extracted from the sound describing its spectral and temporal characteristics (middle box). These are used to classify the sound to a category (usually species) using either automated (e.g. machine learning) or manual methods (e.g. a classification key).

If you develop project-specific tools, consider sharing them in an open-source way. Acoustic monitoring is an evolving field, and sharing data and methods with the wider community will help to expand the toolbox available for ecology and conservation research.

7.8.3 Calculating acoustic indices

Acoustic indices summarise spectral and temporal characteristics of a sound recording without identifying individual sounds. Indices vary in their complexity and applications for the study of acoustic communities; for discussion of their current uses, **see Chapter 4.3**. Measures of mean sound pressure level, or distribution of sound energy across broad frequency bands, can quantify the overall acoustic characteristics of monitored habitats (Merchant *et al.* 2014). These may assist in understanding how the acoustic properties of an environment affect animal ecology and behaviour, or impact sound recording quality.

More complex metrics include acoustic entropy, diversity and complexity indices (Sueur *et al.* 2008b, 2014). Current methods for calculating indices often involve partitioning the spectrogram into frequency bands (Figure 7b), before calculating measures of complexity or diversity that describe spectral and temporal characteristics of the recording (Figure 7c). Many can be calculated directly from spectrograms using software such as the seewave and soundecology packages in R (Sueur *et al.* 2008a; Villanueva-Rivera & Pijanowski 2016).

By reducing the effort and error associated with individual species classification, acoustic indices offer potentially powerful tools for rapid analysis of the large datasets collected by newer acoustic sensors. However, as discussed in **Chapters 4.3 and 7.2.4**, the relationship between indices and biodiversity is not well understood across study systems. Results should therefore be ground-truthed, using either biodiversity data collected by other methods (e.g. traditional surveys, camera trapping), and/or community metrics (e.g. species richness) estimated from a subset of acoustic data in which vocalising species have been identified by an expert listener. Further detail is beyond the scope of these guidelines but see (Sueur *et al.* 2014) for an in-depth review of acoustic indices and their applications.

7.9. Conducting further statistical analyses

It is very likely that you will need to conduct further statistical analyses following data collection and processing. In bioacoustics studies this often includes further signal processing analyses, such as quantifying and comparing the structure of animal vocalisations. For wildlife monitoring it will involve making broader ecological inferences from acoustic data. Sounds detected within acoustic data provide a spatially- and temporally-explicit record of species detections, which can be used in estimating animal density, modelling population trends, or modelling relationships between environmental characteristics and species occupancy, activity and/or behaviour.

Further detail on statistical methods in ecology is beyond the scope of this guide, however **Chapter 4** discusses the breadth of current uses of acoustic data in ecology and conservation. Consult the existing literature, including the further reading in **Chapter 9**, alongside more general literature on statistical modelling with ecological data. Key considerations for designing further analyses are discussed in **Chapter 7.2**. It is vital to understand and how the decisions made during data collection and processing may affect your results (Reason *et al.* 2016). Consider carefully the distinct statistical challenges presented by the analysis of ecological data, including their distribution; ecological data are unlikely to be normally distributed, meaning that appropriate methods must be applied for hypothesis testing (Zuur & Ieno 2016). It is at this stage that metadata collected alongside acoustic recordings, such as land-use and weather information, are likely to be important to include as predictors or covariates in any statistical modelling.

Most current applications of acoustic monitoring endeavour to assess animal population dynamics, behaviour, communities and diversity, or the status of species or populations, often in relation to human activities

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8 CURRENT HARDWARE AND SOFTWARE FOR ACOUSTIC MONITORING

This chapter provides lists of currently available hardware and software for acoustic monitoring, to assist in selection of appropriate tools (**for further information on choosing an acoustic sensor, see Chapter 6**). Current manufacturers of acoustic sensors for ecological and environmental monitoring are listed in Table 5, along with example sensor models for each manufacturer. This list is current at time of publishing, however new models and manufacturers regularly enter the market.

Examples of both proprietary and open-source software tools for analysis of acoustic wildlife monitoring data are provided in Table 6; some are general purpose acoustic software, while others are designed specifically for bioacoustics research. Proprietary software packages often contain intuitive user interfaces that enable users with less statistical computing experience to process audio data, and often offer good customer support; however, they can be costly and the limitations of tools (e.g. sound classifiers) included within proprietary software are often not clearly reported. In contrast, open-source analysis tools are freely available, their limitations are often better documented, and many have very active online communities that may offer assistance with problems. However, many require greater experience with statistics and computer programming.

