Good practice guidelines for long-term ecoacoustic monitoring in the UK

With a particular focus on terrestrial biodiversity at the human-audible frequency range

Foreword

The popularity of ecoacoustics as an innovative environmental discipline has enjoyed immense growth within the last five years, to a point where it is now becoming difficult to keep up with all the new research papers published. What soon becomes apparent, however, is a lack of consensus on which recording and analysis protocols to follow; partly a result of the differing requirements of each research project, but also an historical artefact of the tropical origins of much of this research. As more acoustic long-term monitoring schemes start to become established throughout the UK and neighbouring countries there arises a need to adopt a more common set of protocols, more akin to our temperate conditions, to allow for valid future analysis and comparison. To that end a group of ecoacoustic researchers and practitioners met in June 2022 to discuss the formulation of such a set. This work was then taken forward by the authors to generate the guidelines contained herein.

Digital technologies now allow us the ability to record our acoustic environments widely, with relative ease; and to subject the resulting recordings to an ever-expanding range of analytical methods. This opens up the potential to create new approaches to gauging biodiversity and assessing the changing fortunes of species and their habitats. To maximise these benefits it is vitally important that we secure now, and into the future, data which will illustrate baseline assessments and highlight change. These guidelines therefore provide welcome instruction and conformity, particularly for those new to ecoacoustics. Please use them, as appropriate, to help guide your own contributions to the growing awareness, and use, of sound as an environmental metric within the UK and Europe.
Bob Ashington (Natural England)

Figure I. Urban nesting Kittiwakes *Rissa tridactyla*. Passive acoustic monitoring has been used to effectively monitor large seabird colonies - could these noisy birds be a good candidate for long-term ecoacoustic monitoring?

Aims

Our good practice guidelines represent the opinions of an experienced team of researchers and consultants who have come together to synthesise the latest academic research and expert judgement on field-proven ways to apply ecoacoustic survey techniques, especially tailored to long-term biodiversity monitoring. The guidelines are focussed on the use of ecoacoustic monitoring of audible sounds within terrestrial, temperate ecosystems typical of the UK and elsewhere in Europe, but we hope they will have wider application. We explicitly do not consider biodiversity that sonifies in the ultrasonic, or marine acoustics, as well-developed monitoring protocols already exist for this purpose - although naturally there is a degree of overlap.
The co-production of these guidelines follows a UK Acoustics Network (UKAN+) ecoacoustics symposium held at Manchester Metropolitan University, Manchester, UK on 15-16th June 2022, and attended by over 160 people both online and in-person. The guidelines are intended to reflect the discussions and emerging conclusions from that event - as well as applicable information and research generated around the world on the topic.

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Contents

Executive Summary

Passive acoustic monitoring has great potential as a cost-effective method for long-term biodiversity monitoring. However, to maximise its efficacy, standardisation of survey protocols is necessary to ensure data are comparable and permit reliable inferences.

The aim of these guidelines is to outline a basic long-term acoustic monitoring protocol that can be adapted to suit a range of projects according to specific objectives and size. Here we summarise some basic recommendations for audible-range terrestrial ecosystem monitoring - more detail can be found in the following chapters. A 'Quick start guide' giving further rationale for these recommendations can be found in Appendix 1.

Equipment and settings

Recording devices should be capable of **autonomous recording for extended periods** (Section 2.2) to minimise disturbance of the study site and use microphones with a **flat frequency response** across human-audible frequencies (Section 2.1). **All devices in a study should ideally be the same model** (Section 2.5), and with a **consistent gain setting** across all recorders (Section 2.1). A non-exhaustive list of available devices is available in Table 2.1.

We provide a recommended quick-start protocol for those new to ecoacoustics projects in Appendix 1. This recommends the follow settings and programme:

- Sounds should be recorded in **.wav format**, at a bit depth of **16-bits**, and with a **48kHz sampling rate**.
- Sounds should be recorded as **1 minute length** files, with **one recording every five minutes** (1 minute on - 4 minutes off) through the **full 24 hour** daily cycle.
- Deployments should last for a minimum of **one week**, and take place four times per year, **one in each season**.
- Recording devices should be placed at least **250 metres apart**, with their **locations selected** in relation to habitat type or other features of interest.

Consistent metadata should be collected for each deployment, with each term matching an equivalent in Audobon Core (Section 3.4).

Analysis

We recommend including both targeted and whole soundscape analysis.

Targeted analysis

Birds are readily detectable using Passive Acoustic Monitoring, are a relatively speciose group which are well-studied both in terms of their suitability for passive acoustic monitoring and UK ecology; we recommend including **targeted bird surveys**, although other taxa may be preferential in different circumstances (see Chapter 5).

Targeted studies should be conducted using **recorders set at least 250m apart** over a suitable area (Section 3.2). Sampling should be conducted **across the breeding season** and for at least **one week in each of summer, autumn, and winter** (Section 3.1). At least one hour of data should be sampled for analysis, with recordings of **one minute duration** and spaced **at least 5 minutes apart** during deployment, which **should cover the diel period from 30 minutes before sunrise until four hours after sunrise** (Section 3.1).

Detection and identification of the species present should be conducted either **manually** or using a **well-tested automated identification algorithm** such as BirdNET (Section 5.1). At least some traditional bird surveys should be conducted in parallel to confirm the efficacy of the monitoring protocol.

Soundscape analysis

Soundscape analysis can give insights into environmental sound including anthropogenic noise pollution, and the acoustic community diversity and their interactions (see Chapter 6).

Sampling for soundscape monitoring should comprise at **least one month of deployment of independent recorders (i.e., > 250m apart) during each of the four seasons**, consistently repeated across years, and comprise **one minute of recording for every five minutes across the diel cycle** (Section 3.1). Analyses should be undertaken with **acoustic indices** whose properties are well understood (for example the Acoustic Complexity Index or the Bioacoustic Index), and **at frequency ranges suitable for the environment** (Section 6.2). At least some ground-truthing (such as the targeted bird surveys above) should be conducted.

This basic protocol can be adapted to suit the constraints and objectives of your monitoring project. The discussion in the following chapters aims to provide you with the requisite knowledge and insight to make sensible decisions to this end. Equally, it would be straightforward to extend this monitoring protocol to include species vocalising in ultrasonic ranges such as bats and small mammals, using the pre-existing guidance documents highlighted in Chapter 1.

Figure 1.1. Passive Acoustic Monitoring offers the opportunity to monitor rewilding projects such as this one at Sunart Fields, Derbyshire. Credit Rachel Evatt

Glossary

Note that some of these terms have a more general meaning (e.g. 'array', 'aliasing') - here we define them in the context they are used in these guidelines.

Terminology	Definition
acoustic indices	Statistical summaries of sound energy. Many are designed for use as proxies for traditional ecological metrics like species richness (see Chapter 6).
aliasing	When the frequency of the original sound signal is misidentified during digital representation due to insufficient sampling rate.
anthropophony	Sound produced from man-made sources, e.g. traffic noise (see section 4.4). ***Note:*** *sometimes shortened to 'anthrophony' elsewhere, or described as technophony*
array	Multiple microphones recording simultaneously at a monitoring location (see section 3.2).
attenuation	The energy loss of a sound wave as it travels through air, water, soil or other media (see section 3.2.1.).
audible sounds	Sounds which have frequencies between 20Hz and 20 kHz
autonomous recording unit (ARU)	Audio recording devices which can be programmed to record at set times and left unattended in the field (due to autonomous powering and data storage or transmission) for passive acoustic monitoring (see Chapter 2).
bioacoustics	The study of the production, transmission and detection of sounds by animals.
biophony	Sound produced from biological sources, e.g. bird song.
bit depth	The number of bits (0s or 1s) used to store each sample: a higher number increases the amplitude resolution and decreases the theoretical signal to noise ratio (see section 2.1.1.).
clipping	Sound signal distortion which occurs when an amplifier receives a signal beyond its maximum sound pressure level. The top and bottom of soundwaves are cut off or 'clipped' (see section 2.1.2.).
detection distance	The maximum distance at which a recorder can detect target sound signals. This distance varies depending on the properties (amplitude/ frequency/ etc.) of the emitted sound (see section 3.2.1.).
diel cycle	The full 24 hour period.
dynamic range	The sound pressure level between the highest and lowest amplitude levels that a microphone can handle (see section 2.1.2.).
ecoacoustics	A fundamental and applied science that investigates the ecological role of sound across levels of ecological organisation.
false-colour spectrogram	Spectrograms which use the results of three acoustic indices as the values in the Red-Green-Blue channels to colourise the spectrogram (see section 4.3.).
fast Fourier transform (commonly abbreviated to FFT)	A signal processing method used to transform audio data from the time-amplitude domain to the time-frequency domain. Within a given time window, the frequency components of the signal and their relative amplitudes are calculated. Applied over the recording as a sliding window, a spectrogram is generated enabling visual sound identification.
frequency response	The variation in sensitivity of a microphone to different frequencies within the range that it can detect (see section 2.1.2.).
gain	The amount of amplification the recorder applies to the incoming audio signal before recording it (see section 2.1.1.).
geophony	Sound produced from non-living environmental sources, e.g. wind, water
infrasonic	Sounds with frequencies below the lower limit of human hearing (< 20Hz).
machine learning	Computational models developed using algorithms and statistical models that develop through data-based inference, rather than following explicit sets of rules as in traditional programming (see sections 5.1.5. and 6.5.
passive acoustic monitoring (PAM)	Automated recording of sounds for ecological monitoring, without the need for human presence.
recording format	The file format in which an ARU is able to store sound recordings (e.g. WAV, FLAC, MP3) (see section 2.1.1.).
recording period	Periods of time during deployment of an ARU when the recorder is active, normally arranged for when target ecological activity takes place. An appropriate sampling schedule must be chosen to record a representative sample of acoustic activity from these periods (see section 3.1.2.).

Terminology	Definition
recording time	How long an ARU can record continuously (see section 2.1.1.).
sampling rate	The number of samples of audio taken per second by a recording device. A sampling rate of 48,000 Hz represents 48,000 samples per second and determines the frequency resolution of the recording (see section 2.1.1.).
sampling schedule	The time that an ARU is set to record during deployment. For example, a device may be set to record for 5 minutes out of every hour across the targeted recording period (see section 3.1.3.).
signal-to-noise ratio	Decibel (dB) measure of how clearly the loudest sounds (signals) stand out from quieter background sounds (noise) made by the electronics in the microphone and recorder itself (see section 2.1.2.).
soniferous species	Species which deliberately produce sounds e.g. song, calls, stridulation, drumming, etc.
sound pressure level (SPL)	The pressure deviation from ambient levels caused by a sound wave. Measured in decibels (dB SPL) which is the signal amplitude proportional to the quietest pressure waves humans can hear (2x10-5 Pa). (see section 2.1.2.).
soundscape	The whole acoustic environment resulting from the combination of all audible sounds in an ecosystem (see Chapter 6).
spectrogram	Visual representations of the spectrum of frequencies in a sound file, with frequency on the y-axis, time on the x-axis and amplitude expressed through intensity of colour (see Figure 2.3).
ultrasonic	Sounds with a frequency above the upper limit of human hearing (i.e. sounds above 20,000 Hz).
waveform	The waveform of a signal (sound) is a graph showing amplitude versus time (Figure 2.3).
zero-crossing-rate	The number of times an audio signal crosses zero (negative to positive or vice versa), this serves as a primitive proxy for basic pitch detection.

Chapter 1: Introduction

1.1 Biodiversity monitoring

The entwined global biodiversity and climate crises and their effect on associated ecosystem services pose a serious threat to planetary health as well as human health, well-being and the global economy[1]. This is particularly evident in the United Kingdom, one of the most nature-depleted countries on the planet[2]. Given this context, monitoring biodiversity is vital to provide information on the status of wildlife populations, invasive species, changes in habitat quality and resilience of ecosystem functions. In turn, effective biodiversity monitoring is a requirement for evidence-led conservation policy and the adoption of effective adaptive management protocols.

The UK government and civil society have responded to the threat of biodiversity loss with a range of measures aimed at conserving and increasing biodiversity. These currently include the Biodiversity Net Gain[3] approach to development, an increased focus on agri-environment schemes, and a rapid increase in rewilding projects across the country[4] – alongside the continuation of more traditional conservation actions. Given the recent commitments at COP 15[5] to restore 30% of degraded land and protect 30% of the most important areas for biodiversity globally - it is likely we will see an increase and diversification of these projects in the coming years.

These large-scale projects and schemes require biodiversity monitoring effective over broad spatial and temporal scales. Many of the UK government responses are born from the credo of the Lawton report[6] - *'More, bigger, better, and joined up'* – meaning that they are intended to foster change at large spatial scales. There is also an increased understanding that ecological change, both positive and negative, occurs over long periods and not just as an immediate response to one-off interventions[7]. In consequence, ecosystem monitoring is in increased (and long-term) demand, but is not always feasible with traditional 'boots on the ground' survey methods.

Fortunately, a range of new, technology-driven, approaches are being developed in wildlife monitoring globally[8,9]. These include the use of drones, camera traps, and the focus of these guidelines, autonomous sound recording units (ARUs),which can be deployed in the field to collect sound recordings without regular intervention. These new technologies offer the capacity to accumulate large quantities of environmental data, whilst also presenting novel practical and analytical challenges[10,11]. These challenges are exacerbated by lack of standards. These guidelines therefore set out current good practice for the use of ARUs for long-term biodiversity monitoring.

1.2. Why use ecoacoustic monitoring?

Ecoacoustics is an interdisciplinary science that investigates natural and anthropogenic sounds and their relationship with the environment. An increasing range of ecoacoustic methods support the use of sound to study the environment. This is a rapidly expanding approach for the collection and analysis of environmental data, which offers potential for valuable contributions to long-term biodiversity monitoring and subsequent management9. Recent developments in more affordable ARUs and sophisticated and accessible audio data analysis tools have widened the taxonomic, temporal, and geographical scope of acoustic studies, as well as the research questions being investigated[12,13]. Prior to these developments, terrestrial acoustic research focussed primarily on recording bats with hand-held devices, with either no recording capability, or with subsequent manual acoustic analysis of the recordings. Geographically, passive acoustic studies were largely restricted to Europe and North America and limited in temporal scope. However, the passive acoustic research landscape is now changing dramatically.

The expanding availability of the ecoacoustic toolkit is reflected in a rising number of review papers on the use of ecoacoustics – highly useful resources for those new to the field. These include general reviews on the discipline of ecoacoustics[14,15], together with more targeted reviews on animal communication[16], avian bioacoustics[17,18,19], use in freshwater habitats[20,21], acoustic data processing[22], acoustic indices[23], localisation of individuals[24], and estimation of population densities[25,26].

Ecoacoustics is underpinned by the use of ARUs to record soundscapes in the absence of a human observer[27] thus allowing Passive Acoustic Monitoring (PAM). PAM has several advantages over more traditional survey methods. The biggest benefit of PAM is the capacity to function for long periods without frequent human intervention, allowing studies to be conducted over broad spatiotemporal scales[15,19]. This allows surveys to be conducted in places where regular access is logistically challenging, minimises human impact on the study site, eases surveying at times that are unfavourable for traditional surveys, and enables the collection of large quantities of data. Furthermore, pre-programmed recording schedules allow for a variety of sampling regimes, reducing power consumption and further extending the duration over which ARUs can record without human intervention - in a flexible, predictable, and replicable manner. This reduces the cost of data collection in comparison to traditional survey techniques[19], and facilitates targeting of nocturnal, rare, or hard to detect species that may only vocalise at specific times[28]. ARUs offer the capacity to record continuously and at broad frequency spectra, meaning that PAM can be used to simultaneously monitor all soniferous species in an area, increasing the cost-effectiveness of multi-taxa surveys and facilitating surveys of understudied taxonomic groups such as insects[15,29].

Figure 1.2. A typical deployment of an autonomous recording unit in UK woodland.

Practical obstacles slowing uptake of PAM have diminished in recent years. The cost of recording units has fallen greatly, with some costing as little as £65 (AudioMoth) and a general trend towards miniaturisation assisting with logistical challenges in field placement[22,30,31,32,33.] Similarly, memory cards for ARU devices have increased in capacity while their costs, and that of long-term storage, are falling. Meanwhile, cloud computing increasingly represents a long-term, relatively affordable solution for both data storage and computational capacity for analyses[34,35].

PAM offers several other advantages in both data collection and analysis over traditional in situ methods. For example, it makes standardisation of surveys easier, avoiding effects from observer presence[36] and observer bias in the field[37]. Critically, the collection of raw audio data can provide a permanent record, which has at least six benefits:

- They are permanent records of the surveys conducted, as well as the results encountered, something that may be of particular importance for those wishing to use PAM commercially.
- Due to the permanent data record, it is possible to verify and correct bias introduced at the analysis stage[19.]
- It limits the requirement for specialist observers in the field, as a single expert can independently analyse a large number of surveys afterwards[38,39,40].
- Data are available for reanalysis in case of technological advancements, or for application to new questions[38,41].
- The data can be used as tools to engage local stakeholders or engage wider audiences in conservation, for example around restoration and rewilding projects[42].
- Recordings represent an acoustic 'time capsule', providing historic records that may provide critical evidence of changing soundscapes in the decades to come[43].

Alongside these clear benefits, there are some challenges to the effective use of PAM:

- Acoustic methods can only record soniferous species when they are producing sound. Silent or quiet individuals or species will go undetected.
- Recording hardware is still being rapidly developed, and the microphone, circuitry and firmware varies between manufacturers and models, with consequent effects on the audio data collected.
- The storage of data for large projects can be problematic, and there are few established repositories in which to archive recordings.
- There are also current challenges in the analysis of ecoacoustic data and the interpretation of outputs.

However, with the exponential growth of this interdisciplinary field in recent years, combined with the reducing costs of equipment, data storage, computational power, and ever increasing commitments to address the biodiversity crisis, we believe that many of these challenges will be ameliorated in the near term.

Table 1.1. Benefits and challenges of passive acoustic monitoring and point counts for biodiversity monitoring. Adapted from Darras et al., 2019[19].

Item	Reason	PAM vs traditional methods – effect size*	Confidence that PAM has an advantage/ disadvantage
Soundscape analysis	Can only be undertaken with recorded acoustics	+++	**High**
Temporal scaling	ARUs can be deployed to record for long periods at any time of the day	+++	**High**
Data archiving	Acoustic data and analysis processes can be stored as a permanent record	+++	**High**
Standardisation	Sampling and analysis are easier to standardise with identical ARUs and computational analysis methods	+++	**Medium**
Multi-taxa surveys	The same acoustic data can be analysed for multiple taxa	+++	**Medium-High**
Reanalysing data	Surveys can be played back to find overlooked species, or re-analysed using new methods	+++	**High**
Phenology studies	Long-duration recordings facilitate long-term studies	+++	**High**
Avoiding disturbance	Human presence not required during survey periods	+++	**High**
Species richness	PAM more effective overall at detecting higher species richness	+++	**Medium-High**
Reliance on expert labour	Analysis can be undertaken away from busy survey periods, for instance outside breeding seasons when experts may have more availability	++	**High**
Spatial scaling	ARUs can be deployed at multiple sites to record simultaneously	++	**Medium**
Vocal activity rate	Relatively straightforward to measure with PAM	++	**Medium**
Localisation/ Non-invasive tracking	Complex, but could be done over long periods and in near real-time.	++	**Low**
Detection of rare species	Increased likelihood of detection with longer recordings, but impractical to actively search	+	**Medium**
Species occupancy	Easier to collect replicate samples	+	**Medium**
Material and labour costs	Dependent on number of sites/visits and distances to travel. Equipment is often more expensive, but requires fewer site visits	=	**Low**
Weather	Recordings impacted by wind and rain, but long deployments can allow sampling to avoid bad weather	=	**High**
Density	Can be estimated using PAM, but likely simpler in most cases to estimate density using traditional methods	-	**Low**
Behaviour	Lack of visual observations can make interpretation difficult	--	**Medium**
Number of detections	Not always clear how many calling individuals are present	--	**Medium**
Mobility	Restricted to stationary survey methods	---	**High**
Survey area	Difficult to estimate the exact area covered	---	**High**
Visual detections	No visual data – impossible to detect some species or behaviours	---	**High**

*(+++ indicates the largest advantage of PAM over traditional survey methods; - - - indicates the greatest disadvantage compared to traditional survey methods; = indicates there is no difference between PAM and traditional surveys methods.)

1.3 Purpose of these guidelines

Whilst these guidelines are likely to be of interest to anyone working in ecoacoustics, they are explicitly targeted at those wishing to use PAM for long-term acoustic monitoring of European biodiversity, with a particular focus on the UK and audible sounds. The objective is to provide a clear set of good-practice recommendations, drawing from academic literature and the authors' experience, for those with the greatest opportunity to apply PAM to biodiversity management projects – including land-managers, ecological consultants, conservation practitioners, and rewilders.

There are some ambiguities surrounding both what is meant by 'long-term' monitoring, and by the broad term 'biodiversity'. Whilst we do not wish to limit this document to use only at specific timescales, by 'long-term' we have in mind the sort of periods over which an agri-environment scheme may take effect (approx. 3-10 years), a large construction project that may need to be monitored for ecological impact (approx. 10 years), or the duration of a rewilding or net-gain project (perhaps 30+ years). Long-term monitoring can be conducted in two ways – either continuous or periodic. PAM can lend itself to both approaches. As the choice of intensity and duration of survey periods is likely to be highly dependent on local and project context, we do not attempt to prescribe a 'best' method, but highlight a range of tools and examples that are suitable, as evidenced by the scientific literature.

It is also necessary to define more narrowly what we mean by 'biodiversity'. These guidelines are aimed at facilitating the monitoring of terrestrial biodiversity that produces sound at or near human-audible frequencies (approximately 20 Hz - 20 kHz) - an area where good-practice guidelines are currently lacking. Aquatic biodiversity and species vocalising in ultrasound, such as bats, fall outside the remit of this guidance, in large part because very good guidelines already exist for acoustic monitoring of these taxa[44,45]. In practice, this means the focus is primarily on birds and many mammals, amphibians, and insects that produce sound at frequencies audible to humans. However, some of the information here will still be useful to those wishing to monitor aquatic and ultrasonic species, and these guidelines will apply to those wishing to simultaneously monitor wildlife that produce sound at any frequency. In practice, that means for species-specific considerations, the focus is primarily on birds, along with many mammals, amphibians, and insects that produce sound at frequencies audible to humans. In addition, we explicitly cover monitoring of whole soundscapes and how to relate these soundscapes to the biological components of the environment.

There are two main approaches for the use of acoustic data in biodiversity studies. The first is to detect, identify and analyse specific spectral and/or temporal features of the acoustic environment. We refer to this as 'targeted' monitoring - the detected features will most likely be sounds emitted by a target species. This method can also incorporate the detection and identification of any individual sound - for instance anthropogenic sounds in a study, such as gunshots, which may be evidence of disturbance events. The second approach is soundscape monitoring. Here the entire soundscape is treated as an emergent property of the landscape and environment, and is analysed through statistical representations of this whole. This can entail, for example, understanding whether it is a soundscape with a large variety of sounds from a range of sources, or a simpler soundscape with few and sparse sounds. A great deal more information is included on these differing approaches in Chapters 5 and 6 respectively, with their corresponding benefits and drawbacks. Which of the approaches is chosen (or how the two are combined) will influence all other aspects of study design.