Table 5: Bioacoustics sensor manufacturers for both terrestrial and aquatic environments (current at time of publishing), including information about key sensor models.

Company	Summary	Species/ habitat	Example models and uses	Website
ARBIMON / Sieve Analytics (Puerto Rico)	Hardware, software and data analysis tools for acoustic biodiversity monitoring, including a cloud-computing platform for data storage and analysis.	Terrestrial, audible range	ARBIMON Portable Recorders; ARBIMON Permanent Monitoring Stations (with solar panels and ethernet/wi-fi data transfer capacity); ARBIMON II web-based analysis platform.	www.sieve-analytics.com/#!arbimon/cjg9
AudioMoth (UK)	Low-cost open-source environmental acoustic sensor, which can record both audible range and full spectrum ultrasound	Terrestrial, audible range and ultrasonic	AudioMoth sensor details discussed in Case Study 3 of this report, with further details provided at the website.	www openacousticdevices.info
Chelonia (UK)	Marine passive acoustic monitoring equipment for odontocete monitoring.	Aquatic, odontocetes	C-POD and DeepC-PO, detect odontocete echolocation clicks and record several call parameters (e.g. time, centre frequency, duration) for later analysis. Can record for 4+ months.	www.chelonia.co.uk
Dodotronic (Italy)	Bioacoustic sensor manufacturer producing a range of recorders and microphones (ultrasonic and audible range)	Terrestrial, ultrasonic and audible range	Ultramic, Ultramic384K (ultrasonic microphone/recorder); MOMIMIC (miniature microphone electronics component); Hydromic (ultrasonic hydrophone preamplifier)	www.dodotronic.com
Elekon (Switzerland)	Batlogger range of full-spectrum bat recorders and detectors.	Terrestrial, bats	Batlogger C and A/A+ (for passive monitoring); Batlogger M (for transects); Batscanner (heterodyne detectors). BatExplorer analysis software.	www.batlogger.com/en

Table 5 (cont): Bioacoustics sensor manufacturers for both terrestrial and aquatic environments (current at time of publishing), including information about key sensor models.

Company	Summary	Species/ habitat	Example models and uses	Website
Frontier Labs (Australia)	Recording equipment for bioacoustic and ecological research.	Terrestrial, audible range	Bioacoustic Audio Recorder, includes omnidirectional microphone, integrated GPS unit and sampling rate up to 96kHz. Handheld Audio Recorder to attach to smartphone.	www.frontierlabs.com.au
High Tech Inc (USA)	Hydrophones and recording systems for marine environments. Many models are for industrial/military uses but also produce marine mammal hydrophones.	Aquatic	HTI's Marine Mammal hydrophone, maximum operating depth of >3000m. Produce a range of hydrophones that can be customised to order.	www.hightechincusa.com
Ocean Instruments (New Zealand)	Produce self-contained underwater autonomous recorders for ocean acoustic research.	Aquatic	SoundTrap 300 STD and HF models can record constantly for 13 days and weigh approximately 0.5 kg.	www.oceaninstruments.co.nz
Petterson Elektronik (Sweden)	Ultrasonic bat detectors and analysis softwares, with heterodyne, frequency-division and full-spectrum models.	Terrestrial, bats	D230 (frequency division); D500X (full-spectrum static detector); D1000X (frequency-division/time expansion). Also produce M500-384 ultrasonic microphone that can be attached to a smartphone.	www.batsound.com
Solo (UK)	Open-source, low-cost audio recorder built around a Raspberry Pi microcomputer, with customisable specifications	Terrestial, audible range	Customisable: example configuration provided in publication is costed at UK£167 (Whytock & Christie 2016).	solo-system.github.io/home.html
Teledyne Reson (Denmark)	Marine acoustic monitoring equipment, mainly for industrial and military purposes, but also produce a range of hydrophones useful for bioacoustic research.	Aquatic	Various hydrophone models; website includes a useful hydrophone look-up table.	www.teledyne-reson.com
Titley Scientific (UK)	Anabat Systems range of bat detectors. Mainly use zero-crossing/ frequency-division detection, but some also include heterodyne and full-spectrum/time-expansion modes.	Terrestrial, bats	Anabat SD2 (frequency-division); Anabat Walkabout (zero-crossing/time-expansion/ heterodyne) bat detector; Anabat Express (zero-crossing, waterproof, static sensor). Analook analysis software.	www.titley-scientific.com
Wildlife Acoustics (USA)	Wide range of bioacoustic recorders, microphones, hydrophones and analysis softwares, suitable for a range of taxonomic groups and habitat deployments.	Terrestrial and aquatic, all taxonomic groups	Song Meter audible range (e.g. SM3, SM4) and full-spectrum and zero-crossing ultrasonic (e.g. SM3BAT, SM4BAT) recorders for terrestrial habitats. Song Meter SM3M Deep Water and Submersible for marine habitats at a range of depths. Analysis softwares include Kaleidoscope (bats) and Song Scope.	www.wildlifeacoustics.com

Table 6: Software packages and tools for analysis of acoustic recordings, including both specialist bioacoustics packages, many of which include detection/classification tools, and general use software (current at time of publishing).

Software	Availability	Summary	Website
ARBIMON II	Free initially, charges apply for larger quantities of data	Cloud-computing based bioacoustics storage and analysis platform (Aide 2013); features include visualising and annotated recordings, soundscape analysis and automated call detection via pattern matching.	arbimon.sieve-analytics.com
Audacity	Free, open source	Intuitive, general-use audio software that enables listening, viewing spectrograms, subsetting and annotating files.	www.audacityteam.org
AudioTagger	Free	Free audio software for listening, viewing and manually annotating large volumes of audio files.	github.com/groakat/AudioTagger
AviSoft	Proprietary (AviSoft-SASLab Pro); free (Lite)	Bioacoustic analysis software, functions include visualisation and annotation, automated classification tools (spectrogram cross-correlation), geo-referencing tools and noise analysis.	www.avisoft.com
BatScope	Free	Free software for visualising and analysing full-spectrum bat recordings, including automatic species call classifiers.	www.wsl.ch/dienstleistungen/produkte/software/batscope/index_EN
iBatsID	Free	Free software tool for classifying European bat call recordings to genus and species (Walters *et al*. 2012); requires call parameters extracted by SonoBat (see below).	ibatsid.eu-west-1.elasticbeanstalk.com
CPOD.exe	Free	Free software for analysing data collected by T-PODs and C-PODs. Reads raw data from the C-POD SD cards and detects trains of cetacean clicks and classifies into groups (e.g. narrow-band high frequency clicks and other cetaceans).	www.chelonia.co.uk/cpod_downloads.htm
Ishmael	Free	Specialised bioacoustics software from CIMRS, with a marine emphasis. Includes visualisation and annotation tools and functions for aquatic sound localisation and automated call recognition.	www.bioacoustics.us/ishmael.html
Kaleidoscope	Proprietary (Kaleidoscope Pro), however spectrogram viewer tool is free	Software package by Wildlife Acoustics for bioacoustic analysis, including methods to visualise and annotate files, tools for cluster analysis and classifier training, batch processing, and bat call classifiers.	www.wildlifeacoustics.com/products/kaleidoscope-software
PAMGUARD	Free, open-source	Open-source package for bioacoustic research, with an emphasis on marine mammals. In addition to core acoustic analysis functionality, a variety of plugins are available for more complex signal processing and analysis, including detection, classification and localisation.	www.pamguard.org
Pumilio	Free, open-source	Open-source application for managing bioacoustic recordings, including visualising, annotating and manipulating sound files (see Villanueva-Rivera *et al* 2012).	ljvillanueva.github.io/pumilio
Raven	Proprietary (Raven Pro); free (Raven Lite)	Sound analysis software from Cornell Lab of Ornithology, with functions including visualisation/annotation, call detection and spectrogram correlation.	www.birds.cornell.edu/brp/raven/RavenOverview.html

Table 6 (cont): Software packages and tools for analysis of acoustic recordings, including both specialist bioacoustics packages, many of which include detection/classification tools, and general use software (current at time of publishing).