Figure 1.3. Difficult habitat to survey on foot, such as wet woodland can be an excellent place to deploy autonomous recording units. Credit: Oliver Metcalf.

1.4. Soundscapes from the human perspective

Whilst these guidelines focus on ecoacoustics, another set of guidelines is currently being developed to study the soundscape as perceived by humans, with overlapping applications in acoustics, urban planning and design, and landscape design and management. These guidelines are contained within the following publications: 'ISO 12913 Acoustics - Soundscape Part 1: Definition and conceptual framework[46], Part 2: Data collection and reporting requirements[47], and Part 3: Data analysis', with further parts to be developed (British Standards Institution, 2014, 2018, 2019)[48]. This approach studies the soundscape through qualitative methods first, adopting a bottom-up approach, and afterwards by acoustic measurements, with a particular focus on human perception and amenity. Whilst these sets of guidelines are being developed separately, certain environmental research and industry projects might benefit from the integration of both, and users will likely find complementarity between the two.

1.5 How to use these guidelines

These guidelines are organised to take the reader through the process of carrying out an ecoacoustic monitoring study in the order that it might naturally occur – that is, from purchasing hardware, designing survey protocols, collecting acoustic data, analysing the data and inferring ecological insight. However, this is not necessarily the best order to plan a programme of passive acoustic monitoring. An optimal plan must be informed by the individual context and aims of each project, and inevitably shaped by time and financial constraints. For instance, someone reading the guidelines in the order presented here may determine that three top-of-the-range ARUs are preferable to ten cheaper but lower quality models, but on coming to the analysis chapter realise that the ecological analysis they hoped to conduct is simply not feasible with only three recording units. Similarly, a user with a very clear idea of the ecological objective of their study may determine the necessary analysis, but on reading the hardware chapter realise that undertaking such an analysis falls outside of their time or budget constraints and have to revisit which analyses are possible. Hence these guidelines are not intended to only be read linearly. Each chapter will inform trade-offs between each of the considerations above, and it is likely that a reader will want to move between the chapters as they plan a study.

We have attempted to provide a comprehensive introduction to all stages of ecoacoustic monitoring in these guidelines, but there is a great deal of literature elsewhere that contains valuable information on how to optimally conduct such surveys (see Table 1.2). Whilst we refer to these texts throughout, it is worth highlighting here a number of other excellent existing guidelines which readers may find useful

Figure 1.4. Grassland, wetland, and woodland can hold a diverse range of sonifying biodiversity. Credit: Oliver Metcalf.

Table 1.2. Selected acoustic monitoring guidelines for other taxa and regions.
For the full table see Appendix 2.

Taxa	Region	Title	Authors and link
Amphibians	**USA**	Amphibian Monitoring Protocol (Version 2.0)	National Park Service, Great Lakes Inventory and Monitoring Network https://www.nps.gov/im/glkn/amphibians.htm
Bats	**USA**	Range-wide Indiana bat & Northern long-eared bat survey guidelines.	U.S. Fish and Wildlife Service. (2022). https://www.fws.gov/library/collections/range-wide-indiana-bat-and-northern-long-eared-bat-survey-guidelines
Bats	**USA**	Guidance for conducting acoustic surveys for bats: Version 1 detector deployment, file processing and database version	National Park Service https://irma.nps.gov/DataStore/Reference/Profile/2231984
Bats	**UK**	Designing effective survey and sampling protocols for passive acoustic monitoring as part of the national bat monitoring	Newson, S.E., Boughey, K.L., Robinson, R.A. & Gillings, S. 2021. JNCC Report No. 688, JNCC, Peterborough, ISSN 0963-8091 https://hub.jncc.gov.uk/assets/4cc324dc-1ad8-446e-acdd-a656348025b3
Bats	**Scotland**	Bats and onshore wind turbines - survey, assessment and mitigation	NatureScot, 2021 https://www.nature.scot/doc/bats-and-onshore-wind-turbines-survey-assessment-and-mitigation
Bats	**UK**	Bat Surveys for Professional Ecologists: Good Practice Guidelines	Collins, J. (ed.) (2016). 3rd edition. The Bat Conservation Trust, London. ISBN-13 978-1-872745-96-1 https://www.bats.org.uk/resources/guidance-for-professionals/bat-surveys-for-professional-ecologists-good-practice-guidelines-3rd-edition
Bats	**UK**	Guidelines for passive acoustics surveys of bats in woodland	Bat Conservation Trust https://www.bats.org.uk/our-work/national-bat-monitoring-programme/passive-acoustic-surveys/guidelines-for-passive-acoustic-surveys-of-bats-in-woodland
Birds	**Canada**	How to Most Effectively Use Autonomous Recording Units When Data are Processed by Human Listeners	Bayne, E., Knaggs, M., and Sólymos, P. Bioacoustic Unit, Bayne Lab at the University of Alberta & Alberta Biodiversity Monitoring Institute. 2017 http://bioacoustic.abmi.ca/wp-content/uploads/2017/08/ARUs_and_Human_Listeners.pdf
Birds	**UK**	Bird Bioacoustic Surveys – Developing a Standard Protocol	Abrahams, C. In Practice the Bulletin of the Chartered Institute of Ecology and Environmental Management. December 2018. https://www.researchgate.net/publication/329443381_Bird_Bioacoustic_Surveys_-_Developing_a_Standard_Protocol
Cetaceans	**USA**	Baseline Long-term Passive Acoustic Monitoring of Baleen and Sperm Whales and Offshore Wind Development	Appendix I of: Van Parijs, S. M., Baker, K., Carduner, J., Daly, J., Davis, G. E., Esch, C., … Staaterman, E. (2021). NOAA and BOEM Minimum Recommendations for Use of Passive Acoustic Listening Systems in Offshore Wind Energy Development Monitoring and Mitigation Programs. Frontiers in Marine Science, 8, 1575. doi:10.3389/fmars.2021.760840
Cetaceans	**Scotland**	Use of Static Passive Acoustic Monitoring (PAM) for monitoring cetaceans at Marine Renewable Energy Installations (MREIs) for Marine Scotland	Embling, C. B., Wilson, B., Benjamins, S., Pikesley, S., Thompson, P., Graham, I., Cheney, B., Brookes, K.L., Godley, B.J. & Witt, M. J. https://tethys.pnnl.gov/sites/default/files/publications/emblingetal.pdf
Soundscapes	**Norway**	Management relevant applications of acoustic monitoring for Norwegian nature – The Sound of Norway	Sethi, S. S., Fossøy, F., Cretois, B. & Rosten, C. M. 2021.. NINA Report 2064. Norwegian Institute for Nature Research. https://brage.nina.no/nina-xmlui/handle/11250/2832294
Soundscapes and animals	**Global**	Passive acoustic monitoring in ecology and conservation	Ella Browning, Rory Gibb, Paul Glover-Kapfer & Kate E. Jones. 2017. WWF Conservation Technology Series 1(2). WWF-UK, Woking, United Kingdom. https://www.wwf.org.uk/sites/default/files/2019-04/Acousticmonitoring-WWF-guidelines.pdf
Soundscapes	**UK**	The potential use of acoustic indices for biodiversity monitoring at long-term ecological research (LTER) sites	Andrews, C. and Dick, J. 2021. UK Centre for Ecology & Hydrology https://nora.nerc.ac.uk/id/eprint/531301/1/N531301CR.pdf

These guidelines represent the current opinions of experts in the field on what constitutes good practice for long-term acoustic monitoring of UK biodiversity. That does not mean they are perfect; not every challenge in ecoacoustic monitoring has been investigated, quantified, or properly assessed, and the available hardware and software tools are constantly evolving. The guidelines, therefore, can only supplement the knowledge and experience of those undertaking monitoring studies.

Whilst we have attempted to make these guidelines as comprehensive as possible, there is no substitute for experience. As an emerging interdisciplinary field, it can be challenging to find expertise in all of the relevant subdisciplines when carrying out a project – ecology, acoustics, signal processing, statistics, and in some cases machine-learning. Nevertheless, we urge those wishing to undertake acoustic monitoring of biodiversity without such a range of skills not to be put off, but to reach out to the myriad sources of help and information highlighted in this document prior to designing or undertaking their studies.

Finally, as the ultimate end product of biodiversity monitoring is ecological knowledge, the value of real-world, local, expertise is paramount. It is vital that the information and guidance in this document is interpreted by experienced and skilled ecologists at every step in order to apply these methods in an optimal manner.

Figure 1.5. Difficult habitat to survey on foot, such as marsh can be an excellent place to deploy autonomous recording units. Credit: Oliver Metcalf.

Chapter 2: Hardware

Autonomous recording units (ARUs) underpin ecoacoustic monitoring, enabling the collection of extensive amounts of data with relative ease. Recent years have seen significant developments in the price, quality, and availability of these devices - although, not necessarily simultaneously in the same device. It is, however, a fast-moving area of development, with new devices emerging annually. Choosing which unit to purchase is likely to be one of the first decisions made by those looking to take up ecoacoustic monitoring. Yet, there are complex trade-offs to be made, and deciding on the best unit for a particular monitoring situation should be made after obtaining a clear idea of the objective of the study, potential recording schedules and requisite analysis methods[49]. In this chapter, we provide an introduction to ARUs, describing key considerations for hardware specification, device cost, and the need for device performance calibration.

2.1. ARU Specifications and what they mean

Most passive acoustic hardware comes with a long list of technical specifications, but for the novice ecoacoustician it may not always be clear what these mean, or how important they are. This section explains some of the common specifications found in passive acoustic hardware manuals.

2.1.1. Automated recording unit

Size and weight - these specifications are fairly self-explanatory, but are an important consideration. Larger units can often hold more batteries and memory cards, so can be left in the field for longer, but may take longer to deploy and collect as fewer can be carried in a single trip. In addition, smaller units can be easier to find ideal deployment locations for and are less obtrusive in the field, which also reduces the chance of theft.

Recording Time - how long an ARU can record continuously. Note that these manufacturer values are often given based on battery capacity rather than memory storage limits - recording at a high sampling rate may mean that the memory cards fill before the batteries run out; similarly the battery life will depend upon battery type, recording schedule and temperature. See Figure 6 in Sugai et al. (2020)[12] for an illustration of these tradeoffs. Because there is a greater power draw on start up, non-continuous recording schedules may reduce total record time, but most manufacturer's scheduling softwares are able to estimate the maximum total recording time based on different schedules.

Recording Format - the file format in which the unit is able to store sound recordings. The default option here is the .wav file format, which saves uncompressed data. Some units offer the capacity to record in lossless compression formats (.FLAC or .W4V), or lossy compressed (.MP3), which can dramatically increase the storage capacity. Lossy formats irreversibly alter the acoustic data in a way that is inaudible to humans, but that may potentially lose ecologically valuable sound data.

Sample Rates - the sampling rate is how often the recording device samples the analogue signal in order to convert it to a digital representation. The sound signal needs to be sampled at least twice the rate of the maximum frequency of the sound of interest, e.g. using a sampling rate of 4 kHz will allow recording of sounds up to just 2 kHz, whilst a sampling rate of 36 kHz will allow the recording of sounds up to 18 kHz. It is therefore necessary to ensure that the chosen ARU has an available sampling rate double that of the maximum frequency of the sounds you wish to record. For human-audible frequencies this is generally not an issue, but for those wishing to use the same device to record bats, it is worth ensuring that the device sampling rates go high enough to record ultrasound. Most, if not all, devices offer variable sampling rates. This is a useful feature, as the size of the audio file increases linearly with the sampling rate (e.g. a 1 minute audio file recorded at 32 kHz sampling rate requires twice as much storage space on disk as one recorded at 16 kHz). For projects focussed on only species vocalising at low frequencies, being able to record at a low sampling rate is therefore a useful memory-saving feature.

Figure 2.1. Audiomoths are small and relatively cheap, making them readily deployable in a range of locations and with custom-made covers.
Credit: Oliver Metcalf.

Bit depth - The number of bits (0s or 1s) used to store each sample: a higher number increases the amplitude resolution and decreases the theoretical signal to noise ratio. Digital data are stored in binary values thus a bit depth of n can store a range 2^n. A 8-bit system has a resolution of 256, 16-bit gives 65,536 etc. A higher bit depth therefore uses more memory when recording audio, but also allows for greater recovery of data in the case of audio clipping.

Power Options - ARU devices are run from a range of power sources. Most often they are battery-powered; alkaline batteries are cheaper but tend to hold a lower charge than lithium-ion batteries. Note that the rules around flying with, and posting/shipping of lithium-ion batteries are much more restrictive than those for alkaline batteries. Increasingly, some models allow for additional power sources such as solar panels, 12V or mains electricity to power the units so that they can run indefinitely. However, solar panels remain quite expensive and deep cycle batteries can lose efficiency over time. Note also, the increased obtrusiveness and subsequent increased chances of theft with the use of bulky solar panels. Self-built ARU designs can be run from power banks and other large batteries (including car batteries), meaning they can be exceptionally long-lasting in the field. Note that all batteries are affected by cold and performance will decline in sub-zero temperatures; advances in carbon-based materials may change this in the future.

Data Storage - most devices take SD or micro-SD cards which are widely available and are relatively cheap. If you wish to use larger capacity SD cards (>32 GB) make sure that the device supports exFAT formatted cards, which will be the case for most units. Additional card slots allow the devices to be deployed for longer, and at higher sampling rates, meaning that power supply is the constraining factor on unattended survey times.

Material and design - ARUs face a range of challenging scenarios under field conditions. Users will want to ensure that ARUs are fully waterproof, but also include vents to allow condensation to escape and sound to enter, if microphones are internal. Adding silica absorbent material into the enclosure is a good way to ensure electronics aren't affected by condensation. Additionally, it is not uncommon for units to be of great interest to a range of wildlife, so internal or small external microphones can be desirable, whilst limiting the number of points ants and other invertebrates can gain ingress, as these can damage devices. For external microphones, long-term moisture exposure can cause degradation of recording quality, and additional weatherproofing of the microphone can be desirable. Additionally, as with other autonomous devices like camera traps, theft remains a risk - particularly in more urban areas. Devices in dull colours avoid additional cost and effort in camouflaging them. Plastic surrounds can be adventitious as they allow the owner to brand identification marks directly on the unit reducing resale value. Some devices, such as the Wildlife Acoustics SM4, have additional mounting plates and/or points for attaching security cables.

Figure 2.2. A Song Meter Micro deployed to monitor wetlands. Credit Oliver Metcalf.

Interface - some devices have built in LCD screens and buttons allowing them to be manually scheduled in the field. Others have no interactivity and can only be adjusted through an app that can connect with the device or by loading a program onto the SD card/directly to the unit pre-deployment. Both options can work well. LCD screens allow for impromptu alteration of settings in the field, whereas the requirement to program devices before deployment can lead to more careful consideration and setting up of the devices whilst inside in a more environmentally benign environment - potentially eliminating a source of mistakes and additional water ingress to devices.

Temperature - some devices will function reliably over a broader range of temperatures; all devices are likely to function well within the average temperature ranges expected in the UK.

Gain settings - most recorders offer variable gain settings. Gain settings determine the amplitude with which a given environmental sound is recorded as digital data and therefore determine the effective spatial range. Increasing the gain increases 'background' as well as 'signal' within targeted acoustic research. Setting the gain too high can cause clipping, so tests should always be carried out to determine optimal tradeoffs according to the monitoring aims. Analogue gain increases the amplitude of the sound signal before it is converted into digital data. Note that gain is distinguished from volume which describes the dB scaling of output - for example when listening to a playback of a recording.

GPS - internal GPS units can be useful for two reasons. They allow sound files to be stamped with an accurate recording location, and they permit accurate time synchronisation of units across an array, which is necessary for sound localisation studies. The downside to internal GPS devices is that they have higher battery use, so if precise time synchronisation is not required, a device without GPS may be preferable.

Thermometer - a very few devices offer inbuilt thermometers to record the temperature during recording. As temperature can affect sound transmission through the air, this can be useful for detailed studies wishing to estimate detection distances, localise sound, and other analyses requiring the speed or spatial distribution of sound signals.

2.1.2. Microphones

Directional characteristics - microphones can be either directional or omni-directional. Most microphones supplied with ARUs will be omni-directional, meaning they sample a three-dimensional sphere around the sensor with equal sensitivity . Some ARUs may allow attachment of external directional microphones, which have a cone shaped pick up pattern spreading out in front of the microphone. These produce more 'focused' recordings which may be useful for studies in which the spatial location of targets is precisely known, or potentially for some types of localisation analysis.

Microphone sensitivity - when exposed to the same sound source, different microphone models may produce different output levels, as some microphones are more sensitive than others. Microphone sensitivity is the measure of the microphone's ability to convert sound pressure into an electric voltage. The higher the sensitivity, the less pre-amplification is required to bring the sound to a usable level. The lower the sensitivity, the greater the pre-amplification required. Lower sensitivity does not necessarily mean a poor microphone. Microphone sensitivity differs as microphones are designed for capturing specific sounds. Low sensitivity microphones are designed for capturing loud sounds and generally feature in the music industry for recording sounds such as guitar amplifiers or drum kits. These microphones are not recommended for quieter sounds, as in order to capture quieter sounds more gain will be required, resulting in a poorer signal-to-noise ratio. This also works in reverse, as highly sensitive microphones are designed to capture quieter sounds. However, if the sound to be captured is too loud, then the recording will clip, leading to a distorted recording.

Dynamic Range - The dynamic range of a microphone is the sound pressure level (SPL) difference between the highest and the lowest amplitude levels that the microphone and its circuitry can handle. Generally this is measured as the loudest SPL a microphone can capture without distorting (see Max input SPL below) and the quietest signal above the self noise (hiss) of the microphone and preamplifier. Once transduced to a digital representation, the dynamic range of amplitude is determined by the bit depth.

Signal to Noise Ratio - When conducting species- or taxon-specific monitoring, wildlife sounds are rarely recorded in isolation. A recording will contain both the sound that you want to record (signal) and the sounds you do not want to record (noise). The relationship between these two elements is the Signal to Noise Ratio (SNR). The larger the difference between the signal and the noise, the clearer the recorded target sound will be, and the greater the potential detection distance. Generally there are three types of noise considered when evaluating SNR. The first is anthropophonic noise generated by humans. This can be anything from the low rumble of vehicles such as aeroplanes or cars, the chatter of humans or industrial sounds. Second is the noise generated from the natural world (biophony and geophony) that masks the signal we wish to be recorded, such as wind, rain, the movement of trees or even non-target animal sounds drowning out the target sounds. Finally, there is the self-noise, or Equivalent Input Noise (EIN), which is generated by ARUs themselves which is heard as a faint hiss, even when there is no mic input. This is a result of the movement of electrons in the device circuitry being picked up by the recording process along with the signals coming through and from the microphones. Generally, older or less expensive recorders will produce a higher level of self-noise. A recorder's SNR level, as published by the manufacturer, refers to the self-noise generated from the recorder and microphone.

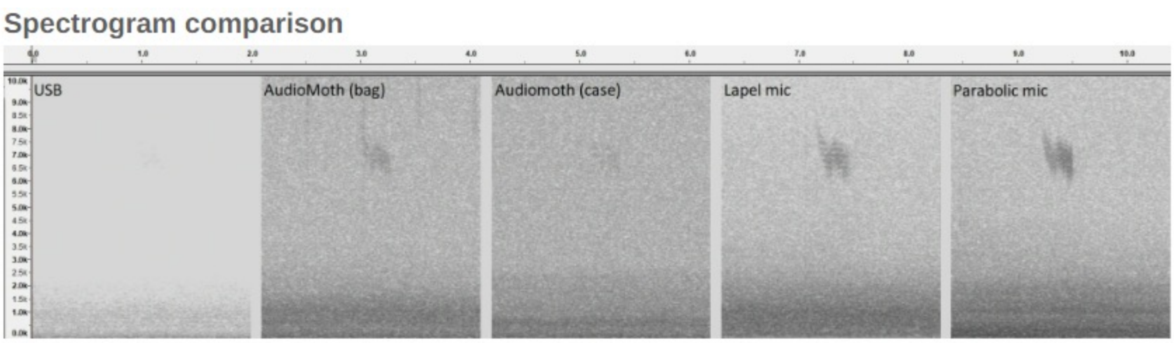

Figure 2.3. An illustration of varying signal to noise ratio across different devices. These spectrograms, created in Audacity[50], show the same Redwing *Turdus iliacus* call on multiple devices. Devices consist of: a cheap USB microphone connected to a desktop PC, an AudioMoth in a plastic bag, an AudioMoth[31] in a homemade waterproof case, a lapel microphone (EM172) with a digital audio recorder (Zoom H4n Pro; record level set to 80/100) and a Dodotronic parabolic microphone with a Sound Devices MixPre 3 digital audio recorder. For full details of the experiment comparing equipment for monitoring nocturnally migrating birds, see https://nocmig.com/2020/02/26/equipment-comparison-february-2020/. ©Simon Gillings

Frequency Response - defined as the range of sound or frequencies which a microphone can reproduce and how these vary within that range. In recording equipment, the frequency response describes the ability of a product to capture sound at a range of different frequencies - a flatter response produces a more faithful representation of the original signal. There is no perfect microphone for all situations, as microphones are developed to perform specific tasks. For example a microphone for recording ultrasonic sounds may not be very good at recording acoustic signals between 20Hz and 20 kHz, and conversely an acoustic microphone is unlikely to be able to record ultrasonic sounds effectively, however flatter responses are preferable in scientific work. The frequency response of a microphone is usually displayed graphically, giving a relative indication of the microphone response at a set range of frequencies. Figure 2.2 gives an example of a typical frequency response chart.

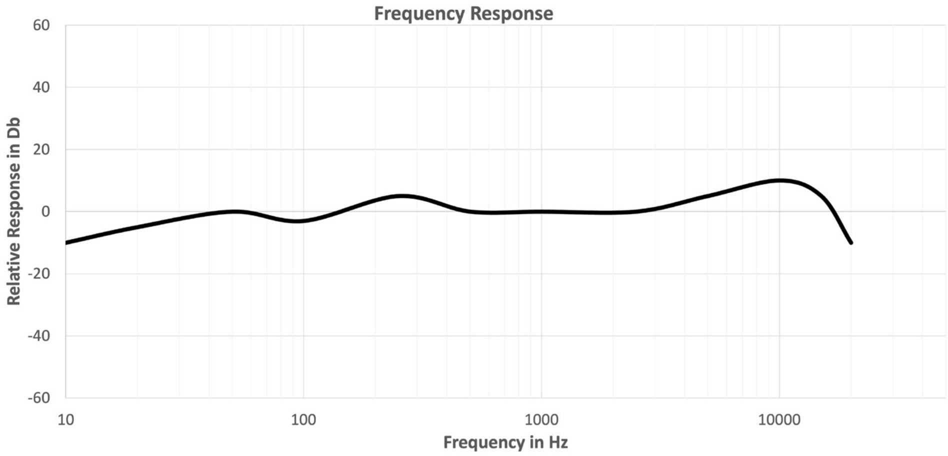

Figure 2.4. A frequency response chart, showing a microphone with a relatively flat response across the human-audible range, but a sharp decline in very low and higher frequencies.