Software	Availability	Summary	Website
Seewave (R package)	Free, open source	Package for the open-source statistical environment R, providing a range of tools for bioacoustic analysis including visualisation, annotation and calculating acoustic indices.	rug.mnhn.fr/seewave
Song Scope	Proprietary	Software by Wildlife Acoustics for spectrogram visualisation, including over long timescales.	www.wildlifeacoustics.com/products/song-scope-overview
Sonobat	Proprietary	Software for analysis of full-spectrum bat recordings; features include visualisation, call detection, parameter extraction and species classification.	www.sonobat.com
SonoChiro	Proprietary	Software for automated analysis of full-spectrum bat recordings, designed for use with large volumes of data. Includes automated species classifiers for Europe and the Neotropics.	www.biotope.fr/fr/accueil-innovation/sonochiro
Soundecology (R package)	Free, open source	Package for R providing functions to calculate soundscape indices from spectrograms.	cran.r-project.org/web/packages/soundecology/index.html
Tadarida	Free	Open software and code for developing and applying an acoustic classifier.	github.com/YvesBas (Bas *et al*. 2017).
WarbleR (R package)	Free, open-source	Package for R providing a range of functions for batch processing of bioacoustic signals, including spectrogram visualisation, feature extraction, cross-correlation functions and recording quality assessment	cran.r-project.org/web/packages/warbleR/index.html

9 RECOMMENDED READING

This section contains a concise list of references, from books and the scientific literature, that provide useful reviews and guides to further conceptual and methodological approaches to acoustic wildlife monitoring. The guidelines in this report are sufficient for initial equipment deployment and basic analysis of data. These references provide further detail on concepts in the study of bioacoustics and more complex methods in sensor deployment, signal processing and acoustic data analysis.

Blumstein *et al.* (2011) Acoustic monitoring in terrestrial environments using microphone arrays: applications, technological considerations and prospectus. J. Applied Ecol., 48, 758–767.

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Pijanowski *et al* (2011) What is soundscape ecology? An introduction and overview of an emerging new science. Landscape Ecol.

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Walters *et al* (2013) Challenges of using bioacoustics to globally monitor bats. In Adams, Peterson (eds), Bat Evolution, Ecology and Conservation: New York, Springer 2013.

10 GLOSSARY OF TERMS

Acoustic index/indices – An acoustic index is a mathematical function calculated to describe some aspect of the spectral and temporal diversity or complexity of a sound recording. The current variety of acoustic indices are reviewed in (Sueur *et al.* 2014). Indices for the study of acoustic biodiversity were originally conceived as analogous to traditional community ecology and biodiversity metrics such as acoustic diversity or complexity. They are generally used to summarise global spectral and temporal characteristics of sound recordings, in order to study their relationships to biodiversity, habitat features and global change (see ecoacoustics).

Acoustic monitoring – In this guide we use the term acoustic monitoring specifically to refer to passive acoustic monitoring. This is the use of acoustic sensors to passively record sound from the environment, which is then used to infer ecological information about vocalising animals or acoustic habitat properties. It is distinct from active acoustic monitoring, which involves the detection of sounds from man made acoustic emitters (such as on-animal tags).

Acoustic sensor – Any combination of sound recorder, detector, microphone and/or hydrophone, designed to detect and record sound in the environment. This could be an integrated bioacoustic recorder, or a custom combination of these components. Most contemporary acoustic sensors record sound digitally (see section 2).

Audible range – Refers to any acoustic signal within the frequency range of human hearing, which is typically 20Hz to 20kHz.

Bioacoustics – a discipline of biology concerned with the study of the emission, propagation and reception of acoustic signals by animals.

Ecoacoustics – Ecoacoustics is an emerging discipline concerned with the analysis of environmental sound recordings for ecological purposes (Sueur & Farina 2015), and is closely related to research under the heading of soundscape ecology (Pijanowski *et al.* 2011a). It is distinct from bioacoustics due to its focus on ecological communities and biodiversity. Acoustic indices are among the major tools used in ecoacoustic research. These summarise global spectral and temporal characteristics of sound recordings in order to study their relationships to biodiversity, habitat features and global change.

Features (in sound classification) – in sound classification, features are parameters extracted from a sound of interest that describe its spectral and temporal characteristics (see Figure 5D). These are generally compared to a library of known species calls to identify a closest match, either manually or using automated machine learning methods.

Frequency – the frequency of a sound wave is its number of cycles per unit time, measured in hertz (Hz; cycles per second) or kilohertz (kHz; thousands of cycles per second). The term spectral relates to a sound's frequency characteristics.

Infrasound (infrasonic) – Refers to any acoustic signal below the frequency range of human heating, which is typically below 20Hz. Some animals, including mysticete whales and elephants, vocalise at infrasonic frequencies.