Max Input Sound Pressure Level (SPL) - The maximum sound pressure level a microphone can take without distorting. Distortion or clipping occurs when the signal exceeds the SPL of the microphone. Fig 2.3 shows two examples of the same recording, the waveform at the top of the first image shows that the signal is well within the range of the microphone, whereas the second example the waveform goes beyond the maximum SPL, the red elements of the sonogram shows the frequency where the sound is clipping.

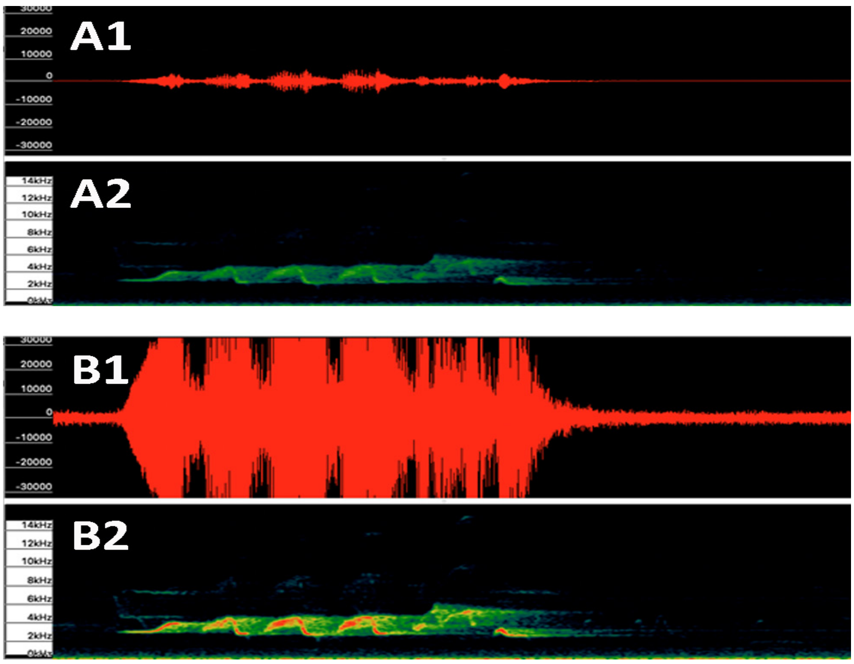

Figure 2.5. Waveform (A1+B1) and spectrogram (A2+B2) plots for recordings showing sound pressure levels within (A) and exceeding (B) the capacity of the recording unit. Regular occurrence of sound pressure levels exceeding the recording unit capacity may indicate that the gain has been set too high. Spectrograms produced in Kaleidoscope Pro[51].

2.2. Cost trade-offs with recording units

2.2.1. Budget options

Budget options are likely to be sufficient for those with simple recording requirements - a single channel able to record the human-audible frequency, and no need for a built-in GPS. AudioMoths[31] have revolutionised PAM since becoming available in 2019, with the low price-point making them widely accessible. AudioMoths have been used in acoustic studies all over the world. Although the microphone quality is somewhat lower than more expensive models, it has proven good enough for studies of many species in the human-audible frequency range. Any loss in detection distance is made up for by the fact that, in most cases, it is still cheaper to buy a second unit than it is to buy an ARU with a better quality microphone. The recent release of AudioMoth version 1.2 includes an affordable weather-proof case and the potential to solder a 3.5mm jack for adding an external microphone, allowing the use of a range of cheaply available, good quality external microphones - as well as the addition of a GPS unit if desired.

Unfortunately, there is currently one major challenge in using Audiomoths, which is their availability. As a non-commercial organisation, Open Acoustic Devices, the producers of Audiomoth, use the GroupGets[52] platform to collect bulk orders of the devices before sending them to be manufactured. The timing of these group purchases are unpredictable, often at short-notice, and typically sell out fast (within hours). Audiomoths are also available for direct sale through Labmaker[53] at a higher price, but production has been highly impacted by the global chip shortage and at the time of writing none are available until at least 2023 - although this is also increasingly the case for all suppliers of ARUs. There is also limited formal customer support, although there are useful forums on the Open Acoustic Devices[54] website. Additionally, AudioMoths are not supplied with a robust weather-proof case and users must separately purchase or make one. Those wishing to leave recorders out in the field for extended periods in bad weather may look to more expensive units with more robust cases. For those undertaking casual or voluntary projects who are prepared to wait for initial purchases and replacement devices, Audiomoths may be an ideal solution, but commercial projects may prefer a more expensive unit that can be more readily obtained. That option may well be the Wildlife Acoustics SongMeter (SM) Micro[55] which has better recording quality than an Audiomoth but is similar in many other respects.

The final option for those with a limited budget but high specification requirements is to self-build an ARU following open-source designs, such as the SOLO[56], ARUPI[57], AURITA[58], BUGG[59], or Sonitor[60] devices. These devices are all variations based on adding components to the cheap Raspberry Pi[61] boards - except Sonitor which is primarily concerned with the cheap construction of taxon-specific microphones that can be attached to one of the previous devices. The resultant products can have external microphones, larger or adjustable power sources from AA batteries, car batteries to solar panels, waterproofing, and optional network connectivity. Performance of these devices is as good as some of the top-end devices listed in Table 1.1. However, obtaining the individual components can be time-consuming (from our own experience some of the recommended components are no longer available, and understanding what replacements are suitable requires at least some knowledge of electrical engineering), and in some cases requires soldering. That means that the process is altogether more difficult than the simple click and purchase of more commercial products, and fully waterproofing the devices can be challenging. Nevertheless, building a device yourself allows a degree of flexibility and customisation not available in off-the-shelf products, and maybe the best, or only, option for more complex acoustic projects.

2.2.2. Mid-range options

The SM Mini[55] offers an upgrade on the SM Micro, with better recording quality. The microphone, like all of the other units in the mid-range and top-end categories, is removable, meaning that it can be changed as performance begins to decline after long exposure to the elements, without needing to replace the entire unit. The main appeal of the SM Mini however, is the ability to add the optional battery lid (£165) and use six 18650 Li-ion batteries giving it a battery life of 1100 hours (over 6 weeks) - meaning it is a very good option for those trying to minimise human time in recorder deployment. The SM Mini and SM Micro can also be programmed and checked through a bluetooth connection app.

The Titley Chorus[62] is a relatively new product, and as far as the authors are aware has not yet been used in any published academic research, or publicly available ecological studies in the UK. However, the manufacturer's specifications and price point mean that for many, this unit may be the ideal trade-off between top-quality recording quality, robustness and price.

2.2.3. Top-end options

The Wildlife Acoustics SM4[55] and its Australian counterpart, the Frontier Labs BAR-LT[63] are considered the market-leaders amongst ARUs, with a price tag to match. Both can be deployed in the field for extended periods of time, with huge storage capacity, robust casing, long battery life and optional capacity to add solar panels to keep them running for even longer. Both units have benefits and disadvantages for particular types of study - the BAR-LT has a built in GPS for localisation, whilst the SM4s are slightly easier to calibrate for long-term recording - but either is likely to be suitable for any of the analyses discussed in this guide.

2.2.4. Localisation-enabled options

Localisation with ARUs is largely still in its infancy, with researchers and hobbyists generally making custom setups or modifying hardware/ software of existing omnidirectional devices. Popular advances include CARACAL[64], Dev-Audio/VoxNet[65], WASN[66] and MAARU[67]. At the time of writing, no dedicated commercial localising devices/ platforms are yet available but may soon become so.

2.3. Maintenance and calibration

Environmental conditions have substantial impacts on the durability and reliability of acoustic sampling units. As recorders are repeatedly exposed to adverse environmental conditions, they will degrade in performance - especially exposed parts of the equipment such as microphones and their windshields. Protection from temperature extremes, rain or humidity may therefore be required for both microphone and recording unit[68] - this may consist of the standard case normally provided as part of the recording system, potentially with other modifications to protect the unit further from rainfall, wind and animals. Procedures for the regular inspection, maintenance and calibration of recording systems are also needed to support field studies[69,70,71]. Microphone management, calibration and checking is very important before and after field deployments, as degradation in microphone quality over time can significantly affect results. To aid this, recorders and microphones should be individually numbered, checked and calibrated on a regular basis (at least once per year), using a piston-phone, standardised sound emitters, sweep tests, or other evaluation set-ups to confirm that the sensitivity of the recording system has not been adversely affected (useful maintenance resources are available from the Alberta Bioacoustic Unit[72]). Where smaller and cheaper ARUs cannot be directly calibrated, it is important to check microphones are still working within acceptable limits.

Table 2.1. Table of common ARU choices available in the UK. Adapted from Darras et al., 201919.

Model	Audiomoth 1.2 with case[I]	BAR-LT[III]	Chorus[V]	SM Micro[VI]	SM Mini[VII]	SM4[VII]	ARUPI, AURITA, BUGG, Solo Sonitor[IX, X, XI, XII, XIII]
Manufacturer	Open Acoustic Devices	Frontier Labs	Titley	Wildlife Acoustics	Wildlife Acoustics	Wildlife Acoustics	Raspberry-Pi based recorders
Channels	1	1or 2	2	1	1	2	1 or 2
Signal-to-noise ratio at 1kHz	63	80	80	73	78	80	80
Price in GBP (on 25/07/2022)	95[II]	879[IV]	474	239[IV]	489[IV]	845[IV]	Variable, approx. 100-300
Storage	1 micro-SD card	4 SD cards	1 SD card	1 micro-SD cards	1 SD card	2 SD cards	1 micro-SD card
Power	3 AA cells	6 18650 cells	4 AA cells	3 AA cells	18650 Li-ion cell or 4 AA batteries	4 D cells	Power bank/car battery/ solar
Solar panel	no	optional	no	no	no	optional	optional
Continuous recording time	187	600	300	200	1200	510	variable
GPS	no	integrated	integrated	no	no	optional	no
Frequency range	yes	yes	yes	no	no	no	yes - some

I. https://www.openacousticdevices.info/audiomoth
II. Price taken from the most recent round of sales in GroupGets https://groupgets.commanufacturers/open-acoustic-devices/products/audiomoth and converted to GBP
III. https://www.frontierlabs.com.au/bar-lt
IV. Price obtained from NHBS on 25/07/2022: https://www.nhbs.com/frontier-labs-bar-lt-bioacoustic-recorder
V. titley-scientific.com/uk/chorus.html
VI. https://www.wildlifeacoustics.com/products/song-meter-micro
VII. https://www.wildlifeacoustics.com/products/song-meter-mini
VIII. https://www.wildlifeacoustics.com/products/song-meter-sm4
IX. https://www.instructables.com/ARUPi-A-Low-Cost-Automated-Recording-Unit-for-Soun/
X. https://www.tandfonline.com/doi/suppl/10.1080/09524622.2018.1463293?scroll=top
XI. https://www.bugg.xyz/
XII. https://solo-system.github.io/home.html
XIII. Darras, K., Kolbrek, B., Knorr, A., Meyer, V., Zippert, M., & Wenzel, A. (2021). Assembling cheap, high-performance microphones for recording terrestrial wildlife: the Sonitor system. F1000Research, 7, 1984. doi:10.12688/f1000research.17511.3

2.4. Software for programming ARUs

Most of the devices listed above come with their own software for programming, synchronising, and scheduling devices. In the case of Audiomoth, Wildlife Acoustics, and Frontier Labs (which the authors have experience of), these are simple, reasonably intuitive programs that allow for a great deal of flexibility and make the process of preparing recorders for deployment relatively straight-forward. However this is not generally the case for the self-built devices (SOLO/ARUPI/AURITA), and although some rudimentary software may be available, the flexibility of recording protocols is inevitably lower, and coding skills are often required.

2.5. Future-proofing

Whilst the fast-paced development of acoustic hardware is a great benefit to acoustic monitoring, it also presents particular novel challenges for long-term monitoring. Ensuring that any acoustic differences recorded in the same study ten years apart are due to real-world ecological change and not differences in the performance of the recorder used is of paramount importance. However,it is an issue that has been largely neglected in the academic literature. The simplest solution is to ensure that the same devices are used throughout any monitoring project, with regular calibration and replacement of deteriorating parts.

However, this sort of continuity may not be possible for several reasons. The first is that manufacturers are unlikely to maintain production of the same models with the same specifications over long enough periods to allow like-for-like replacement - for instance two highly popular devices, Audiomoth v1.0[31] and Wildlife Acoustic SM 2[55], have been discontinued in recent years, and are no longer available for purchase new. Secondly, the capacity of a team to visit the field may change, meaning that they may require devices with different characteristics that can be left to record for longer. Similarly, when devices such as the BUGG[59], which are able to record continuously using solar powered chargers and transmit data in real-time using a mobile phone SIM card, are available for commercial purchase - the power and memory benefits of such advances may outweigh the negatives of lost continuity.

To these challenges we cannot offer a certain solution, but several prudent measures could be taken in anticipation of better solutions emerging in the future. Firstly, we recommend playing broadband white noise at a known amplitude and distance from the recorder, from an unobscured point. White noise sound files are easily sourced from a range of locations on the internet, or can be easily generated in Audacity[50,73] (see Chapter 4.2 for more on analysis software). Climatic conditions (temperature and humidity in particular) should also be recorded. This should be done when the ARU is first deployed, and at regular intervals thereafter. Additionally, when a device is being replaced, the new ARU and old ARU should be deployed simultaneously for a period of time. This will allow some reference data for comparison and may allow some degree of calibration between the devices.

Chapter 3: Study Protocol

As with any ecological study, survey design is vital for drawing robust inferences from the data collected. When considering survey design, there are likely to be complex trade-offs to be considered between landscape, size of the study site, budgetary limitations and human effort available - experienced ecologists with familiarity of the study area are likely to be best placed to make these decisions. This chapter discusses some of the most important aspects for consideration when designing an acoustic monitoring study.
Placement of ARUs and timing of deployment requires careful planning - the key objective here should be to obtain acoustic data that are representative of the ecological features being investigated.

3.1 Temporal considerations

Temporal programming within the ARU deployment period can be usefully considered at different temporal scales: deployment schedule, recording periods, and sampling schedule. Deployment schedule refers to the times when an ARU will be placed in the field during weeks, months, seasons. Recording periods describe the time that recording takes place within a 24 hour cycle - either continuously or targeted, for instance during the dawn chorus. The sampling schedule describes the pattern of recording within a given recording period This could range from continuous recording to short recordings of just a few seconds every hour and is determined by the recording length and inter-recording intervals.

3.1.1. Deployment Schedule

When considering optimal deployment schedules for long-term monitoring, it is necessary to consider both the temporal and spatial aspects of the survey design together in order to ensure the study objectives can be met. In general, there are two approaches to deployment schedules that can be taken when assuming equal survey effort. For studies that prioritise tracking temporal patterns, using a continuous or near continuous deployment at the expense of a higher number of recording devices is likely to be preferable.

Imagine here a small area of 20 hectares allocated for a rewilding project and where assessing habitat change over time is the priority. In this case, four recorders could be placed, either at random locations, or at selected important sites such as key habitats, and left to record throughout the year. In contrast, for studies more concerned with the spatial aspects of target species presence, then using short but intensive study periods with a greater number of devices distributed spatially is likely to be preferable. Imagine a large farm, concerned about the effect of land management changes on the site's bird population. An array of 15 recorders could be placed in a regular grid across the site for a month-long period during the breeding season, and again for a similar period in winter, with annual repeats in order to assess community turnover.

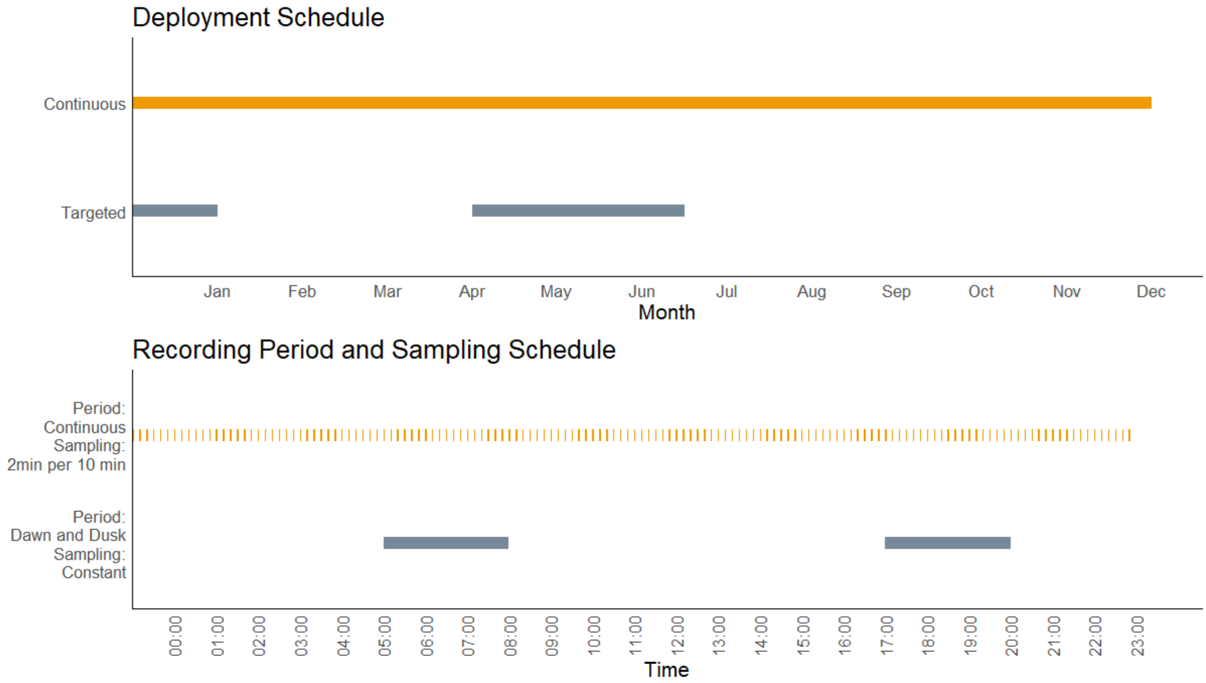

Figure 3.1. Illustration of possible temporal scheduling of PAM surveys. Deployment of ARUs (top) can be continuous throughout the year, or targeted at certain significant periods. Recording periods and sampling schedules (bottom) can be programmed to only collect data when desired - illustrated here is a continuous recording period across the diel cycle with a sampling schedule of two minutes every ten (orange), and a non-continuous recording period targeting dawn and dusk but sampling continuously during these periods (grey).

3.1.2. Recording period

Most ARUs come with the capacity to set recording periods. Non-continuous recording periods and sampling schedules are useful when resources are limited; they enable study designs that can be robust enough to meet the study aims, whilst reducing the amount of data collected and battery power used, therefore increasing how long ARUs can be left in the field and reducing overall effort. A key consideration here is that it is impossible to analyse data that doesn't exist, but it is easy to discard or disregard data if too much is collected. In most cases, it will be desirable to conduct a pilot study to establish exactly how much data collection is required to make the desired analysis feasible. It may often be sensible to have some data redundancy and collect more than necessary, but this must be balanced with the carbon cost of data storage as the big data of remote-sensing scales globally. Guidance in Chapters 5 and 6 can be used to assess survey completeness.

Choosing recording periods within a deployment is relatively straightforward. For general soundscape studies or studies without strong hypotheses about key periods for target taxa vocalisation, they should cover the entire diel cycle. Other more targeted options where biophonic activity is of interest may be to only sample at day or night, at dawn, or avoiding periods of high anthropogenic activity[12]. Alternatively, it may be desirable to only record during periods of expected peak activity in studies with strong hypotheses about the timing of the vocal activity of focal species (e.g. Natterjack Toad *Epidalea calamita* chorusing at dusk).

3.1.3. Sampling schedule

The choice of sampling schedule is dependent on the type of study being conducted, and the goals of the study. For projects aimed at sampling ecological communities (Chapter 5), studies have shown[74,75,76] that using samples with shorter recording length and smaller inter-recording intervals, dispersed over long periods, are likely to be more effective in obtaining a good representation of the community present than longer duration samples with greater inter-recording intervals over shorter periods. A UK study aiming to obtain a good representation of the bird community at a single location with one hour of sampling effort would likely capture a high proportion of the species present using sixty samples of 1 minute duration spread across the entire bird breeding season rather than a single hour during one morning[75]. However, it is likely that this effect declines with lower species richness, and is unlikely to have a very strong impact in the UK. The optimal selection will depend on the sampled community, how often species make identifiable sounds, and daily behaviour patterns of the species of interest.

For soundscape studies (Chapter 6), the optimal sampling schedule will depend upon the phenomena of interest. Where diurnal patterns are of interest and events of interest are not too rare a common approach is to have a sampling schedule recording one minute in every ten (e.g. a recording length of one minute, with a nine minute inter-recording interval and a continuous recording period), particularly when deployment periods are throughout the year or across entire seasons. Shorter or more targeted deployment periods are likely to require a more frequent sampling schedule.

3.2 Spatial considerations

The exact number and placement of ARUs should be determined by an ecologist following the same principles of representativeness and sample size that would be applied to any ecological study. Distance between recorders will be determined by the objective of the study and the target species, but for small passerine birds, spacing of approximately 250m should be enough in most habitats to ensure independence of recordings if desired, or under 50m if overlap in recordings is necessary (e.g. for localisation). Note that recording distance will also be determined by input gain, see section 1.

3.2.1. Detection distance

Understanding the 'detection distance' being monitored by a single ARU is one of the most important considerations when designing a study. However, it is also one of the most difficult to calculate. The amplitude of sounds at source hugely vary across potential ecological targets (e.g. the sound of a barking Roe Deer *Capreolus capreolus* or duetting Tawny Owls *Strix aluco* will carry much further than a singing Goldcrest *Regulus regulus*). Additionally, there are a number of factors that impact sound attenuation. Sound attenuation is the energy loss of a sound wave as it travels through air, soil, water or other media - once enough energy has been lost, a sound wave becomes indistinguishable from background noise. These factors include environmental parameters that vary throughout the day, such as background noise level, temperature, air pressure and humidity - meaning that detection distances at a single location will vary over time. Attenuation is also impacted by the physical surroundings, such as vegetation type and density, and local topography. Sound attenuation occurs at different rates at different frequencies. In general, lower pitch sounds have less sound attenuation than higher pitch sounds, but this can vary, as some frequencies carry better through vegetation than others. There is an increasing body of academic research on measuring detection distances and ecological sound attenuation[77,78], but none of the methods so far proposed are straightforward. Some problems with estimation appear intractable, such as animals moving or facing in different directions whilst vocalising, or intraspecific variation in vocalisation amplitude, and these rely on assumptions that using an average is reasonable (e.g. that a deer barks as often facing the microphone as it does when facing away).

In consequence, most ecoacoustic studies do not estimate detection distances precisely[12]. Instead many studies use broad estimates obtained by playing sounds at increasing distances and at regular time intervals, or relying on rules-of-thumb. At the UKAN+ Long-term Acoustic Monitoring of UK Biodiversity Symposium, one such approximation that had widespread agreement was that if a human observer could hear a call, then a good quality ARU was likely to be able to record this as well.

It is worth noting that not knowing precise sound attenuation rates limits the types of analysis possible, as measures of estimating abundance often require a strong understanding of the location/distance of calling individuals. This means that comparisons of community composition and soundscape characterisation tend to be favoured in ecoacoustic studies, although even here limitations in understanding detection distances should be carefully considered when making comparisons between sites.

3.2.2. ARU Positioning

Having identified ARU sites, and the deployment schedule, the microsite location of recorders can also have an impact on the data collected. Although ARU microphones are mostly omnidirectional, sound can be blocked by solid objects. For instance, placement of an ARU against a very broad tree trunk will inhibit collection of sounds from directly behind the tree; too close to the ground will introduce reflections. If the study is targeted towards a particular area or species, care should be taken to ensure there is a clear line of sight between the ARU and the position the target sounds are most likely to occur. For general recording of the environment, locating the ARU with as open an aspect as possible will be beneficial. Most studies place recorders 1-2m off the ground, both to avoid reflections and interference by curious ungulates. This is likely to be suitable for most UK-based studies, but placing them higher may be beneficial if a focus on canopy dwelling species is desirable, or there is concern that equipment may be vandalised.

In many cases, ideal sites for the ARUs may not be possible. Careful consideration should be given to the risk of theft, potential damage from passing bovines, and to the privacy of any passers by who are using the area (see Chapter 3.3 for more on privacy concerns). It may well be necessary to make considerable concessions in concealing the location of ARUs to avoid theft - imperfect data is better than returning after several months to an absent ARU! In the experience of the authors, locating an ARU tucked in on the edge of a bush does little to limit the collection of soundscape data, assuming that rustling branches can be avoided. Additionally, there is some research[79] that suggests the use of personal and polite labels left on the recorder, as opposed to neutral or aggressive messaging, is most effective in deterring thefts of unattended scientific equipment, although this must be hugely culturally variable. In addition, warning signs that recording is taking place, possibly at some distance from the actual devices, may go some way to alleviating privacy concerns, especially on private sites. Landowner permission should always be obtained before deployment of ARUs for ecological monitoring.

3.3 Audio settings

A major decision in relation to programming audio settings on ARUs is the sampling frequency. As mentioned previously, the sampling rate needs to be at least double the frequency at which you wish to record data (or triple if the intention is to use the same data to survey ultrasonic acoustic diversity). For general studies of human-audible sound, we recommend using a sampling rate of 48 kHz. The reasoning behind this is purely pragmatic, it covers the entire human audible range, and is a common sampling frequency available on the majority of sound recorders.

The file size of audio data increases linearly with sampling rate, meaning that in some cases it may be preferable to use a lower sampling rate. This will be primarily in studies targeted at species with low frequency calls. For instance, a study on Common Cuckoo *Cuculus canorus* which sing at ~1 kHz and below, could use a sampling frequency of 4 kHz. This would give audio data for everything below 2 kHz - capturing all cuckoo song, whilst also requiring just 8.3% of the storage capacity of a 48 kHz sampling rate. However, this would inevitably constrain future questions that might be investigated with the same set of recordings, and low sample rate can result in poor data resolution.

The other options likely requiring input when scheduling an ARU are the file type, bit-depth and gain. One study has shown that compression of .wav audio to MP3 had a surprisingly small impact on the calculation of some acoustic index values, while others were more severely affected[80]. Other studies have found similarly mixed effects in targeted analysis. Nevertheless, this form of compression does entail some loss of original data. Most users tend to record using uncompressed files (.wav) or lossless compression (e.g. .flac), which avoids any risk of losing information. Furthermore, it is increasingly standard for long-term audio storage to be in .wav format, so we recommend that initial recordings are made in this format and converted later if necessary.

Bit-depth determines the number of steps in the amplitude scale of a recording, with increasing bit-depth representing higher resolution in the amplitude, and hence providing more discrimination between loud and quiet sounds. Bit depth determines the dynamic range of capture and will impact the amount of information collected, meaning that incorrect gain settings are less likely to impact data collection. Here, we strongly recommend a bit depth of 16 or higher, as a bit-depth of 8 tends to be of relatively poor quality. There is ongoing debate about whether the difference in quality between 16 and 24 bit recordings are discernible to the human ear using most audio equipment, and consequently a bit depth of 16 is a common choice.

Finally, gain is the amount of amplification the recorder applies to the incoming audio signal before recording it - an inverse to the volume control on a television. In most cases a medium gain setting of ~+20 dB will likely be most appropriate, it will help in collecting some quieter sound at a high enough quality to be recognisable, without resulting in excess clipping. However, if target species are known to be at a great distance, or are particularly quiet and there is reason to think clipping won't be an issue, then using higher gain settings may be appropriate - it is important to test this if at all possible. Note that gain settings will be hardware specific - this is a good reason for only using one type of ARU across a survey - but if it is necessary to use more than one type they will require calibration across devices.

3.4 Metadata

Metadata is the information about the recorded data: date, time, location, recording device, gain settings, etc. Sound files contain a great deal of valuable information for biodiversity scientists. Without appropriate metadata, however, these files have no significant purpose. Metadata allows the contextualisation of audio data within an informative context in the same way that appropriate labels provide meaningful context to voucher specimens deposited in a museum collection. As a bare minimum, this information should provide the location, date, time, details of who made the recording, the equipment and settings used. Spoken metadata at the start of a recording has the advantage of being hard to separate from the data itself, and has the disadvantage of potentially interfering with, or at least complicating, automated analysis pipelines and can only be done at the start and end of PAM deployments. Spoken metadata is not a substitute for metadata that enables quick searching by humans and machines. Searching effectively for a file by date, time and location requires the metadata to be in text form. Many devices will embed this in the file name, and generated text file.

There are two options for metadata storage: within the file and in an associated database. Both have advantages and are not mutually exclusive, so a combination of both is often the best solution. Many tools allow for encoding metadata within files (examples); the metadata are stored within the file and persist if the files are accidentally renamed.

The primary advantage of a metadata database is that complex queries are easily constructed and executed quickly. Another advantage of a database is that relationships between files and the results of analyses can be defined. Machine learning algorithms may find numerous species of birds singing within an audio file at different times. A properly constructed metadata database can quickly identify periods where a Eurasian Blackbird *Turdus merula* is singing from many thousands of audio files. Depositing your files into an appropriate repository may provide the level of functionality required (and long-term storage) in exchange for making the files publicly available (either immediately or after an embargo period).

Ensuring interoperability with existing and future bioacoustics infrastructures such as repositories and aggregators should also be considered. Generally, this means using the most atomic metadata fields that are practical.

Audubon Core[81] (the Biodiversity Information Standards (TDWG) standard for audio-visual data) is yet to be as widely used as its sister standard DarwinCore[82] but has an increasing number of users within the biodiversity community. Over the last two years, the standard has actively engaged with the bioacoustics community to ensure the metadata needs of the bioacoustic and ecoacoustic communities are met by the standard. Additionally, the recent "RegionOfInterest" addition expands the standard to include metadata about regions within a file (e.g. periods of blackbird song as discussed above). Making sure that each field in the metadata matches an equivalent AudubonCore term will help to future-proof your metadata. There is work within the AudubonCore Maintenance Group to provide a user guide for audio files and analyses, which will soon become a helpful document for the ecoacoustics community.

Standardised metadata will have long-term benefits for the community, making it easier to archive and aggregate datasets. An interesting example of this, the Global Soundscapes Project[83], aims to collate metadata from soundscape recording datasets globally, and currently holds metadata on 392 projects - and is actively looking for new collaborators.

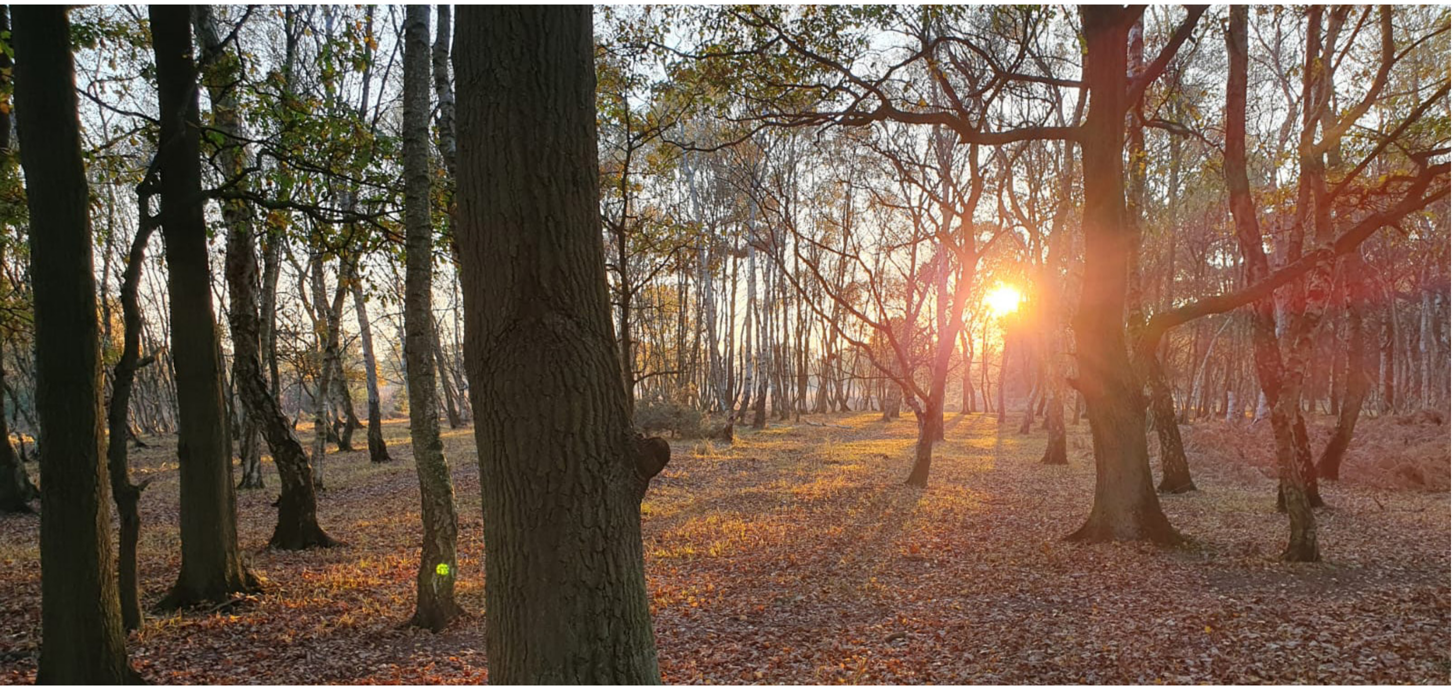

Figure 3.2. Woodland can have a diverse range of vocalising species and can vary greatly by season – a woodland soundscape will sound very different in autumn compared to spring. Credit: Oliver Metcalf.

3.5 Data storage

Data storage remains one of the most challenging aspects of ecoacoustics. It is easy to collect terabytes of acoustic data, even over relatively short survey periods. When planning surveys it is important that storing the collected data in triplicate - and at a minimum of two independent locations - is budgeted for. When working in the field in remote areas, aim to work with duplicate copies on portable hard drives, until they can get backed up to more permanent storage solutions.

Cloud based computing appears to be the future for long-term large data storage, as it is scalable, flexible, and provides data security and regular data back-up. However, the cost can be prohibitive for smaller projects and the carbon cost is invariably higher. Slow internet connections can result in local storage being far faster for analysis. Cloud storage also offers the potential for easier sharing of data and more collaborative projects - however there are few options available for large datasets. Free longer term cloud storage facilities for scientific projects are being developed at national level in some countries, but the UK lags behind. One potential option is to upload data to Arbimon[35], which offers free storage in exchange for sharing data. For small amounts of acoustic data, such as good recordings of rare species or particularly interesting soundscapes, short audio files or sets can be uploaded to online repositories such as xeno-canto[85] or the Macaulay Library[86] - both of which hold a huge amount of ecoacoustic reference material useful for acoustic identification or as training data for classification models.

One other option to reduce data storage requirements is to compress the files being stored. A lossless file compression such as .flac may be a good option here. One of the largest long-term acoustic monitoring projects globally, the Australian Acoustic Observatory[87], advocates an extreme form of acoustic data compression, converting the original audio files to a series of acoustic indices from which some of the most relevant ecological data can be retrieved[88]. This is estimated to require six to eight orders of magnitude less storage than preserving the original audio. Nevertheless, we would recommend storing the original audio data (or at the very least a representative subsample) and only using this method as a last resort as it entails a high degree of information loss.

Chapter 4. Data Exploration

Having collected audio data from a PAM study, the sheer quantity of data collected can seem overwhelming. It is generally desirable to undertake some preliminary data exploration to determine whether the ARUs have worked correctly, assess the quality of the data, and to get a feel for the soundscapes recorded. This last point in particular can be vital for gaining an understanding of the acoustic environment being recorded and the way it changes across the diel cycle and over longer periods, and for formulating hypotheses for future or additional studies. Several processes which can help handle large quantities of audio data are discussed in this chapter

4.1 Basic data checks

Often the simplest of checks are the most important in ensuring the data collected is what it is expected to be. Some of the most important and useful file metadata can be accessed by viewing the collected files on a computer. For instance, in Windows operating systems (OS), opening the folder that contains the relevant audio files, selecting the View tab and the 'Details' option, then using the 'Add columns' menu to add the relevant file information to the screen can be a very useful way to quickly view the recording metadata (the same information is available in the Finder sidebar on Mac OS). Spending ten minutes checking the start and end dates of recordings, numbers of files from each ARU, file sizes, file duration, stereo/mono, sample rate and bit-depth are all as expected can be invaluable in identifying any problems carried over from set-up or recording.

4.2 Spectrograms

Spectrograms provide a visual representation of the audio data, with the frequency on the y-axis, time on the x-axis, and the amplitude represented by the intensity of colour (Figures 2.1, 2.3, 4.1). Spectrograms are produced by transforming the raw audio data from the time-amplitude domain to the time-frequency domain typically using a fast Fourier transform (FFT). It is one of the commonest ways in which to assess audio data.

Generally it is a good idea to make a quick inspection of any new data collected by visually inspecting a small portion of the data, and displaying it with 15 seconds to 1 minute viewable on the x-axis at a time. Visual inspection of audio at this timescale is likely to be significantly faster than listening to the data directly. This will help to identify any periods in which the recorder may have malfunctioned, or anomalous sound events such as a period of construction work close to the recorder. Most spectrogram software has a playback function and we strongly advocate listening to as much data as possible, sampling whilst viewing to develop your understanding of the soundscape patterns at the study site in order to support interpretation of later statistical analyses.

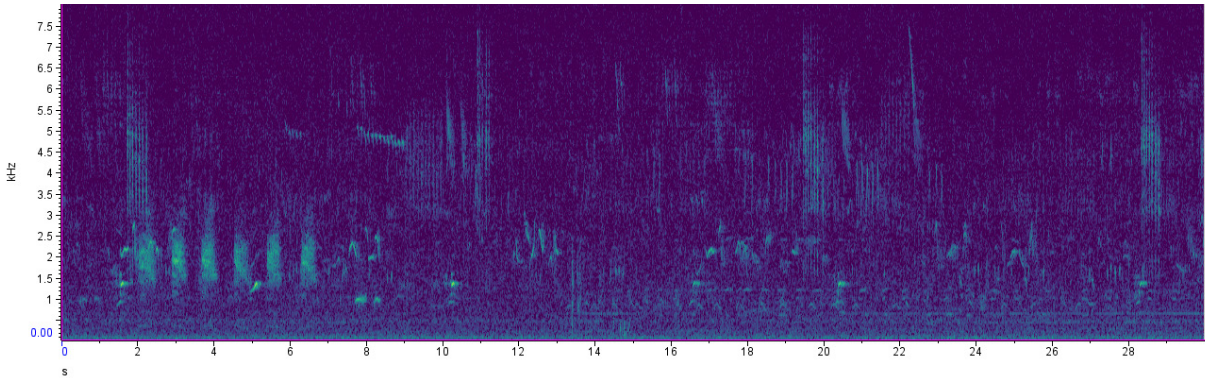

Figure 4.1. An example of a busy spectrogram. Recorded during the dawn chorus in the Lower Derwent Valley NNR on 05/05/2020. Spectrogram produced using Raven Pro[91].

Most generalist sound-editing software can display spectrograms, and allow the sound displayed to be listened to simultaneously, whilst also offering various options for editing sound. We do not provide a comprehensive list of all of the software available, instead focussing on some popular choices in ecoacoustics. We have illustrated this guidance document with spectrograms created from a range of software to provide comparisons. For a wider range of software options, an extensive list has been made by Tessa Rhinehart[89].

One of the most popular choices for viewing and editing audio files is Audacity[50], a free, easy to use open-source audio editor (see Figure 2.1). It is a powerful piece of software capable of a wide range of visualisation and editing processes. As Audacity is intended as a general purpose audio editor, it is not necessarily optimised for conducting ecoacoustic analysis - however, a good article on setting up Audacity for this purpose (focussed on birds) can be found on the xeno-canto website[90].

Raven Lite (free) and Raven Pro[91] (licensed) offer a program explicitly designed for bioacoustic analysis, meaning it is somewhat more intuitive to use, at least initially, than Audacity. It is convenient for paging through large audio files, or large quantities of smaller files. Raven Pro is also good for easy labelling of audio data, although some of the automatic measurement and labelling options are limited to Raven Pro only. The Raven User Guide is also an excellent document for anyone looking for an explanation as to how to configure a spectrogram for maximum clarity, and what the different settings do, in a way that is applicable to many different programs.

Kaleidoscope Pro, and its free viewer option, Kaleidoscope Lite, is produced by Wildlife Acoustics[51]. It can load and close sound files with a single keyboard click, allowing extremely rapid visual review of spectrograms for a batch of files, which can be easily tuned for gain and contrast. Sonic Visualiser[92] is a free tool for visualisation, analysis and annotation which was designed for music analysis but with high resolution and fast loading spectrogram viewing capacity.

It is also possible to create your own spectrograms using R[93] (e.g. in the 'seewave' package[94]), Python[95] (e.g. in Matplotlib[96] or SciPy[97]) or MatLab[98] code (e.g. Signal processing Toolbox), although these tend to be less interactive and it can be tricky to obtain as much clarity as in the custom made sound-editing software without good knowledge of the scripting language. There are multiple well-documented packages available in each language.

4.3 False-colour spectrograms/plots

False-colour spectrograms[99] and plots are methods to visualise sound over long time periods, normally using time on the x-axis and frequency or date on the y-axis. Unlike standard spectrograms, instead of using the raw audio data as the input to ascertain amplitude, false-colour spectrograms take the results of three acoustic indices (see Chapter 6 for more on acoustic indices), and use these as the values in the Red-Green-Blue channels to colourise the spectrogram (Figure 4.2). This means that the input data is far less granular than a standard spectrogram, allowing for clearer visualisation of patterns and trends over longer time periods. The principle behind false-colour spectrograms can be extended to false-colour Extended Acoustic Summary images[100], replacing frequency on the y-axis with another measure of time (e.g. month, year), to allow visualisation of acoustic change over prolonged periods (Figure 4.3).

The developers of the false-colour spectrogram, Queensland University of Technology Ecoacoustics Lab, currently provide the Ecoacoustic Analysis Programs software package for easy generation of false-colour spectrograms, freely downloadable from GitHub[101]. In addition, code to create false-colour spectrograms in R is available in Appendix 3, and the Python package scikit-maad[102] contains functions to create your own, or Python code to do so is available on Sarab Sethi's GitHub[103].

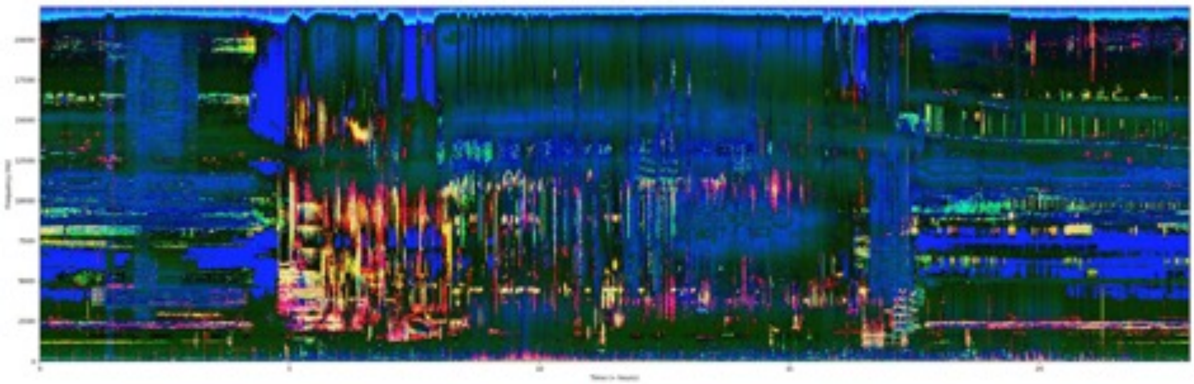

Figure 4.2 False-colour spectrogram showing a 24 hour period, and a frequency range up to 22 kHz. The dawn chorus is visible between 5-8am, with corresponding high values in the acoustic indices assigned to the red and green colour bands. Credit: Sarab Sethi.

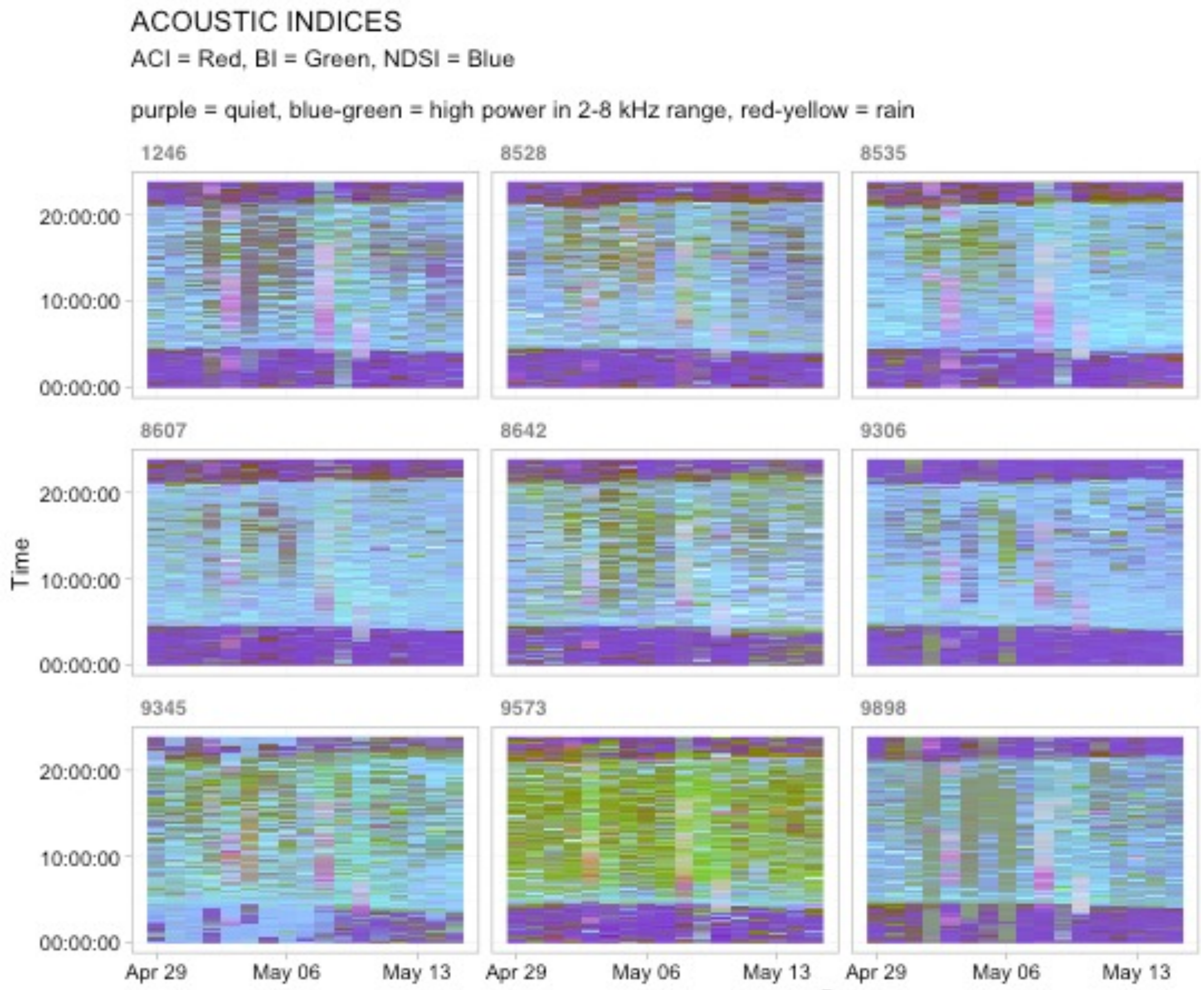

Figure 4.3 False-colour plot for nine ARUs deployed simultaneously across a site over a 17 day period. The purple bands visible in most plots show low acoustic index values during the night, with the green blocks in site 9573 showing high levels of acoustic activity at this site.