Machine learning – Machine learning methods are a family of computational data analysis tools that employ algorithms to learn patterns from, and then make predictions on, data. In acoustic analysis they are mainly used for detection and classification of signals within sound recordings. In essence, machine learning classifiers compare an unknown signal to a learned library of known species calls (call library) and report the closest match with a probability of correct classification. They include methods such as random forest, Hidden Markov Models, artificial neural networks and support vector machines, as well as newer deep learning methods such as convolutional neural networks.

Monitoring – Ecological monitoring involves the repeated collection of ecological data over long timescales, usually years to decades, in order to assess changes over time. These include trends in species populations and distributions, phenology, and how these are impacted by global change processes such as climate change and land-use.

Nyquist frequency – see sampling rate.

Passive acoustic monitoring – the use of passive acoustic sensors to survey and monitor wildlife and the acoustic environment (see acoustic monitoring and acoustic sensor).

Sampling rate – the rate at which an incoming sound wave is sampled during the process of digital recording, typically measured in kilohertz (kHz; thousands of samples per second). The sampling rate determines the ability to accurately resolve frequency information from a digitally recorded sound. Sampling rate must be at least twice as high as the highest frequency of interest (Nyquist frequency). For audible range sound this is typically 44.1kHz, whereas to fully resolve bat and cetacean echolocation calls, full spectrum ultrasonic recorders must sample at between 200 and 400kHz.

Signal detection – The process of locating signals of interest within a sound recording. This may be manual (done by eye/ear) or automated (using computational tools).

Signal classification – The process of classifying a signal of interest to a particular category, for example identifying it to an animal species. This may be carried out manually or with automated tools; the latter estimate the probability that a particular classification is correct.

Survey – Ecological surveys involve the systematic collection of ecological data about a given species, habitat or region, generally over a short time period. These data may then be used to estimate factors such as population size and density, species occupancy and distribution and habitat associations. Surveys are distinct from monitoring, which involves carrying out surveys over multiple years in order to assess ecological trends. In the context of this report, a survey refers to short-term ecological data collection carried out using acoustic sensors.

Spectral – Relating to the frequency of a sound (see frequency).

Ultrasound (ultrasonic) – Refers to any acoustic signal above the frequency range of human hearing, which is typically above 20kHz. In order to detect ultrasound, specialised recorders or detectors are needed that record at sufficiently high sampling rates (if recording in full-spectrum), or convert a signal into audible range sound (e.g. time expansion detectors).