4.4. Data pre-processing

Having initially visually assessed the data, it may be apparent that some of the data are problematic. Problematic data can occur for a range of reasons, including recorder faults, an excess of anthrophony or geophony (e.g. from roadworks nearby, or a period of high wind and rain), or the absence of any acoustic signals of interest. Careful thought needs to be given as to what constitutes unwanted noise in the data, and what could be an important part of a site's acoustic character - this will vary by the study objectives.

In general, there are few automated processes or documented methods for the removal of such problematic data. The hardRain package[104] in R can identify and remove periods of intense rainfall from datasets, but is primarily aimed at data collected in tropical forests, and is less effective in temperate environments. There are also published methods for identifying wind affected files and 'denoising' them (i.e. minimising the impact of wind noise)[105]. In many cases, it is likely to be easiest to manually search for outliers by extracting a range of acoustic index values, and then either visually examining false colour spectrograms, or by standard statistical methods of identifying outliers in a dataset. It is also a good idea in large datasets to remove the first 15 minutes of recording after deployment (or longer if possible), and the last 15 minutes prior to collection to limit any impact from the presence of people during this period.

A type of problematic data that may be less apparent during a visual inspection is private conversations of people in proximity to the recorders. The presence of human speech in passive acoustic data raises a number of ethical concerns, but has received little attention in the ecoacoustics literature. The simplest way to eliminate human speech from audio data is to apply a high-pass filter at a frequency that would remove all or most human sound , for instance ~2 kHz would certainly be enough, however, a large amount of biophony would also be removed; for instance Great Bittern *Botaurus stellaris* and Common Cuckoo *Cuculus canorus* vocalisations would also be entirely eliminated. There are a number of well-developed voice activity detection softwares available, however they are primarily developed for indoor use with voices in close proximity - only one program has been designed for identification of (Norwegian) speech in ARUs[106] - the Python code is freely available online. Another option is to set a recording schedule of intermittent short clips that would break up any unintentionally recorded conversations into unintelligible snippets. However, this may have a significant impact on the detection of target sounds or temporal analysis of the soundscape.

Ultimately, it is better to deal with privacy issues by avoiding collecting human speech and warning of the risk of being recorded at the deployment stage, than it is to deal with once collected. We are not in a position to advise on the legality of storing PAM data in respect to the UK General Data Protection Regulations, and practitioners should take care to ensure they are fully compliant.

Figure 4.4. Hay meadows and wet grassland often have strong dawn choruses dominated by Skylark *Alauda arvensis*, Reed Bunting *Emberiza schoeniclus*, and Sedge Warbler *Acrocephalus schoenebaenus*. Credit: Oliver Metcalf.

Chapter 5: Targeted Monitoring

Once data is collected and been subject to initial pre-processing, there are a range of available analysis options. This chapter deals with those methods that deal with detecting and identifying specific ecologically relevant signals, such as bird calls, within the audio data (Section 5.1 Acoustic analysis), and how they can be used to gain ecological insight (Section 5.2 Ecological analysis). The chapter is labelled 'Targeted monitoring', as many of the methods can be applied equally to individual target species, multiple species, or ecologically relevant anthropogenic sounds, such as gunshots.

5.1 Acoustic analysis

5.1.1. Manual analysis

In many cases, the most accurate and efficient method for obtaining useful ecological data from audio files will be manual analysis. This is especially true if community data are required (e.g. data comparable to point counts conducted in the field), or if data on the detection and non-detection of a single species are required with a high degree of accuracy. In these cases, the effort involved in manually reviewing data is likely to be less than that of training a highly accurate single-species automated classifier, or reviewing predictions of off-the-shelf multi-species classifiers.

The process for retrieving specific data from audio files is similar to that described in Chapter 3.1, visualising audio files using spectrograms and then listening to them as necessary to identify signals of interest. Labels, such as species identifications or call types, can be attributed to the relevant section of the spectrogram, then used later in ecological analysis. All of the software listed in Chapter 3.1 support labelling of specific sections of the spectrograms and would be suitable for this type of manual analysis. Although this process requires considerable human input, visualising the data with spectrograms can speed up analysis considerably for experienced practitioners. Birdwatchers using ARUs to record nocturnally migrating birds over their gardens report being able to analyse a night's recording of eight hours with average migration activity in about one hour, identifying and labelling all significant bird vocalisations[107].

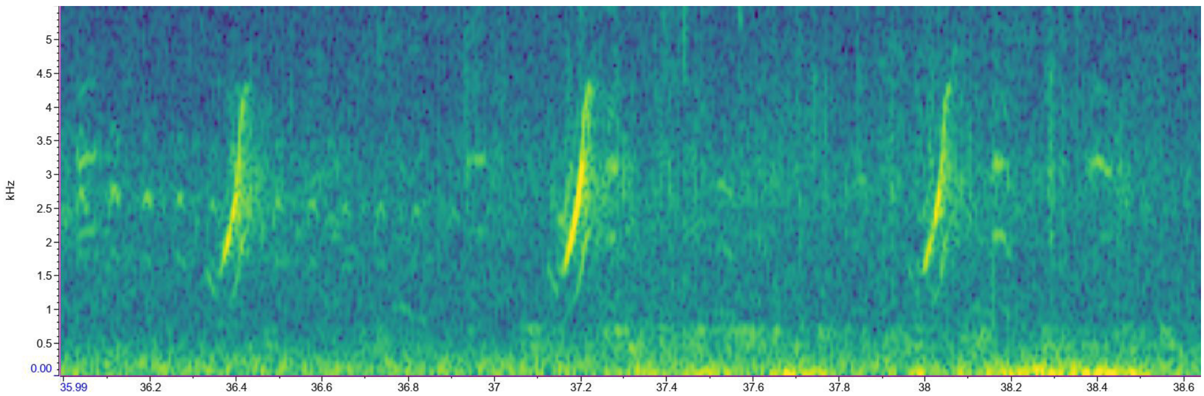

Figure 5.1. Three vocalisations from a rare breeding bird, the Spotted Crake Porzana porzana, recorded during a targeted PAM survey of the Lower Derwent Valley NNR on 05/04/2022.

Given the relatively high amount of human effort required in analysing audio data this way, the benefits compared to traditional field-based surveys may be less immediately obvious. However, manual analysis of species data from recordings is likely to produce better assessment of community species richness in birds compared to conducting point-counts in the field[19], detecting an average of 10% more species. Additional benefits include allowing analysis to be undertaken at any time (e.g. outside of busy fieldwork periods), can allow the same observer to analyse temporally synchronous data (i.e. effectively undertake multiple surveys simultaneously) thus reducing inter-observer error, and allows for repeated analysis by other observers to correct for errors. Importantly for commercial enterprises, it also provides a fully evidenced analysis workflow, should the presence or absence of certain species be queried later.

5.1.2. Automated and semi-automated approaches

Automated approaches to detecting and in some cases identifying signals of interest are potentially time saving alternatives to manual analysis. There are a range of approaches available, varying in complexity and output, ranging from simple algorithms used to detect when any sound event occurs, right up to cutting-edge neural networks to detect and identify the songs of multiple species from across the globe, that push at the boundaries of deep-learning development.

5.1.3. Sound event detection

When choosing an approach to take, it is important to be aware of the difference between sound event detection models and classification models. Sound event detection models are useful when looking for rare sound events during long quiet periods, or when the majority of sounds are of interest and it is valuable to isolate them. These are often relatively simplistic approaches that look for sounds that pass predefined thresholds for amplitude or signal-to-noise ratio (e.g. Raven Pro[91], Kaleidoscope Pro[51], Tadarida D[108]), but can be parameterised to only apply at certain frequencies or with minimum or maximum time intervals. Given their simplicity, these sorts of models, which exist on a range of acoustic analysis software, can be quick to configure and fast to apply to large quantities of data. They can be an effective way of quickly removing large quantities of audio that is not of interest, with reasonable confidence. What they do not do, however, is identify the detected sounds as belonging to any species or source.

Figure 5.2. After the sun sets wetlands can come alive with bird and amphibian sound – passive acoustic monitoring offers a great way to monitor this. Credit: Oliver Metcalf.

5.1.4. Template matching

One method to obtain detections of an identified sound type is through template matching. In this method, the user provides one or more templates of the desired sound, and an algorithm compares the template to the dataset provided. The output is then a series of detection periods and sometimes frequencies, with an associated confidence score. Users can determine their own thresholds for accepting a confidence score as a true detection. This method has distinct advantages over more complex algorithms as it requires limited user input in training the algorithm, doesn't require a high level of technical skill to undertake, and is conceptually simple. However, template matching can be quite slow to run over large quantities of audio data, and is only likely to be highly accurate for stereotyped calls in relatively simple acoustic environments[109]. Although, the process can be applied to less stereotyped calls or noisier environments; in most cases users choose to set a relatively low threshold to avoid missing too many calls, then manually reassess the detections produced to eliminate false positives. This can still be quite time consuming, but potentially less so than manually assessing all of the data, or building a more complex classification algorithm[110].

There are several methods available for template-matching analysis. The most user-friendly is the Arbimon online platform[35], which allows data to be uploaded, stored, and analysed in various ways, including template matching, free of charge. Arbimon uses a slightly more complex form of template matching, in which initially provided templates are then used to train a random-forest detection model - although this process requires very little user input beyond the initial template[111]. This type of template matching has been used in academic ecoacoustic studies successfully across the globe[112,113]. However, uploading large quantities of audio data to the web can be time-consuming, and it may not be suitable for commercial or sensitive projects due to the somewhat opaque policies about data re-use. It is however an interesting integrated analysis platform that is worth exploring as an analysis option, especially for those without coding skills in R or Python, or the time to develop their own pipelines.

For those with the capacity for basic coding in R, development of a template-matching pipeline is straightforward thanks to the monitoR package[114]. There is a tutorial video on basic setup of such an approach by Danielle Texeira available on the UKAN+ Youtube page[115]. Again, this approach has been well used in academic studies globally, and there are several papers outlining ways to optimise the use of such an approach,[116,117].

Figure 5.3. Targeted passive acoustic monitoring can be a good way to establish the presence of rare or scarce nocturnal and crepuscular species such as this Short-eared Owl *Asio flammea*. Credit: Oliver Metcalf.

5.1.5. Machine learning

Contemporary approaches to machine learning for acoustic analyses include supervised and unsupervised learning. Supervised machine learning relies on labelled input and output training data, whereas unsupervised learning processes unlabelled or raw data, such as the clustering algorithms used in Kaleidoscope[51].

Early supervised learning models are a type of machine-learning algorithm that use acoustic features identified by the user to train a model capable of distinguishing between pre-specified classes. The algorithm is provided with large quantities of training data, from which it can 'learn' the patterns in the provided features. The trained model then makes predictions on the probability of the new data belonging to a particular class. For instance, imagine a simple soundscape in which only two species sonified. Someone looking at the respective calls could observe that there is a great deal of difference between the two species in the rate they repeat their calls, and the pitch at which the calls are given. The algorithm would therefore be provided with measurements of inter-syllable gap and frequency from calls belonging to each class (species), and a model trained to predict the probability of which species the calls emanated from. Generally in complex acoustic classification tasks, many more features are selected. These types of models have been used with reasonable success for automated classification of call types, but are generally being used less as they are out-performed by deep-learning methods.

Figure 5.4. Small mammals such as this Pygmy Shrew *Sorex minutus* often make sound, so can be a good target for acoustic monitoring, although some of the sounds can be beyond the range of human hearing. Credit: Oliver Metcalf.

An overview of many of the software options that use machine-learning approaches (amongst others) is available in Table 4 of Priyadarshani et al., (2018)[118]. We do not go into great detail here on these programs as for most people interested in ecological sound classification, the BirdNET app[119] or Kaleidoscope Pro[51] programs will likely be the best approach, and are discussed in more detail below.

For those interested in having more control over the classification process, the Tadarida toolbox108 has been used successfully in Europe to classify a range of bird, insect, and small mammal sounds, although is most effective in ultrasonic frequencies. In many cases developing bespoke pipelines in R or Python can be most effective. R in particular has several packages that can help with this, in particular gibbonR[120] has many useful functions - but it is also possible to extract acoustic features using a package such as warbleR[121], before using a specialist machine-learning package such as caret[122] to perform the classification.

Clustering algorithms are not provided with training data. Instead a sound event detection method is undertaken first, after which the clustering algorithm groups sounds by similarity. In theory, as call variation should be greater among species than within species, if configured correctly these algorithms should result in clusters of single species calls that can then be identified by an ecologist.

One of the most popular commercial software for ecoacoustic analysis, Kaleidoscope Pro[51] uses clustering. Kaleidoscope Pro can quickly analyse large quantities of data, and is user-friendly. In many cases, it is likely to be the optimum species-specific analysis software for commercial projects, although it is expensive and still requires ecological knowledge to identify sounds once they are placed in a cluster.

5.1.6. Deep learning

Deep learning neural network models follow the classical machine learning paradigm, but instead of requiring a primary feature extraction step the raw audio (or more commonly its spectrogram) is presented as input and a high dimensional representation of the audio is learned.

Supervised, unsupervised and increasingly semi-supervised and reinforcement deep learning paradigms exist. The most popular approach to classification of acoustic data are convolutional neural networks[123]. Large quantities of data labelled with a single species or taxa (binary classification) or for multiple species (multi-label classification) are provided. The algorithms are able to independently 'learn' which features are most relevant in telling them apart from other sounds. The principle is that this learned representation can generalise to new data. Convolutional neural networks have produced the best accuracy metrics for automated classification of any of the methods mentioned here[124]. Deep learning algorithms can be effective in quickly and accurately assessing large quantities of acoustic data, and is the only classification method that can realistically be fully automated. However, there is a high level of technical knowledge required to initially train one of these algorithms, and the process of finding, identifying, and labelling enough appropriate training data to create an accurate classifier can be very time consuming. For those with basic Python skills, the OpenSoundscape[125] package offers a relatively straightforward way to build classification models, and has a very clear user guide on how to do so.

An alternative to training classifiers for individual use is to use pre-trained classification models built by others and made available for use. As the production and use of deep-learning models is still relatively new in ecoacoustics, the number of open-source models is limited, but is likely to increase. Fortunately one of the few available, BirdNET developed by Cornell Lab of Ornithology[119], works for almost all European bird species and is freely available to download as a standalone program. These multiclass models have advantages, they only need to be run once over the data to obtain a complete list of all species present, but also have disadvantages - they can produce some obscure false predictions, and can in some cases be less accurate than models trained for one or a few species. Nevertheless, the freely available and user-friendly nature of the software is likely to make BirdNET a game changer for analysis of acoustic data for birds, although currently it is only available under a non-commercial Creative Commons licence. Note also that BirdNET is most accurate when using the feature that allows it to be constrained by local lists of birds generated from eBird.

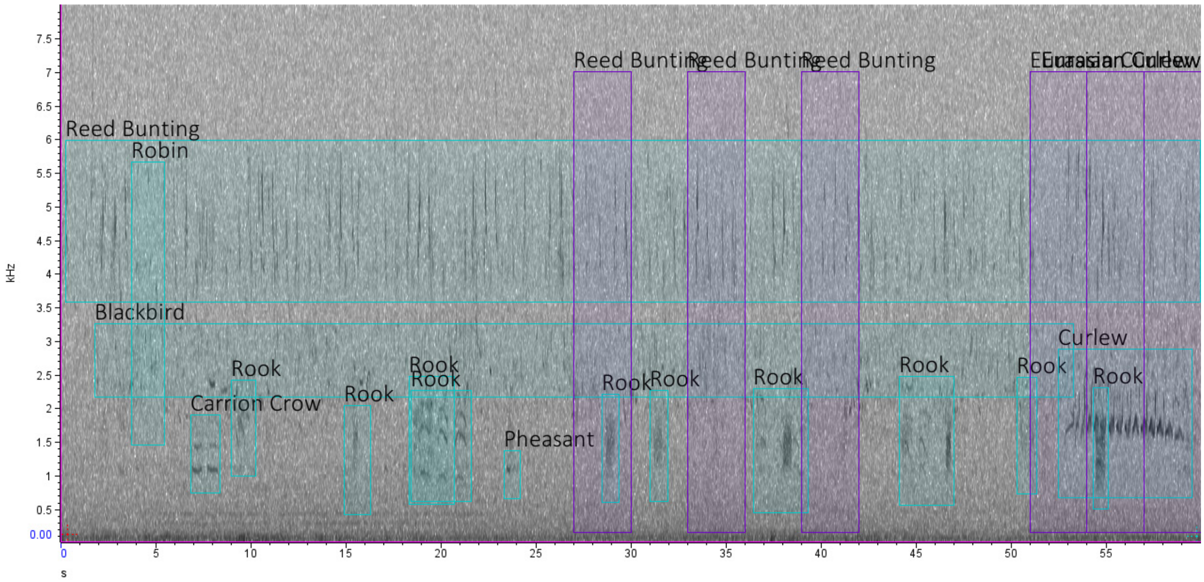

Figure 5.5. A comparison of manual annotation (light blue) vs BirdNET classification (purple) of 1 minute of audio from the Lower Derwent Valley NNR at 04:00 on 4th May 2020. Manual annotations were made in Raven Pro by Oliver Metcalf and took approximately 6 minutes. BirdNET was run through the desktop graphical user interface, was given the latitude and longitude of the recording, the week of the year, with overlap set to 2 seconds, sensitivity of 1.0, minimum confidence of 0.1 and 4 threads and took 5.6 seconds. The spectrogram was produced in Raven Pro.

Similar automated classification algorithms are available commercially for bats, and through the BTO Acoustic Pipeline[126] for a range of bats, small rodents, and insects. The BTO Acoustic Pipeline is free for small quantities of non-commercial audio analysis, but a paid-for model is available for larger and/or commercial projects, and provides a very good way to obtain a suite of accurate automated identifications of non-bird species without building individual classification algorithms. However, as the Acoustic Pipeline was originally designed to process ultrasonic data it requires data with a sampling rate of 192 kHz or higher (recommended at 384 kHz for AudioMoths), so it may not be suitable for long periods of monitoring, as SD cards in ARUs would fill rapidly.

Finally, for those with access to experienced data scientists, it is possible to develop your own deep-learning classification models. Labelling enough training and test data to develop these models will represent a significant start-up cost in terms of time and effort, so this approach is likely only cost-effective if it is to be applied to very large quantities of acoustic data over a long period, potentially for multiple species, and when a high degree of accuracy is required. The development of deep-learning models for ecoacoustic classification is a field of active research in computer science, and as such the field is developing rapidly - it is worth undertaking a review of the latest academic literature in the field before undertaking any such projects.

5.1.7. Assessing classification performance

When using automated classification, one of the most important questions to answer is how accurate the model is in its predictions. Unfortunately this is not straightforward to answer, and even the most user-friendly classification software do not offer reliable estimates of model accuracy. Standard machine-learning methods for assessing classification performance involve splitting the labelled dataset in ratio of 80:20 or 70:30, and using the larger sample to train the algorithm and the smaller set for testing model performance. Unfortunately this approach does not translate very well for ecoacoustics, as the labelled data are often highly unrepresentative of the acoustic data it will be applied to, because the training data needs lots of examples of the target species calls, but these will likely be far rarer in the natural environment. Consequently, when using automated classification, it is necessary to budget a substantial amount of effort to manually assess an independently sampled test dataset. Knight et al., (2019)[127] provide an excellent set of guidelines for which accuracy metrics should be used, and how to benchmark results.

Note that automated classification models can be very sensitive to different soundscapes, so if the classifier is applied to data taken from large spatial or long temporal scales, it is also a good idea to check for variation in classification performance across the study data - some methods for how to do so are provided in Metcalf et al., (2022)[128]. There is an additional need for caution when using 'closed', off-the-shelf, sound classification tools. Where the training data and call/ sound features used to train the models are not published, it is not possible to assess how the algorithm is making classifications and what the potential biases or errors might be, which ultimately will affect the inference.

The metrics used to assess model performance will be dependent on the objectives of the particular study being undertaken, and the use to which the classification data will be put. In ecoacoustic studies, precision (the proportion of correctly predicted presence amongst all predicted presence) and recall (the proportion of all true presences which are predicted) are generally considered most useful. When calculating accuracy metrics it is commonplace to use an initial confidence score threshold of 0.5, so that for any confidence scores below 0.5 the target species is predicted absent, and above 0.5 the species is predicted as present. If initial accuracy metrics have not achieved the desired level of accuracy, there are two methods to remedy it. The first is to retrain the model, using more (or better/ augmented) training data. However, this can be time consuming, and it is likely to be more effective to first try to adjust the confidence score threshold to achieve an optimal trade-off between precision and recall. Assessing precision-recall trade-offs at different thresholds can be done formally by building precision-recall curves (there are various R and Python packages available to do this, such as ROCR[129] and PRROC[130]) using the test dataset, or less formally by taking stratified subsamples from across the range of predicted confidence scores post-classification - an approach that may be particularly useful for pre-built classifiers like BirdNET.

Figure 5.6. Caledonian pine forests hold a range of biodiversity suitable for passive acoustic monitoring. One of the rarest – Capercaillie *Tetrao urogallus* – lek in early spring and are readily disturbed by human presence, autonomous recorders have proven to be a good alternative monitoring method. Credit: Oliver Metcalf.