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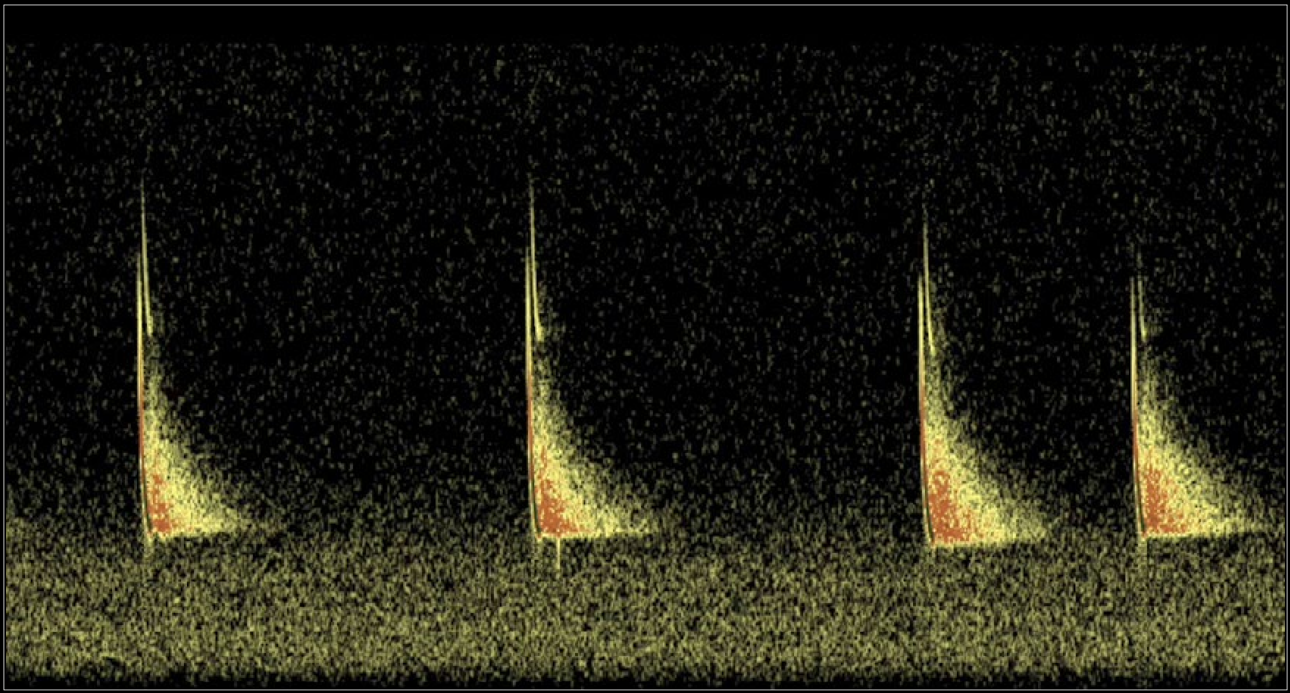
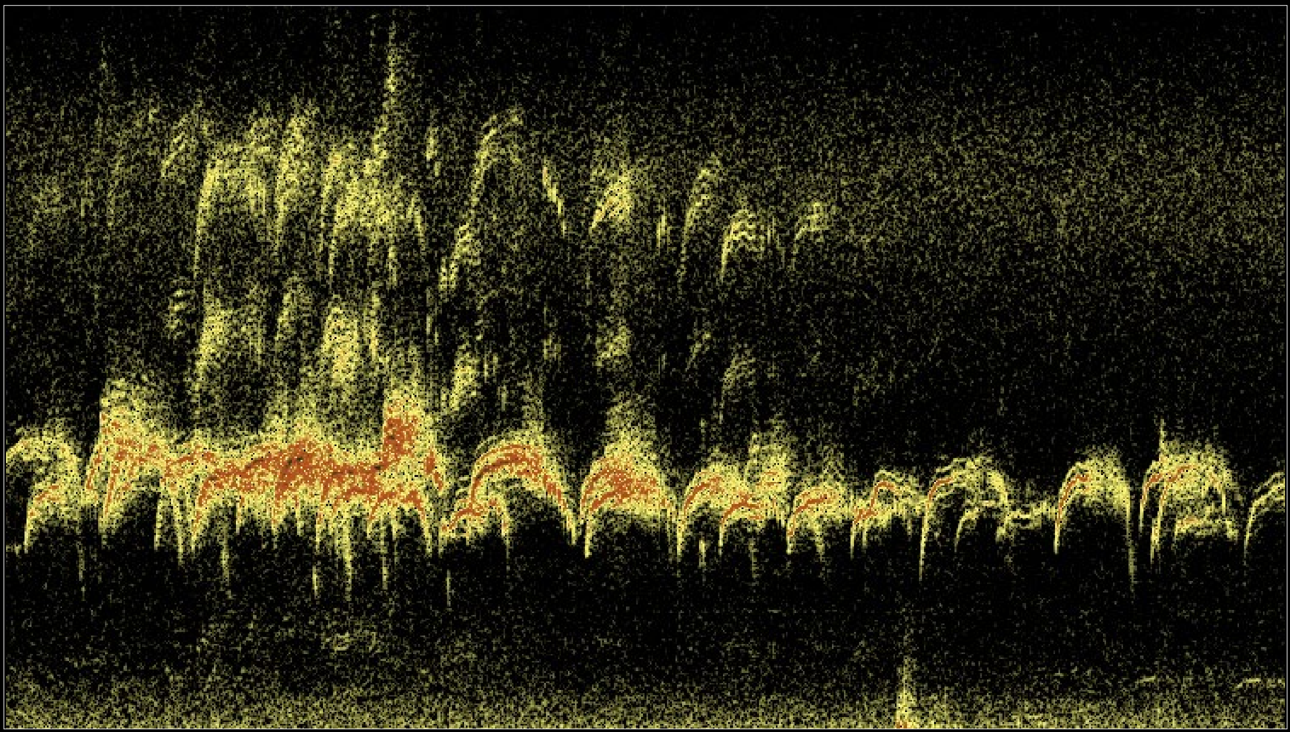
A spectrogram of recording of bat bats and birds, with time on the x-axis, frequency on the y-axis, and amplitude (power) shown as colour intensity. The calls are visible as bright yellow markings against a black background.





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