Very large studies generating large numbers of positive predictions will require a fully automated workflow, it is likely to be necessary to set a high confidence score threshold to minimise false positives (i.e. predicted presences when the target species is in fact absent). Precision scores of >0.9 and recall of >0.5 are probably good targets for most studies. The disparity between these scores is because when setting thresholds, we recommend focussing on achieving a low number of false positives (i.e. the algorithm predicting species present when in reality it is absent) at the expense of missing some true presences (i.e. prioritising precision over recall). This is because i) species usually vocalise multiple times, often in quick succession and most classification algorithms give predictions over short timescales, missing the presence of a species in one 3 second clip is mitigated by detecting it in the next, and ii) falsely assuming a species is present when it's not is generally more detrimental to ecological studies than missing presence. To mitigate this further, it can be effective to summarise classifications over time - e.g. turn multiple predictions from three second files into a single prediction of presence over ten minutes.

For smaller studies, when all cases a target species is predicted to be present in can be manually assessed, the inverse approach can be taken. This process is known as semi-automated classification. Here, the threshold is set low to maximise recall, so that very few true presences are missed. This will necessarily produce a higher number of false positives, but these are then weeded out by manual assessment. This will result in a dataset with fewer classification errors at the expense of greater manual labelling effort. Other than in the cases of small datasets, this approach is likely to be desirable for studies in which it is important to know exactly how often a species vocalises or is present, or when a classification model performs poorly overall.

5.2 Ecological analysis

5.2.1. Presence and absence

The most basic ecological data obtainable from PAM is the presence or absence of certain species. In many cases, especially when dealing with wildlife legislation, even a single data point confirming species presence can be critically important. PAM can be a very good choice for this sort of survey, and has been proven effective for a range of species globally[131,132,133,134]. In particular, if only a single presence is required, an automatic workflow heavily weighted in favour of precision presents a potentially very efficient way of obtaining confirmation of species presence. When attempting to establish absence, the opposite approach should be taken, and either manual analysis should be adopted, or a semi-automated approach heavily favouring recall. It is quite clear that for many vocal species, such as those that are elusive, nocturnal, live in difficult to survey habitats such as reedbeds, or are at low density - well-designed acoustic surveys over long-durations can be more effective at confirming presence than manual surveys. Given this, it is unfortunate and somewhat illogical that the UK Bird Survey Guidelines[135] advise that PAM should not be used to establish species absence.

5.2.2. Community analysis

A list of species from a location is likely to be high on most ecologists' lists for desirable products from an ecoacoustic study. A list of species is relatively easy to generate, either through manual assessment of the data or by running a multi-species classifier such as BirdNet. However, acoustic data is not a census of the species within an area - ARUs may not cover the entire area, recording schedules may not be continuous, or recordings may be subsampled for manual analysis after collection. Further, species will not be equally represented in the acoustic data, as some make more sound, or are easier to detect. It is often therefore desirable to assess how representative any species list is of the whole community.

There are several methods that can be used to assess the completeness of the species list, although this exercise is somewhat circular. One very informal way to do so is to compare the generated list to pre-existing lists of species present in the area at similar times of year, using data from local recording schemes, and/or from online citizen science repositories such as eBird[136]. This process can help to ensure that a disproportionate number of species aren't being missed and also identify any species which may be erroneously identified from the acoustic dataset, but are not present in other datasets. To more formally assess survey completeness, species accumulation curves can be easily and quickly built in R using the iNext[137] or vegan[138] packages, in which the number of species found is predicted by the number of survey samples used. Once the accumulation curves plateau, more survey effort is unlikely to result in the detection of many more species, so it is reasonable to assume the species list obtained from that much survey effort is representative of the entire community present. This can also be used to identify that more survey effort is needed if accumulation curves do not plateau.

Figure 5.7. A Fronter Labs Bioacoustic Recorder deployed in a Spotted Crake Porzana porzana territory to help monitor this rare, nocturnal, and elusive wetland breeding species. Credit: Oliver Metcalf.

5.2.3. Occupancy models

Occupancy models estimate the probability of species occupying a site, in relation to environmental covariates. Importantly, occupancy models estimate detectability from a structure of multiple visits, and can infer species occupancy in suitable habitat, even if the species is not detected at a site. Acoustic data can be divided into discrete, independent, temporal units, and then treated as 'repeat visits' to a site. They have been widely used as a method to analyse data derived from acoustic studies both in the UK where they have been used to study rare heathland bird species[139] and abroad for elusive forest passerines[140,141]. They are well suited to acoustic data as they take presence/absence data as input and allow for imperfect detection of the sort caused by classification error or silent individuals. They can also be extended to multi-season or dynamic occupancy models to allow for understanding of changes in species occupancy, which are especially useful in long-term monitoring[142,143]. Additionally, they can be used for multi-species models to investigate the impact of co-occurring species, which may be useful in monitoring the impact of reintroduced or newly occurring species at rewilding sites or conservation projects. There are various R packages for fitting occupancy models, the most widely used of which is 'unmarked'[144]. There are also an increasing number of papers looking at methods to deal with the sort of errors caused by automated classification workflows for acoustic data[145].

5.2.4. Localisation

Localising acoustic signals has a multitude of applications spanning: non-invasive behaviour monitoring, abundance counting, and locating the position of chainsaws used in illegal logging[146] or gunshots[64]. As with the hardware, there are few off-the-shelf software solutions for sound localisation. Fortunately, there is an excellent review of the approaches taken to sound localisation so far, which should give anyone wishing to undertake such an analysis a good starting point, and an idea of the analytical challenges they are likely to face[24]. Increasingly open localisation processes are being released, often with user-friendly interfaces e.g HARKBird[147], and ODAS[148]. There are also functions and tools in the Python packages scikit-maad[102] and OpenSoundscape[125] likely to be useful to anyone attempting sound localisation.

5.2.5. Density/Abundance

Another highly desirable output from acoustic data is obtaining a measure of species abundance or density - which was recently reviewed[149] and would be recommended reading for anyone wanting to explore the topic. . Estimating abundance or density is not a simple task, and whilst there isn't yet one proven method successful in all scenarios, there are three general approaches.

The first is to use vocal activity rate. The second is to use localisation of sounds and complex statistical approaches. The third is to use individual identification. Each of these has their own strengths and weaknesses and currently each is only appropriate for a few species or studies that meet the stringent assumptions.

Vocal activity rate[150] is predicated on the idea that if individual animals vocalise at a consistent rate, then vocalisations from a species are linearly related to the number of individuals present. The challenge with this simple approach is that accurate information is needed on the average sound production rate of individuals (or cue rate)[151]. The approach assumes that average cue rate is the same between individuals and that detectability is the same at different sites. Much of the development of this work has been with marine mammals[152]. In the terrestrial realm, this approach may be applicable to some species, such as amphibians and territorial bird species during the breeding season. Importantly, it has also been paired with template matching for classification of Forster's Tern *Sterna forsteri* in the USA[153] and automated classification for Cory's shearwater *Calonectris borealis* calls on the Azores to successfully estimate the size of nesting colonies[154] - a potentially very valuable use in the UK for monitoring potential development impact on colonially nesting species, or the effects of rat eradication. For other species, it seems unlikely to be successful or requires a great deal further research - for instance for nocturnally migrating flocks of birds where call rate is influenced by a wide range of factors[155], or large flocks of wintering geese where a saturation point in call rate seems likely to be quickly reached.

A word of caution. The approach outlined above can be used to estimate the number of individuals within the area surveyed by the acoustic sensor and associated identification algorithms. However, this is not an estimate of density without a concurrent estimate of the area surveyed. Therefore, estimating the density of a species requires more complex methods to estimate the area surveyed. With colony-nesting species, it may be straightforward to be sure that the entire colony could be detected by the sensors. However, in wider-landscape situations it is more complicated. In these scenarios, the cue-counting method above can be used to estimate the number of individuals detected at each sensor. Without this, the cue-counting approach can be assumed to estimate relative abundance at different sites, but not to estimate density.

A second approach involves the localisation of calling individuals[156,157,158]. These locations are then used to estimate distances and distance-sampling methods are applied. Or alternatively, the localisation is used to identify the same sound detected on multiple sensors and spatially-explicit capture-recapture methods are used. Both of these are complex approaches that have only been successful on a small number of studies, with bespoke analytical development for each situation. Anyone looking to adopt such an approach in the UK is, for the time being, likely to need to develop their own bespoke methods. However, some academic studies have been able to successfully localise passerine species in North America and estimate density, and the scikit-maad package[102] in Python has several useful functions to facilitate the analysis process.

Finally, some species have calls or songs that are unique to individuals and thus estimate abundance by knowing the identity of the individuals present. In some cases, such as Cetti's Warbler[159] and Tawny Owl[160], the songs contain unique phrases or ordering that make this process feasible using PAM, albeit time-consuming. In other species, the individual differences are likely to be subtle and require better quality recordings than are standardly collected with ARUs equipped with omnidirectional microphones. As with the first approach, without estimates of area sampled, this method estimates species abundance, but not density.

Chapter 6: Soundscape Analysis

Soundscape analysis considers the whole soundscape, combining biophony, geophony and anthropophony. In doing so, soundscape analysis gives space to less charismatic, unheard, or understudied species, and can also be used to monitor the manner, extent and perhaps impact of anthropophony. Currently, soundscape analysis is primarily conducted through the use of acoustic indices - a family of methods used to quantify variation in acoustic energy and relate that variation to the sonic environment.

Acoustic indices have been used to monitor species richness[161,162], community composition[163], the relative contributions of biophony, geophony and anthropophony to a soundscape[164], approximating species abundance[165], as means of more intuitively visualising soundscapes[100], or even as a means of mapping an area's wildness[166]. However, acoustic indices have yielded mixed results. A recent meta-analysis[167] exploring their association with biodiversity highlighted a weak relationship and highly variable effect sizes between many of the most commonly used acoustic indices and species diversity metrics.

Increasingly, deep-learning based methods are being used as an alternative to acoustic indices for soundscape analysis. Soundscape descriptors built from deep-learning embeddings make for informative visualisations and are successful predictors of landscape, biomass, and species[168]. Deep-learning embeddings have been shown to outperform acoustic indices on landscape classification tasks and are more robust to experimental variation[80,168]. However, they can be complicated to generate, and their opaque nature makes interpretation difficult (see below).

6.1. Introduction to acoustic indices

Soundscape analysis with acoustic indices represent an entirely different analysis paradigm to species-specific analyses. This approach pre-supposes that soundscapes from different locations, habitats, and ecological communities are different and that those differences are possible to quantify using statistical measures of acoustic energy to provide ecological information that may complement species data. The varied statistical methods of measuring variation in acoustic power are collectively termed acoustic indices[161]. Of the dozens that have been proposed, most entail calculation of power ratio between multiple frequency and/or time bins across a recordings, creating more nuanced versions of conventional sound pressure and spectral density metrics. This approach has been increasingly popular in the academic literature, used both as a means to characterise soundscapes and the corresponding landscapes, and in some situations as proxies for traditional biodiversity metrics such as species richness and species diversity[169].

There are a range of reasons for supposing that the spectro-temporal structures of a soundscape would be reflective of its ecological components. The most developed theories in this field are the Acoustic Niche Hypothesis and the Acoustic Adaptation Hypothesis[169]. The Acoustic Niche Hypothesis[170] suggests that species that have evolved together will also have evolved their own niche in time and frequency space, in which they can communicate clearly to conspecifics without interference from other species. For example, birds may call at frequencies lower than more dominant cricket species, whilst other species may avoid vocalising when the avian dawn chorus is at its peak. The theory posits that a soundscape with fewer quiet gaps in frequency or time will be reflective of higher species richness, as more species have co-evolved to fill the space. Conversely, degraded habitats will show empty gaps in the soundscape, which represent the niches of species no longer present. The Acoustic Adaptation Hypothesis[171] suggests that species adapt their vocalisations to the habitat they occur in to maximise how far the signal is carried. Think for example of the high-pitched and sibilant calls of species such as Common Kingfisher *Alcedo atthis*, Grey Wagtail *Motacilla cinerea*, and White-throated Dipper *Cinclus cinclus*, as species that have all evolved alongside noisy fast-flowing water. This convergence of calls due to the impact of habitat gives the soundscapes of different areas and habitats unique and recognisable properties. However, it is worth noting that both of these theories are controversial[172,173], and there is evidence both for and against them.

6.2. Acoustic Analysis

Soundscape analysis has several major benefits over species-specific analyses. It is generally easy and quick to calculate acoustic index values, and computationally relatively inexpensive. Additionally, taking a soundscape approach reduces the need for complex algorithms or species identification experts. In combination, this can be an attractive proposition. However it is worth noting that what is gained in ease of application is somewhat lost in ease of interpretability - it is not always clear what differences or changes in acoustic index values mean ecologically.

Careful use of acoustic indices is therefore necessary. One of the most effective uses of acoustic indices is to 'characterise' soundscapes[174,175]. Whilst all soundscapes are unique, those coming from similar places, times, and habitats tend to have similarities. Indices can be used to quantify these similarities and differences, to identify change, or to make predictions about the environment in which the recordings were made, without needing to necessarily understand the underlying causal mechanisms. Indices are also commonly used as proxies for traditional biodiversity metrics, although this approach may only be reliable under certain conditions (see section 6.5 for more details) and it is necessary to ensure there is a great deal of ground-truthed data also available.

Acoustic indices range in complexity - the most basic are simple audio descriptors (e.g. zero-crossing rate, counts of acoustic events, background noise levels), whilst others have been designed heuristically to capture the intensity of biophony, ratio of biophony to anthropophony or distribution of energy across the spectra under the assumption that this may reflect composition of the acoustic community.

Acoustic indices are not a magic solution and must be applied and interpreted in context. For example, a measure of the number of acoustic events in an urban park is unlikely to say very much at all about the number or types of non-human species present in the park as it is likely to be dominated by anthropogenic sounds. However, there may likely be a relationship between the number of acoustic events and the number of several seabird species breeding at a colonial nesting site, for instance[176]. More heuristic indices may reflect some aspect of ecology. However, it is necessary to check the assumptions of the individual index to ensure that the circumstances it was designed to reflect pertain to the data it is applied to, and "sound-truthed" against some form of manually assessed data.

Table 6.1. An overview of some of the most commonly used acoustic indices adapted from Bradfer-Lawrence et al (in prep).

Index and original reference	Index description	Soundscape patterns
Acoustic Complexity Index (ACI)[177]	Determines the difference in amplitude between one time sample and the next within a frequency band, relative to the total amplitude within that band. The concept underlying this index is that biophony is often of variable intensity, whilst anthrophony such as engine noise is generally constant. Acoustically rich habitats may produce low ACI values if intensity does not vary greatly over time even if there are multiple contributing sound sources. It is also impervious to constant biophony such as tropical insect noise.	High values might indicate storms, intermittent rain drops falling from vegetation, stridulating insects, or high levels of avian biophony. Low values are associated with constant noise that fills the whole spectrogram, for example from loud technophony or excessive cicada chorus. ACI value is cumulative; longer recordings will give higher values. Taking a mean is sensible.
Acoustic Diversity Index (ADI)[178]	Derived by calculating the Shannon entropy of the distribution of acoustic energy among frequency bands. ADI ranges from 0 to the log of the number of frequency bins used. ADI will increase with greater evenness of energy among frequency bands. An even signal will give a high value (could be noisy across frequency bands or completely silent) and a pure tone (i.e. all energy in one frequency band) will be closer to 0.	High values associated with high levels of geophony and technophony, which fill the spectrogram with noise, or from very quiet recordings with little variation among frequency bands. Lowest values reflect dominance by a narrow frequency band, such as nocturnal insect noises in the tropics.
Acoustic Evenness (AEve)[178]	Derived by calculating the Gini coefficient of the distribution of acoustic energy among frequency bands. Values lie between 0 and 1. Higher values indicate greater unevenness among frequency bands, i.e. most of the sound is in a restricted frequency range.	Inverse of the patterns in ADI. High values identify spectrograms dominated by a narrow frequency band. Low values indicate many evenly-occupied frequency bands, although this can also occur in near silent recordings.
Activity (ACT)[100]	Proportion of values in the noise-reduced decibel envelope that exceed 3 dB.	Higher values indicate greater acoustic activity
Acoustic Space Use (ASU)[179]	A matrix derived by calculating the number of time-frequency bins (of given duration and frequency bin size) that are 'active' -e.g. surpass a predetermined amplitude threshold.	Higher values reflects the times and frequencies when acoustic activity is high
Background noise (BGN)[100]	The mode of the sound energy distribution of the waveform envelope.	Higher values indicate a greater level of acoustic energy, such as during rainstorms.
Bioacoustic Index (Bio)[180]	Derived from the sum of the mean amplitudes of individual frequency bands between 2 – 8 kHz minus that of the quietest frequency band.	High values are produced by recordings with high amplitude and greater disparity between loudest and quietest frequency bands. Low values arise when there is no sound between 2 and 8 kHz.
Spectral entropy (Hs)[163]	Calculated from the relative mean amplitude of individual frequency bands of a spectrogram. Uses the Shannon diversity index on those values as a measure of evenness. Scaled to range between 0 and 1.	Larger values imply a more even distribution of acoustic energy among frequency bands.
Temporal entropy (Ht)[163]	Calculated with the relative values of the amplitude envelope. Uses the Shannon diversity index on those values as a measure of evenness. Scaled to range between 0 and 1.	Larger values imply greater temporal evenness.
Acoustic entropy (H)[163]	Derived by multiplying spectral entropy (Hf) and temporal entropy (Ht), again scaled to range between 0 and 1. Within recording sets this tends to be dominated by Hf.	Higher values reflect greater evenness of amplitude among frequency bands (from either noisy or completely silent soundscapes). Lower values indicate acoustic energy concentrated in a narrow frequency range.
Events per second (EVN)[100]	Number of times per second the noise-reduced decibel envelope crosses a 3 dB threshold. Given as the mean per-second value over the recording.	Higher values indicate more frequent changes in amplitude.

Median of the amplitude envelope (M)[181]	Louder recordings will give higher values, and so reflect noisier soundscapes.	High values associated with high amplitude events such as storms. Low levels from very quiet recordings.
Normalised Difference Soundscape Index (NDSI)[164]	This index relies on the theoretical frequency split between anthrophony (1 – 2 kHz) and biophony (2 – 8 kHz) (although this may not hold in many systems, see text). NDSI is calculated from the power spectral density of the largest biophony band against that of the anthrophony band: (bio - anthro) / (bio + anthro) NDSI ranges from -1 to +1, with +1 indicating no sound in the anthrophony range.	High values reflect large amounts of sound somewhere in the 2 – 8 kHz range, with minimal noise between 1 – 2 kHz. Low values associated with more noise in the 1 – 2 kHz band.
Number of frequency peaks (NP)[182]	The number of individual peaks in the mean amplitude spectrum of a recording, scaled between 0 and 1. A peak is defined as having an amplitude slope > 0.01 and being > 200 Hz from the next.	Higher diversity of sounds should generate a higher number of peaks. Although in highly saturated soundscapes, there may be very few peaks if these sounds overlap.
Signal-to-Noise ratio (SNR)[100]	The difference between the maximum dB value in the decibel envelope and the Background Index (see above)	Higher values should reflect a transient sound event with a much higher amplitude above the background noise level.
Soundscape Saturation (Sm)[183]	The proportion of frequency bins that are acoustically active per minute. Derived from the power (maximum amplitude in dB) in each frequency band minus the modal amplitude of that same frequency band. If these values exceed a threshold then the band is active.	Higher values indicate a more active spectrogram, the soundscape is more saturated.

6.3. Computation of acoustic indices

Computing acoustic indices is relatively straightforward, so it is somewhat surprising that there are not more user-friendly programs available to calculate them. The *Analysis Programs* software package from Queensland University of Technology Ecoacoustics Lab[101] provides a wide range of index calculations, whilst Arbimon[35] offers some soundscape calculations akin to acoustic space use. Kaleidoscope Pro[51] offers a small number of simple acoustic descriptors, but none of the more commonly used heuristic indices.

Fortunately, it is simple to calculate acoustic indices using the R or Python coding languages – an index value for a single sound file can be generated in just two lines of code. The first line to read in a sound file, the second to calculate the index. The excellent seewave[94] and soundecology[184] packages in R and the scikit-maad package[102] in Python offer functions that will compute a wide range of the most commonly used acoustic indices very simply. For other less common indices code is often freely shared as supplementary information in associated scientific publications. In general, acoustic indices are calculated over 1 minute sound files, with any indices that generate values at a finer temporal scale averaged to that duration, and that is the recommendation here.

Technically it is possible to calculate indices over longer time periods. If your ecological hypotheses or questions motivate this, it can be advantageous to calculate variance, median, minimum and maximum as well as mean for frame-based indices (ACI, RMS, ZCR etc.) Note that this will reduce the sample size of the data collected, and likely slow down computation time as reading in and calculating indices over larger sound files generally takes disproportionately longer, and could use up a high proportion of RAM memory on smaller computers.

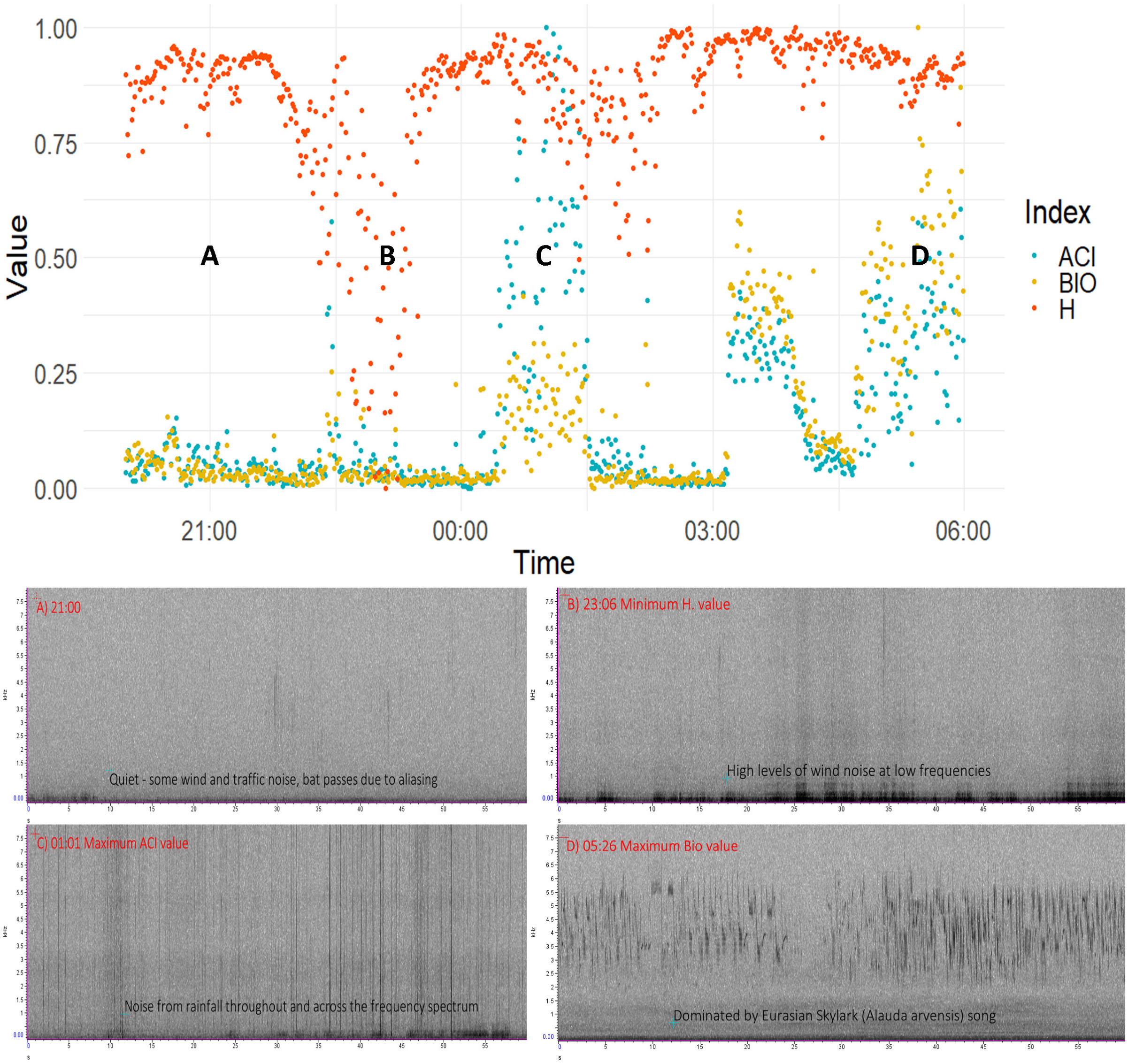

Figure 6.1. An example of the advantages and disadvantages of acoustic indices with real data. The top panel shows acoustic index values calculated for 600 1min audio files - recorded every minute between 20:00-06:00 on the night of 3rd-4th May 2020 in the Lower Derwent Valley NNR. Acoustic Complexity Index (ACI) and the Bioacoustic Index (Bio) were calculated using the soundecology package in R, with Acoustic Entropy (H) using the seewave package. All indices were calculated between 0.2-8 kHz and were centred between 0-1 afterwards. Calculation took <5 minutes. The quiet period before midnight is clearly visible, as is the onset of the dawn chorus shortly after 03:00. The bottom panel illustrates some of the complexity in interpreting index values. A) shows the quiet period, without a strong response from any of the indices. B) shows the minimum H value, with very little increase in ACI or Bio values - caused by strong wind at low frequencies, C) shows the maximum ACI value, paired with small changes in ACI and Bio, caused by heavy rainfall across the frequency range and D) the maximum Bio value, with similar increase in ACI but no change in H - caused by bird song. It is worth noting however that the sound file at D only contains sound from a single species - Eurasian Skylark *Alauda arvensis*, that has a broadband song, conspicuous vocal mimicry and high temporal variation.

6.4. Sampling effort to capture soundscape variability

Generally, it is not necessary to collect data continuously for soundscape analysis. However, it is important to be confident that the recordings have captured the naturally occurring variation in a soundscape. This should be checked before any further analyses, such as through comparisons among sites. As a rule of thumb, indices should be calculated from at least 120 hours of recordings from the target period - e.g. if a study wished to compare index values from dawn at different seasons, it would be necessary to record for 3 hours each morning for 40 days in each of winter, spring, summer, and autumn. However, it is worth noting that the 120-hour threshold was estimated from data collected in the tropics, and using indices calculated across both the entire frequency range and the entire diel cycle. It is likely that the number of hours needed to capture biophonic soundscape variability in the UK is considerably less, and that measuring indices at narrower time and frequency bins could reduce this still further. To be confident that the subsequently derived indices values are still representative of the variation in the soundscape would require a more formal assessment of survey completeness.

One option for assessing the level of precision with which soundscapes have been captured involves assessing reduction in the variance of the cumulative standard error of acoustic indices[185]. Standard errors stabilise when natural variability rather than data paucity is driving index variance. Bradfer-Lawrence et al (2019)[185] found that variance in indices standard errors reached ~10% with 120 hours (five days) of continuous recording. Although the quantity of recordings required to reach this 10% threshold will vary among systems, standard error variance will follow a similar shape of exponential decline with increasing quantity of recordings (TBL pers. obs.). Logistical constraints may necessitate deployments of less than 120 hours, but acousticians should strive to ensure they have at least passed the modelled inflection point, and recognise that shorter deployments result in less comprehensive capture of the soundscape.

The steps to calculate reduction in variance are as follows:

1. Generate acoustic indices values for each recording.
2. Randomly assign the recordings from a single site into groups*. Each group comprises recordings equivalent to one hour of deployment time.
3. Calculate the standard error of each index at each site. Standard error is cumulative, use progressively larger quantities of recordings by adding data for an additional group for each calculation. For example, standard error for the third deployment hour is calculated using the index values from the first three groups, for the fourth hour with index values from the first four groups, and so on.
4. For each acoustic index, divide each group's standard error by the maximum value across all groups from that site's recordings1, to give proportions of the maximum.
5. Quantify the reduction in variance with increasing quantities of recordings using non-linear regression with a Weibull distribution. The forthcoming 'AcousticIndices' R package includes functions to automate standard error calculations and the non-linear modelling.

* Or a single site-by-deployment combination if there was more than one deployment at a site.

6.5. Ecological Analysis

6.5.1. Indices to characterise landscapes

Indices have been used in a number of studies to successfully characterise soundscapes. What this means in practice is that each soundscape is unique, but that soundscapes from similar habitats have enough in common that machine-learning algorithms can differentiate them based on index values generated from recordings in those habitats. In general, it is a good idea to use a suite of acoustic indices to characterise soundscapes in order to represent different aspects of the sound present in the recordings. Commonly used indices for this purpose include Acoustic Complexity Index[177], the Bioacoustic Index[180], Acoustic Entropy[163], Acoustic Evenness/Diversity[178] and the number of frequency peaks[182], although a wide range of others can and perhaps should be used[186].

Additionally, the sensitivity of soundscape characterisation can be improved by calculating indices over a range of time and frequency bins[187]. These subsets of the entire soundscape are best selected by choosing periods and frequencies that are representative of when the target community or taxa are likely to have a strong presence in the soundscape - for instance around dawn and between 0.5-10 kHz for a study targeting birds. This is because soundscapes change across the diel cycle - think of the difference in sound between the dawn chorus and the middle of the afternoon, and at different frequencies - the insects stridulating at higher frequencies may be more different between sites than mammals and birds at lower frequencies. Calculating single values across the entire temporal and frequency ranges mask these subtle differences, so it is better to generate indices values at a range of different frequency and temporal bins, ideally based on prior ecological knowledge of the timings and frequencies of species groups communication. If taking this approach, ensure that you adjust any parameters of the indices as some have default values (NDSI, ADI, BI etc.)

Once acoustic index values have been generated, these values can be used in standard ecological analyses - exploratory ordination, classification or regression models. Random Forests[188] are a common choice as they have no formal distributional assumptions and are non-parametric so they can handle skewed, as well as categorical data. Random forests are an ensemble learning method that can be used for classification or regression and can be used for multivariate data.

These algorithms are 'trained' on a subset of labelled data (e.g. a series of index values which are labelled as having come from a certain habitat), learning what aspects of the data are most characteristic of that particular habitat. Having done so, it is then possible to use the algorithm to make predictions as to whether a new recording belongs to that habitat or not. In theory, this could provide an indication of habitat quality - several studies have shown that degraded or secondary forest in the tropics can be distinguished accurately from undisturbed primary forest using acoustic indices[162,187,189], as well as broader land-use types such as woodland and farmland[162]. In some situations acoustic indices have been shown to predict habitat type more accurately than species lists, suggesting that soundscape analyses may provide complementary ecological information to targeted analyses[162]. This possibility requires further investigation. If exploring this approach in new habitats, ecological ground-truthing should be conducted.

This research also highlights the potential to track habitat changes over time through soundscape analysis. For example we might expect the soundscape of a rewilding project on farmland would start out with acoustic index values similar to neighbouring farmland, but as scrub habitat and then woodland develops, index values should grow closer to neighbouring natural habitats. This is potentially a cost-effective and efficient way of tracking long-term changes in a landscape.

The potential for this approach is supported by a study demonstrating that three acoustic indices - acoustic richness, median amplitude and temporal entropy - successfully characterised the difference between islands with invasive predators still present, and those in which predators had been removed and had recovering populations of Leach's Storm-petrels *Oceanodroma leucorhoa*[190]. Elsewhere, acoustic indices have been used to assess the impact of construction and drilling at a gas platform development in tropical forest[113].

6.5.2. Indices as proxies for biodiversity metrics

Early ecoacoustic research investigated the potential for acoustic indices as proxies for biodiversity metrics, however a recent review reveals mixed success. This approach is heavily grounded in the Acoustic Niche Hypothesis, and relies on the idea that a more 'complete' soundscape entails more species being present. In general, heuristic indices designed to capture this soundscape 'completeness' are modelled against some metric of biodiversity, often species richness, derived from traditional survey methods. Simple Spearman's Rank correlations and linear models are often used to do so, although these are too simple a method to model what is likely a complex relationship. Under this approach, in order to try and eliminate masking sounds from sources not relevant to the biodiversity metrics, it is important to only calculate acoustic indices at appropriate times and frequency bins[187,191,192].

Overall, whilst some studies have successfully shown a strong relationship between acoustic indices and species richness, there is a great deal more research needed before we understand the relationship between the number and abundance of species present in an area and the emergent soundscape[193]. In particular, the impact of species with song mimicry is poorly understood, as is the level at which acoustic indices may saturate - e.g. it may be possible to establish differences in the soundscape between one and ten vocalising frogs, but not between 100 and 1000.

In contrast, the relatively simple measure of soundscape saturation has been effectively used to measure community turnover in selectively-logged tropical forest in Papua New Guinea[194]. Here, the spectrogram was gridded, and each cell was considered to be acoustically active when the amplitude power passes a threshold. These measures of soundscape saturation were then used to measure the dissimilarity between the different forest types - finding that logged forest leads to increasing homogeneity of the soundscape, with a loss of characteristic dawn and dusk choruses. This approach (and the conceptually similar Acoustic Space Use) could be applied to large restoration projects, especially when it is ecologically rational to hypothesise that restoration will increase ecological and soundscape diversity whilst unrestored areas will remain homogenous.

6.5.3. Deep Learning for Soundscape Analysis

Just as deep neural network models can be used to support automated species detection, deep learning methods can be used to learn soundscape representations[168]. Rather than training a new model from data, numerous pre-trained models are now readily shared. It has been shown that a large model trained on hundreds of hours of labelled YouTube data (VGGish) can be applied to ecological tasks. How does this work? The power of deep learning models comes from their many layers - VGGish has 24 layers, for example. Typically data is presented to an input layer and predictions read from the output layer. Under this approach the 'hidden layers' are inspected and the representations learned by the model to make predictions that can be adopted as a 'learned' representation, akin to a multivariate acoustic index. These learned representations have been used to characterise soundscapes, to detect anomalous sound events such as gunshots or chainsaws, and to predict with a high degree of accuracy the presence or absence of a range of forest indicator species in Borneo[195].

Pre-trained models can be further "tuned" with local soundscape recordings using self-supervised methods - greatly reducing the human effort in labelling data and increasingly the accuracy of the representation. However, as with all things there are trade-offs. Learned representations can be very powerful, as they can provide detailed representations and are not based on human assumptions about potential links between soundscape facets and ecology. However traditional approaches are notoriously opaque, making it difficult to interpret results. Current research applies methods from visual learning to investigate the relationships between these abstract learned representations and the spectrogram representations they are trained on, and that are more humanly accessible. Current approaches provide potential for monitoring change; in the future we may gain insight into ecological significance of this change.

Research in this field is fast-moving and implementation requires strong technical skills. However, these advances will likely support accessible, interactive interfaces for data exploration in the near future.

Figure 6.2. Passive acoustic monitoring can be an effective way to monitor wildlife on farmland. Credit: Oliver Metcalf

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Appendix 1: An evidence-based quick-start guide for ecoacoustics deployment

The programming and deployment of automated acoustic recorders can be confusing to new practitioners, with a bewildering array of decisions to make on machine settings and fieldwork approaches. Research studies have used a wide variety of methods, with little coordination or development of good-practice - the limited guidelines previously available have been scattered throughout the literature.

Below, we set out some recommendations for implementing an ecoacoustics study focussed on long-term monitoring and the use of Acoustic Indices. The recommendations are based, where possible, on evidence from the scientific literature. The recommendations advise on audio settings for the recorders, recording schedules, and how best to deploy detectors in the field spatially and temporally. The choices provided will not be optimal for every project, but this quick-start guide is intended to advise those who are starting with ecoacoustics, or who are seeking consistency in approach. The recommendations are not intended to constrain experienced researchers who fully understand the best options for their own field of study.

As part of the evidence gathered for these recommendations, a questionnaire was circulated to attendees at the UK Acoustics Network (UKAN+) ecoacoustics symposium held at Manchester Metropolitan University on 15-16th June 2022. This asked a series of questions related to the parameters of a recommended survey protocol for an ecoacoustics study, focussed on developing audio data for analysis with acoustic indices. The favoured choices of the 84 respondents to the survey are included below (referred to as 'UKAN questionnaire').

Sample Rate

Sample rate is the number of sound samples recorded per second. It affects the temporal resolution of acoustic data, and sets the highest frequency of the sound that will be recorded. The sample rate is programmed within the recording device settings.

We recommend using a 48 kHz sample rate

Research evidence

UKAN questionnaire: 55% of respondents selected a sample rate of 44.1/48 kHz for ecoacoustic studies.

Within the Global Soundscapes Project database (Darras, 2022), 183 of the 325 projects listed used a 48 kHz sample rate.
https://doi.org/10.5281/zenodo.6486836

The Silent Cities project used a 48 kHz sample rate in its global scale study of soundscapes during the Covid-19 lockdown.
DOI: 10.17605/OSF.IO/H285U

The most common (37%) sampling rate used in the 35 acoustic index studies reviewed by Alcocer et al. (2022) was 44.1 kHz.
https://doi.org/10.1111/brv.12890

Burivalova et al (2017) used a 44 kHz sample rate when using soundscapes to detect the effects of human influence on tropical forests.
https://doi.org/10.1111/cobi.12968

For bird surveys, Darras et al. (2018) recommended recording all frequencies in the audible range - with a sampling frequency of 44.1 kHz.
DOI: 10.1111/1365-2664.13229

Rationale

A 48 kHz sample rate will record the full range of human hearing, and be able to capture a wide range of biological and environmental sounds in high resolution.

The sample rate you should use for audio files in ecoacoustic studies depends on the specific requirements of your study and the types of sounds you are trying to capture. In general, a higher sample rate will result in a greater temporal resolution and allow for more accurate representation of the original sound. However, higher sample rates also result in larger file sizes, which can be an issue with large datasets.

The sample rate needs to be twice the highest frequency of sound that is to be recorded. For example, the upper range of human hearing is ~20kHz, so needs a sample rate of 40kHz to be recorded (as defined in the Nyquist theorem). Similarly, lesser horseshoe bats have a call at 110 kHz, and so a sample rate of 256 kHz is normally used to ensure these calls are captured.

In ecoacoustic studies, it is common to use sample rates in the range of 44.1 kHz to 48 kHz. These sample rates are sufficient for capturing a wide range of sounds, including most vocalizations and other biological sounds. Some studies may require higher sample rates if they are focused on capturing very high frequency sounds or if they are trying to capture very fine temporal detail. In these cases, sample rates of 96 kHz or higher may be necessary.

The large Silent Cities citizen-science project used a 48 kHz sample rate, and the widely used BirdNET algorithm for birdsong classification is designed to work with a 48 kHz sample rate.

Most audio recorders have a number of potential sample rate options, with rates such as 16, 24, 32, 44.1, 48, 64, 96, 128 and 256 being fairly standard.

Sample rate determines the size of audio files, with high sample rates having a correspondingly high file size. A mono .wav file at 256 kHz sample rate of 8 seconds length may be around 4 MB in size, while a file of the same length at 44.1 kHz might only be 640 KB.

High sample rates can be 'downsampled' to reduce file size if necessary - the opposite is not possible.

Bit depth

The bit depth of an audio file refers to the number of bits used to represent each sample of the audio signal. A higher bit depth allows for a greater dynamic range, which means that the audio file can capture a wider range of amplitude levels. However, higher bit depths also result in larger file sizes.

We recommend using a 16 bit depth encoding

Research evidence

There has been little study of the effects of bit depth on ecoacoustic studies.

Rationale

In ecoacoustic studies, it is common to use bit depths of 16 bits or 24 bits. These bit depths are sufficient for capturing a wide range of sound volumes. Higher bit depths, especially 32 bit recordings, reduce the potential for 'clipping' with loud sounds.

For the majority of automated acoustic recorders, the bit depth is set by the unit's firmware and can not be changed. Hence, no decision on this parameter is normally necessary by the user. The majority of automated units, e.g. Wildlife Acoustics, Audiomoth, Frontier Labs and Swift all record 16 bit files. Handheld recorders from manufacturers such as Tascam and Zoom can also record at 24 or 32 bit depth, which provide a wider amplitude scale.

File type

There are a number of different file types that can be used for audio files in ecoacoustic studies. Some common file types include WAV, AIFF, FLAC, and MP3.

We recommend using .wav files

Research evidence

The meta-analysis of acoustic index studies by Alcocer et al. (2022) revealed that 94% of the projects used WAV format audio files.
https://doi.org/10.1111/brv.12890

Heath et al (2021) describe how, with compressed recordings, the signal is altered in relation to the level of compression, with higher frequencies and quieter sounds most severely altered. Lossless compression should be preferred in ecoacoustic studies, but if data storage is an issue, then MP3 encoding can be used while potentially having minimal impact on most acoustic indices.
https://doi.org/10.1002/ece3.8042

For bird surveys, Darras et al. (2018) recommended recording all audible frequencies in uncompressed WAV or FLAC audio file format.
https://doi.org/10.1111/1365-2664.13229

Rationale

WAV (Waveform Audio File Format) is a ubiquitous file type that can be produced by most recorders, and processed by most software. Although file sizes can be larger than other file types, the files are uncompressed and lossless, preserving all the data from the original recording.

FLAC (Free Lossless Audio Codec) files are a lossless compressed format. The file sizes often being approximately half of an equivalent WAV file. Some researchers therefore use this format to archive recordings, saving space (and cost), while not reducing the information held within the audio recording.

AIFF (Audio Interchange File Format) is another lossless file format that is similar to WAV. It is also widely supported and is a good choice for preserving the quality of the original audio.

MP3 (MPEG Audio Layer 3) is a compressed file format that is widely used for storing audio data. It is a lossy format, which means that it removes some of the audio data in order to reduce the size of the file. While MP3 files are generally smaller in size compared to WAV and AIFF files, they may not be as suitable for preserving the quality of the original audio.

Zero-crossing audio files are simple representations of when the recorded audio signal crosses the zero line. They can be used to reconstruct a sound wave, and hence provide data on frequency, but not on amplitude. Zero-crossing audio files are typically created by applying a threshold to the original audio signal, such that only those samples that exceed the threshold are retained. The file sizes are very small compared to other types.

The choice of file type depends partly on the recorder used. For example, Audiomoths record only in WAV format, while Wildlife Acoustics can save files as WAV, a proprietary W4V compressed format, and as ZC zero-crossing files. The Frontier Lab's BAR-LT supports WAV and FLAC files.

File length

Acoustic recorders can be programmed to record file lengths ranging from seconds to hours. The choice of recording length normally depends on issues around practical file management and how the recorded data will be processed.

We recommend using a 1-minute file length

Research evidence

UKAN questionnaire: 31% of respondents selected a 1 minute file length, with 20% selecting 5 minutes.

The 35 acoustic index studies reviewed by Alcocer et al. (2022) used file lengths equal to (40%) or shorter than 1 minute (40%).
https://doi.org/10.1111/brv.12890

When manually processing birdsong recordings, Bayne et al. (2017) found that shorter duration (1 min) files increased detection rates for species and allowed for wider coverage of times of day and different dates.
http://bioacoustic.abmi.ca/wp-content/uploads/2017/08/ARUs_and_Human_Listeners.pdf

A literature review by Minkova et al. (2020) found that a small number of studies have contrasted alternative file-length choices, indicating that short duration files (e.g. 15 s–1 min) are most effective and efficient for detecting species, particularly for species that are relatively common. Minkova et al. (2020) chose to use 1 min audio clips.
https://www.dnr.wa.gov/publications/lm_oesf_pac_sp.pdf

For all species considered during the tundra breeding bird survey by Thompson et al. (2017), analysis indicated that for most species of birds, a single 10 min survey during times and dates of high availability (June, between 0500 hours and 2000 hours) is likely sufficient to establish occupancy status. However, in any single 10 min recording, the majority of species are detected within the first few minutes; thus shorter duration recordings are likely to be more efficient in detecting species occupancy
https://wildlife.onlinelibrary.wiley.com/doi/abs/10.1002/jwmg.21285

Cook & Hartley (2018) used two different time-sampling methods to calculate species richness and acoustic prevalence of birds, comparing 5 min sections of recordings with the first 10 s of each minute to create a composite of 5min duration. The 10 s composite samples detected 26% more species and produced improved prevalence indices, requiring 60% less listening time to detect as many species as the 5 min sections.
doi.org/10.5751/ACE-01221-130121

Metcalf et al. (2021) compared the results of sampling one-hour of data by using 240 15 s samples spread randomly across a survey window, with sampling of four 15 min samples. They found that the shorter files, providing a 'higher temporal resolution', outperformed the less frequent longer files in every metric considered, detecting 50% higher alpha diversity, and 10% higher gamma diversity.
https://doi.org/10.1111/2041-210X.13521

Cifuentes et al (2021) suggest that short recordings sampled throughout the survey period accurately represent acoustic patterns, with an optimal schedule of ten 1 minute samples per hour.
https://doi.org/10.21068/c2021.v22n01a02

Melo et al. (2021) employed a 2 minute file length (with a single recording per hour), and were able to detect a large number of anuran species with an appropriate level of sampling effort and temporal scale.
https://doi.org/10.1016/j.ecolind.2021.108305

The review by Sugai (2019) found that for studies with 24 h diel recordings, the most commonly used recording lengths were up to 3 min (59%), or between 3-10 min (31.8%).
https://doi.org/10.1093/biosci/biy147

Rationale

Analysis of data for ecoacoustic studies has commonly been undertaken using 1 min length files, such that this has become a de facto standard: https://research.ecosounds.org/2019/08/09/analyzing-data-in-one-minute-chunks.html

This relatively short file length enables a greater range of time periods to be covered for the same data volume, aids parallel computation with manageable file sizes, retains sufficient detail of vocalisation structures (e.g. birdsong sequences), and can be easily viewed in reasonable temporal detail on a standard computer screen. In addition, when calculating acoustic indices, this file length seems to achieve a compromise between introducing boundary effects from cropping sound sequences into short segments, and over-smoothing temporal variation to gross averages. Finally, one minute has been shown to be an efficient length for listening by analysts, without attention fading and signals being missed.

Files per hour

A number of studies have found that a stratified 'on-off' time sampling programme (e.g. recording 1 minute in every 10), can capture comparable data to continuous recording, with consequent benefits in terms of battery life, data storage and processing time.

We recommend recording 12 files per hour

Research evidence

UKAN questionnaire: 27% of respondents selected 6 files per hour, with 17% selecting 12 files per hour.

Bradfer-Lawrence et al. (2020) assessed the length of time required to generate stable acoustic index values at a location, and concluded that continuous recordings are more effective for rapidly capturing soundscape character, while sparse time-sampling delayed this process. As a result, their recommendation was to sample continuously to minimise the required deployment period.

https://doi.org/10.1111/2041-210X.13254

Pieretti et al. (2015) simulated five different recording schedules from continuous sound files: (i) one minute every five; (ii) one minute every 10; (iii) one minute every 20; (iv) one minute every 30; and (v) one minute every 60. For each schedule they calculated the Acoustic Complexity Index. The 1 min in five schedule closely correlated with the soundscape captured by continuous recordings (r>0.90; p<0.01), while providing an 80% storage space and battery power reduction compared to the continuous sampling. https:///doi.org/10.1111/2041-210X.13254#mee313254-bib-0035

Shaw et al. (2022) investigated the effort required to estimate bird species richness and composition in European forests. They compared sampling intensity for 1 min files, in intervals from 1-in-3 (n = 20 per hour) to 1-in-60 min (n = 1 per hour). The highest species richness was with recordings at the highest intensity of one every 3 mins. https://doi.org/10.1002/ece3.9491

The studies in the literature review by Minkova et al. (2020) recorded a daily total of recordings ranging from 10-240 min per 24-hour period (equal to 0.4-10 minutes per hour). However, the sampling protocol was often influenced by study limitations such as availability of personnel, hardware and data storage capacity. Minkova et al. (2020) used two sampling densities: four 1 min clips from each hour 0400-1000 , and two 1 min clips from each hour 1000-2200. https://www.dnr.wa.gov/publications/lm_oesf_pac_sp.pdf

The review by Sugai (2019) found that for studies with 24 h diel recordings, most used a single recording per hour (47%), with the remaining studies using 2, 4, or 6 recordings per hour.
https://doi.org/10.1093/biosci/biy147

Rationale

In combination with file lengths of one minute, as recommended above, 12 recordings per hour provide a 20% time-sampling coverage. This level of sampling effort has been shown to adequately capture soundscape characteristics or species directions, while balancing data storage and processing requirements.

Daily programme

Detection probability for bird and other taxa normally varies with time of the day, so recording times distributed throughout the day will sample the entire community most effectively.

We recommend recording for the full 24 hour cycle

Research evidence

UKAN questionnaire: 67% of respondents selected the full 24 hr daily cycle

Bradfer-Lawrence et al. (2019) found that characteristic diel patterns are important for determining differences between habitat types. Acoustic indices may be highly similar between habitats at some times of the day, while differing widely at other times. A wide range of recording times is therefore useful in characterising habitat types.
https://doi.org/10.1111/2041-210X.13254

The bird study by La & Nudds (2016) found that morning-only acoustic recordings underestimated species richness, and that the greatest number of species per unit of sampling effort was detected with on-the-hour samples between 07:00 and 12:00, and at 21:00.
https://doi.org/10.1002/ecs2.1294

Shaw et al. (2022) investigated the effort to estimate bird species richness and composition in European forests. They compared recording in a dawn period (1 hr before sunrise), a morning period (1 hr beginning 3 hr after sunrise), and a combined period including both day phases. Species richness was significantly higher when including both day phases compared to dawn alone, and was slightly higher in the morning compared to dawn (yielding 80% of recorded species). However, certain nocturnal/crepuscular species could only be observed in the dawn period.
https://doi.org/10.1002/ece3.9491

Thompson et al. (2017) deployed recorders to assess how avian detection at different times of day, and dates. In their subarctic tundra sites, without a distinct dawn or dusk, most species displayed circadian patterns, with detection peaking at 0800-1200 hours, but remaining high through the day for some species. Between 2200 hours and 0500 hours, detection rates dropped to near zero, signaling a rest period for most species. The peak time of detection for most species took place in the late morning (0900–1000hours)
doi/abs/10.1002/jwmg.21285

Sugai et al (2019) reviewed the recording periods for 460 studies that used passive acoustic monitoring. Due to a concentration on bat and anuran studies, sampling effort was mostly concentrated during the night. However, soundscape studies, not targeted at particular taxa, recorded through more of the diel cycle, with most effort at dawn and dusk.
https://doi.org/10.1093/biosci/biy147

Froidevuax et al. (2014) showed that sampling the full night was essential to fully capture the maximum number of bat species in forest habitats - covering the dusk and dawn peaks in bat activity only, did not record the rarer species with low detection probabilities.
https://doi.org/10.1002/ece3.1296

Linke et al. (2020) demonstrated that acoustic activity is highly sensitive to diurnal variation, with only 25-50% of sound types in tropical freshwaters detectable in any 4 hr period. A comprehensive sampling strategy therefore needs to include a 24 hr recording schedule to capture soundscape patterns.
https://doi.org/10.1111/fwb.13227

Rationale

Recording through the full 24 hour period will capture all time events during the day, including the avian dawn and evening choruses, and nocturnal animals. It also allows the soundscape to be characterised evenly through the diel cycle.

Recording sound through the 24 hour diel cycle can be important in ecoacoustic studies to capture the full range of sounds produced in an ecosystem, and to study the effects of diel patterns on sound production. Many ecosystems are characterised by changes in the soundscape produced over the course of a day in response to the natural history and behaviour of different species. By recording sound over a full diel cycle, it is possible to study these effects.

Deployment period

Automated recorders are able to be powered for extended periods, particularly if using extended battery packs or even solar power. The storage capacity of SD cards has also expanded to the extent that days or weeks of sound data can be recorded on single deployments.

We recommend that deployments should last for a minimum of one week

Research evidence

UKAN questionnaire: 22% of respondents considered that a one week deployment was appropriate for ecoacoustic studies, with 20% selecting two weeks.

The 35 acoustic index studies reviewed by Alcocer et al. (2022) recorded for an average of 44 days (range 1–282 days).
https://doi.org/10.1111/brv.12890

Bayne et al. (2017) state that, for singing birds, deployment over several days results in higher detection and occupancy rates than using a single day. However, there are diminishing returns - with fewer benefits from month-long deployments in comparison to covering more locations.
http://bioacoustic.abmi.ca/wp-content/uploads/2017/08/ARUs_and_Human_Listeners.pdf

Bradfer-Lawrence et al. (2019) recommend collecting at least 120 hr of continuous recordings per site, to fully describe the soundscape in tropical habitats. These soundscapes are often more complex than those of temperate systems, and so less time may be required in (e.g.) European contexts.
https://doi.org/10.1111/2041-210X.13254

Minkova et al. (2020) studied breeding forest birds and recorded for a 10 day period, before extracting four discrete 24 hour periods from this total.
https://www.dnr.wa.gov/publications/lm_oesf_pac_sp.pdf

The acoustic bird survey by Franklin et al. (2020) recorded for 15hrs/site and resulted in an average of 88% completeness of the assemblage, 73% completeness could be achieved with 5hrs of recordings.
https://www.researchgate.net/publication/339665372_Establishing_the_adequacy_of_recorded_acoustic_surveys_of_forest_bird_assemblages

Shaw et al. (2022) investigated the effort to estimate bird species richness and composition in European forests. They compared durations of 1–4 recording days for each recorder. Bird richness significantly increased with each added day up to 3 days, with no difference from adding the 4th day.
https://doi.org/10.1002/ece3.9491

The bird study by La & Nudds (2016) found that a survey period of at least 3 days was required to maximise species richness.
https://doi.org/10.1002/ecs2.1294

Furnas & Bowie (2020) stated the importance of adopting a temporal schedule that represents the range of conditions likely to effect detection probabilities (e.g. changes in weather, phenology and movement of animals). In most cases, this requires sampling over several days, with appropriate environmental covariates being recorded as part of the study protocol.
https://doi.org/10.2989/00306525.2020.1788829

Melo et al (2021) considered that species detection in monitoring programs is strongly associated with both sampling effort and temporal range of monitoring. Their study compared six potential sampling scenarios: single hour/day, five night/full-day, thirty night/full-day using recordings of 2 mins every hour. The greatest species richness was recorded with the thirty full day scenario.
https://doi.org/10.1016/j.ecolind.2021.108305

Rationale

Automated passive acoustic methods enable long-term deployments that can not normally be matched by observers. They thus enable a higher sampling effort and wider temporal range of sampling than traditional approaches, and consequently produce higher probabilities of species detection.

Number of deployments per year

While many studies focus on particular times of year, such as the spring bird breeding period, for long-term ecoacoustics studies there will be considerable value in recording audio data throughout the annual cycle.

We recommend that deployments should take place a minimum of four times per year, once per season

Research evidence

UKAN questionnaire: 51% of respondents selected 4 deployments per year (one per season).

Bradfer-Lawrence et al., (2019) considered that short deployments during distinct seasons may be as suitable as a single long deployment (e.g. to total 120+ hours).
https://doi.org/10.1111/2041-210X.13254

Siddagangaiah et al. (2022) studied the annual variation in underwater soundscapes, finding a phenology of fish chorusing that changed between seasons, reflecting species behaviour.
https://doi.org/10.1038/s43247-022-00442-5

Rationale

Species occupancy and vocal activity levels will vary throughout the year, as will the overall soundscape of an ecosystem. To adequately capture this annual variation, it is recommended that ecoacoustic studies should cover all seasons: summer, autumn, winter and spring.

Spatial layout

When using multiple recorders, a decision needs to be made on how to arrange these spatially. Random, transect, grid or fractal patterns can be used, or the location of recorders can be selected based on target features such as habitat types or nesting locations.

We recommend that recorder locations should be selected based on parameters such as habitat type

Research evidence

UKAN questionnaire: 58% of respondents would use a selected/optimised spatial distribution of sensors (e.g. by habitat type), with 17% choosing a grid-based arrangement.

Wood & Peery (2022) discuss two different sampling frameworks for acoustic studies. Recorders may be deployed preferentially in areas known to be important to a species, such as nest sites, implying an 'area of occupancy' concept of a species range, Alternatively, recording locations may be randomly determined without relation to any knowledge of species use, e.g. in a survey grid, within a wider 'extent of occurrence'. Preferential sampling requires substantial pre-survey information, but leads to intuitive parameter interpretation and greater precision due to its finer spatial scale; while greater survey coverage is attainable with random sampling.
https://doi.org/10.1111/ibi.13092

Piña-Covarrubias et al. (2018) tested how the placement of acoustic sensors could be optimized, as an alternative to the use of standard grids. They found that, on hilly terrain, selected placements on higher ground could halve the required number of sensors to cover an area, compared to a square grid.
https://doi.org/10.1002/rse2.97

In their study on bats, Froidevuax et al. (2014) showed that the three-dimensional structure of forests, including all microhabitats, must be sampled to adequately record the full species complement of bat communities.
https://doi.org/10.1002/ece3.1296

Rationale

The spatial layout of recorders in a study will largely depend on the aims of the project. Investigations of environmental gradients will promote the use of linear, i.e. transect, layouts, while studies examining differences between habitat types will likely employ a selected or stratified grid layout. Projects to determine occupancy of particular habitat features, such as amphibian presence in ponds, will clearly make use of closely targeted locations. Many studies have used survey designs where detectors are rotated across a number of locations to increase geographical coverage. This reduces comparability between sites in terms of the dates when sampling occurs, but can be effective in maximising limited hardware resources.

Spatial density

Unless simultaneous recordings are specifically required across an array of recorders (for the purposes of localization), then spacing between units is normally set to prevent any replication of sounds between sites. When undertaking species-specific studies, the spatial density of recording sites may usefully correspond to typical territory size of the target species.

We recommend that recorder locations should be a minimum of 250m apart

Research evidence

UKAN questionnaire: 30% of respondents selected a 500m separation distance between recorders (equal to 4 recorders/km2), with 23% choosing a 250m distance (equal to 16 recorders/km2).

Minkova et al. (2020) aimed to evaluate bird habitat use in forest stands of different ages and management types. Their preliminary field tests (in Kuehne et al. 2019) showed that the effective detection range of their Songmeter units was unlikely to exceed 125m for their species of interest, and so they spaced sampling locations ≥250m apart. https://www.dnr.wa.gov/publications/lm_oesf_pac_sp.pdf

The Yip et al. (2017) study on bird sounds confirmed that, for all species calls and broadcast tones, detection probability declined with increasing distance and decreasing sound amplitude, and was higher in open vegetation than in closed vegetation.

Furnas & Bowie (2020) state the recommendation, following traditional point counts, that independent sampling locations at least 250m apart should be used for autonomous sound recorders. This separation distance will address the potential for double counting and spatial autocorrelation, with their resulting biases on results and precision.
https://doi.org/10.2989/00306525.2020.1788829ttps://doi.org/10.2989/00306525.2020.1788829

Rationale

For coverage of a site, the aim is normally to sample across the range of the habitats and species of interest, with recorders placed to limit overlap of detection radii so that counts are independent. The effective radius of most recorders is in the region of 50m, so a minimum separation distance of at least 100m should be used. As a recommended standard, a larger 250m spacing between recorder locations would provide 16 sampling locations/km2. This is dense enough to provide a good level of survey data, and is also likely to be relevant to the territory sizes of many species of interest within ecological assessments.

Appendix 2: A table of acoustic monitoring guidance documents from around the world

Taxa	Region	Title	Authors and link
Amphibians	USA	Amphibian Monitoring Protocol (Version 2.0)	National Park Service, Great Lakes Inventory and Monitoring Network https://www.nps.gov/im/glkn/amphibians.htm
Bats	USA	Range-wide Indiana bat & Northern long-eared bat survey guidelines.	U.S. Fish and Wildlife Service. (2022). https://www.fws.gov/library/collections/range-wide-indiana-bat-and-northern-long-eared-bat-survey-guidelines
Bats	USA	A Plan for the North American Bat Monitoring Program (NABat)	USDA (2015) https://www.srs.fs.usda.gov/pubs/gtr/gtr_srs208.pdf
Bats	USA	Guidance for conducting acoustic surveys for bats: Version 1 detector deployment, file processing and database version	National Park Service https://irma.nps.gov/DataStore/Reference/Profile/2231984
Bats	UK	Designing effective survey and sampling protocols for passive acoustic monitoring as part of the national bat monitoring	Newson, S.E., Boughey, K.L., Robinson, R.A. & Gillings, S. 2021. JNCC Report No. 688, JNCC, Peterborough, ISSN 0963-8091. https://hub.jncc.gov.uk/assets/4cc324dc-1ad8-446e-acdd-a656348025b3
Bats	Scotland	Bats and onshore wind turbines - survey, assessment and mitigation	NatureScot, 2021 https://www.nature.scot/doc/bats-and-onshore-wind-turbines-survey-assessment-and-mitigation
Bats	UK	Bat Surveys for Professional Ecologists: Good Practice Guidelines	Collins, J. (ed.) (2016). 3rd edition. The Bat Conservation Trust, London. ISBN-13 978-1-872745-96-1 https://www.bats.org.uk/resources/guidance-for-professionals/bat-surveys-for-professional-ecologists-good-practice-guidelines-3rd-edition
Bats	UK	Guidelines for passive acoustics surveys of bats in woodland	Bat Conservation Trust https://www.bats.org.uk/our-work/national-bat-monitoring-programme/passive-acoustic-surveys/guidelines-for-passive-acoustic-surveys-of-bats-in-woodland
Birds	Canada	Species detection survey protocols: Forest bird surveys	Saskatchewan Ministry of Environment. 2014. Forest Birds Survey Protocol. Fish and Wildlife Branch Technical Report No. 2014-10.0. 3211 Albert Street, Regina, Saskatchewan. http://www.environment.gov.sk.ca/Default.aspx?DN=bcaf2087-feef-4e7e-acbf-e788a0734e71
Birds	New Zealand	Protocols for the inventory and monitoring of populations of the endangered Australasian bittern (Botaurus poiciloptilus) in New Zealand	O'Donnell, C., and Williams, E., New Zealand Department of Conservation. 2015. https://www.researchgate.net/publication/275465977_Protocols_for_the_inventory_and_monitoring_of_populations_of_the_endangered_Australasian_bittern_in_New_Zealand
Birds	UK	Bird Survey Guidelines: Passive audio recording	Bird Survey & Assessment Steering Group. (2022). Bird Survey Guidelines for assessing ecological impacts, v.0.1.7. https://birdsurveyguidelines.org/803-2/
Birds	Canada	How to Most Effectively Use Autonomous Recording Units When Data are Processed by Human Listeners	Bayne, E., Knaggs, M., and Sólymos, P. Bioacoustic Unit, Bayne Lab at the University of Alberta & Alberta Biodiversity Monitoring Institute. 2017 http://bioacoustic.abmi.ca/wp-content/uploads/2017/08/ARUs_and_Human_Listeners.pdf
Birds	UK	Bird Bioacoustic Surveys – Developing a Standard Protocol	Abrahams, C. inpractice the Bulletin of the Chartered Institute of Ecology and Environmental Management. December 2018. https://www.researchgate.net/publication/329443381_Bird_Bioacoustic_Surveys_-_Developing_a_Standard_Protocol

Taxa	Region	Title	Authors and link
Birds	Canada	Terrestrial ABMI Autonomous Recording Unit (ARU) and Remote Camera Trap Protocols	Alberta Biodiversity Monitoring Institute. 2021. https://www.abmi.ca/home/publications/551-600/599
Cetaceans	USA	Baseline Long-term Passive Acoustic Monitoring of Baleen and Sperm Whales and Offshore Wind Development	Appendix I of: Van Parijs, S. M., Baker, K., Carduner, J., Daly, J., Davis, G. E., Esch, C., … Staaterman, E. (2021). NOAA and BOEM Minimum Recommendations for Use of Passive Acoustic Listening Systems in Offshore Wind Energy Development Monitoring and Mitigation Programs. Frontiers in Marine Science, 8, 1575. https://www.frontiersin.org/articles/10.3389/fmars.2021.760840/full
Cetaceans	Global	Position Statement 3: Passive Acoustic Monitoring	Marine Mammal Observer Association, 2013 https://www.mmo-association.org/mmoa-activities/position-statements?id=111
Cetaceans	Scotland	Use of Static Passive Acoustic Monitoring (PAM) for monitoring cetaceans at Marine Renewable Energy Installations (MREIs) for Marine Scotland	Embling, C. B., Wilson, B., Benjamins, S., Pikesley, S., Thompson, P., Graham, I., Cheney, B., Brookes, K.L., Godley, B.J. & Witt, M. J. https://tethys.pnnl.gov/sites/default/files/publications/emblingetal.pdf
Cetaceans	New Zealand	Report of the Marine Mammal Observer/Passive Acoustic Monitoring Requirements Technical Working Group	DOC (Ed) 2016. Marine Species and Threats, Department of Conservation, Wellington, New Zealand. 47 p. https://www.doc.govt.nz/globalassets/documents/conservation/marine-and-coastal/seismic-surveys-code-of-conduct/twg-reports-2016/01-scr-mmo-pam-reqs.pdf
Devices	Canada	Autonomous Recording Unit Deployment Protocol: SM2, SM3, and SM4 Models of Song Meters	Lankau, H., Bioacoustic Unit, Bayne Lab at the University of Alberta & Alberta Biodiversity Monitoring Institute. 2017 http://bioacoustic.abmi.ca/wp-content/uploads/2018/01/DeploymentProtocol_e.pdf
Devices	Canada	SongMeter (SM3) Maintenance Protocol	Bioacoustic Unit, Bayne Lab at the University of Alberta & Alberta Biodiversity Monitoring Institute. 2016 https://www.wildtrax.ca/dam/jcr:9a5ad9ac-c684-4712-a811-74f882acfd5b/BU_2019_SM3MaintenanceProtocol.pdf
Devices	Australia	Deployment manual for solar powered acoustic sensors	The Australian Acoustic Observatory | A2O. https://acousticobservatory.org/deployment-information/
Fish	Northeast Atlantic	ICES Survey Protocols – Manual for Acoustic Surveys Coordinated under ICES Working Group on Acoustic and Egg Surveys for Small Pelagic Fish	Doray, M., Boyra, G., and van der Kooij, J. (Eds.). 2021. 1st Edition. ICES Techniques in Marine Environmental Sciences Vol. 64.100 pp. https://doi. org/10.17895/ices.pub.7462
Whole Soundscape	Norway	Management relevant applications of acoustic monitoring for Norwegian nature – The Sound of Norway	Sethi, S. S., Fossøy, F., Cretois, B. & Rosten, C. M. 2021.. NINA Report 2064. Norwegian Institute for Nature Research. https://brage.nina.no/nina-xmlui/handle/11250/2832294
Whole soundscape	UK	Bioacoustics for Agri-Environment Monitoring	Excerpt from: Developing technologies for agri-environment monitoring Developing approaches to agri-environment monitoring (M&E Baseline/ Programme Development) - LM04108 CEH Project reference: 7379 Date 22/02/2021 Roy, D.B., Abrahams, C., August, T., Christelow, J., Gerard, F., Howell, K., Logie, M., McCracken, M., Pallet, D., Pocock, M., Read, D.S. & Staley, J. https://randd.defra.gov.uk/ProjectDetails?ProjectId=20551
Whole Soundscapes	Global	Silent·Cities: A participatory monitoring programme of an exceptional modification of urban soundscapes	Samuel Challéat, Amandine Gasc, Nicolas Farrugia, Jérémy Froidevaux https://osf.io/h285u/
Whole Soundscapes	Global	Passive acoustic monitoring in ecology and conservation	Ella Browning, Rory Gibb, Paul Glover-Kapfer & Kate E. Jones. 2017. WWF Conservation Technology Series 1(2). WWF-UK, Woking, United Kingdom. https://www.wwf.org.uk/sites/default/files/2019-04/Acousticmonitoring-WWF-guidelines.pdf
Whole Soundscapes	UK	The potential use of acoustic indices for biodiversity monitoring at long-term ecological research (LTER) sites	Andrews, C. and Dick, J. 2021. UK Centre for Ecology & Hydrology https://nora.nerc.ac.uk/id/eprint/531301/1/N531301CR.pdf

Appendix 3: R code for false-colour plots

```
# Kaleidoscope False Colour Plot
# Carlos Abrahams 2022-12-23
library(tidyverse)
library(scales)

# Example dataset #######
# Generate example data for hourly samples over five days
set.seed(123)
ai_data <- tibble(
  ACI = runif(120, min = 150, max = 200),
  BI = runif(120, min = 50, max = 100),
  NDSI = runif(120, min = -1, max = 1),
  ai_dtime = seq(ymd_hms('2018-08-06 00:00:00'),
                 ymd_hms('2018-08-10 23:59:00'),
                 by = '1 hour')
  )

# Extract year_day and hour from ai_dtime POSIX
ai_data <- ai_data %>%
  mutate(ai_date = yday(ai_dtime),
         ai_time = hour(ai_dtime))

# Rescale all Acoustic Index scores to 0-1 for RGB plotting #######
ai_data <- ai_data %>%
  mutate(
    ACInorm = rescale(ACI),
    BInorm = rescale(BI),
    NDSInorm = rescale(NDSI)
  )

# Plot false-colour raster #######
ggplot(ai_data, aes(x = ai_date, y = ai_time)) +
  geom_raster(fill = rgb(
    red = ai_data$ACInorm,
    green = ai_data$BInorm,
    blue = ai_data$NDSInorm
  )) +
  labs(
    x = "Year Day",
    y = "Time",
    title = "False-colour plot of acoustic indices",
    subtitle = "ACI = Red, BI = Green, NDSI = Blue"
  )
```