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Woodland soundscapes: Investigating new methods for monitoring landscapes.

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Thesis submitted for the degree of Doctor of Philosophy in
Biodiversity Management.

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Declaration

I declare that this thesis has been composed by myself and has not been accepted in any previous application for the award of degree in any university. All quotations have been distinguished appropriately, and sources of information have been specifically acknowledged.

Anthony Turner

March 2018

Dedication

I would like to dedicate this thesis to my mum and dad. I am a lucky person and much of this ‘luck’ is down to their love and support throughout my life – thank you both. I also dedicate it to my sister Catherine and my brother Graham – two people who have shared my luck. And to Saskia…who is brilliant.

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Abstract

Biodiversity is an important provider of ecosystem services. There is a sense of urgency running through the scientific community regarding its protection and conservation. This urgency is fuelled by a wealth of research into the effects of habitat destruction, intensive agriculture, destructive industries (such as mining and oil exploration) and the insidious threat of climate change. It might reasonably be suggested that the biodiversity crisis we are facing today is in large part due to a lack of regulation around human-activities with regard to biodiversity impacts. In order to impose regulations, protecting biodiversity has been incentivised through various governmental and non-profit private-sector certification initiatives that aim to minimise the negative impacts that industry can have on the environment. Agri-environment schemes are largely governmental initiatives that aim to enhance the biodiversity and societal values of farmland. Timber certification initiatives, such as the Forest Stewardship Council, promote woodland management that takes into account the economic, environmental and social aspects of forestry with equal measure. Protection and enhancement of biodiversity is integral to achieving the environmental aims of certification. However, several studies have highlighted that many schemes (notably agri-environment schemes and some timber certification schemes) ultimately fall short of their projected targets, which is often due to a lack of suitable monitoring with regard to biodiversity. This is unsurprising since biodiversity monitoring is not a straightforward process. Many considerations need to be made when choosing suitable indicators of ecosystem health such as whether to measure species-diversity or functional diversity. But perhaps one of the biggest issues is the ability of landowners and managers to contribute to efficient, objective, standardised data collection. Acoustic monitoring offers a means of producing unbiased data that can be analysed objectively and stored indefinitely. With significant advances in hardware and software technologies, the proliferation of acoustic monitoring is evident in the scientific literature. The field of soundscape ecology was in many respects borne out of these technological advances. It has since been usurped by the newer field of ecoacoustics (I use these two terms interchangeably throughout this thesis). Ecoacoustics offers a range of soundscape analytical techniques that aim to understand the spectral and temporal composition of the soundscape. As such a number of acoustic indices can be used to measure different facets of acoustic diversity. This study offers an overview of the current literature in bioacoustics and ecoacoustics. It applies several of these indices to studying the soundscape of Forest Stewardship Council certified plantation forests in the UK. Specifically it investigates the soundscape in relation to habitat and landscape metrics and explores temporal variation in acoustic activity. It offers insights into the relationship between man-made/machine noise (technophony) and biological sounds (biophony) and suggests future directions for research and large-scale monitoring of habitats. Finally it provides a set of instructions on how to build an automated recording unit using readily available parts and provides links to necessary software and guidance on types of hardware available. The key findings indicate that the use of acoustic indices for monitoring landscapes could be a useful tool. Clear relationships were observed between forest structure and stand age, and vegetation structure, with acoustic diversity in Thetford forest over two consecutive years. Although these relationships were not clear in Bedgebury forest, the effects of landscape structure were statistically significant, particularly when using automated recording units. Road proximity had a strong influence on the soundscape in all study sites. And the use of ecoacoustic methods to explore this offers an insight into a new means of investigating the impact of roads on acoustic biodiversity. The development of a low-cost automated recording unit is a significant contribution to the field of soundscape ecology in terms of encouraging participation by the non-governmental organisation (NGO) sector. Likewise, the use of a handheld recording unit and the application of traditional ecological survey methods provide evidence that soundscape/ecoacoustic studies that yield interesting, informative and biologically meaningful results can be done on a relatively low budget. As such this thesis offers a significant contribution to the field of soundscape ecology in terms of both data and logistics. It may be particularly relevant to researchers on a limited budget and/or the NGO and citizen science sector.

Publications

Chapter 2 was published in January 2018:

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Appendix 5 was published online in September 2016:

http://www.instructables.com/id/ARUPi-A-Low-Cost-Automated-Recording-Unit-for-Soun/

I plan to submit chapter's 3 and 4 for publication as well.

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Chapter 1 - Introduction

Unsustainable forestry and intensive agriculture pose great threats to biodiversity worldwide and have resulted in the loss of biodiversity, which continues to decline in the face of further exploitation (Kleijn *et al.* 2011; Laurance, Sayer & Cassman 2014). This has led to the development of commodity certification schemes, eco-labelling and agri-environment schemes that aim to redress the balance between economic viability, social equality and environmental destruction (Merger, Dutschke & Verchot 2011; Edwards & Laurance 2012). These initiatives offer industries that have historically had a negative impact on biodiversity, an opportunity to lessen, and in some cases attempt to reverse, the impact they have had so far (Edwards & Laurance 2012). However, due to the complexities associated with monitoring biodiversity, both in terms of suitable methods and the costs associated with monitoring, few schemes offer quantitative evidence-based protocols on how to monitor biodiversity within participating landscapes (Kleijn & Sutherland 2003; Angelstam *et al.* 2013). This is not surprising since ecological sustainability is often only one of several criteria considered in complex social negotiation processes (Angelstam *et al.* 2013; Forest Stewardship Council 2015). However, without suitable monitoring of biodiversity the efficiency of management practises can be misinterpreted and misunderstood (Yoccoz, Nichols & Boulinier 2001; Kleijn & Sutherland 2003; Guynn *et al.* 2004).

During the 1980s, agri-environment schemes (AESs) were implemented throughout much of the European Union (Primdahl *et al.* 2003). In 2003 a review of 62 studies evaluating the impact of AESs on biodiversity throughout the European Union found there was a lack of robust data and that reliable assessment of management strategies was not possible in many cases (Kleijn & Sutherland 2003). One limiting factor in effectively monitoring the impact of different management strategies is the lack of pre-treatment data (Kleijn & Sutherland 2003; Herzog 2005). This problem is often addressed by pairing AES management areas with non-AES management areas and then comparing the two (Kleijn *et al.* 2001; Pocock & Jennings 2008; Hiron *et al.* 2013) but this approach is scientifically flawed. AES areas are often selected due to their heterogeneous nature and higher levels of biodiversity so comparing these sites to none AES areas is somewhat biased from the outset (Perkins *et al.* 2011; Whittingham 2011). Today, the general consensus is that AESs can offer moderate to limited gains to biodiversity but the overall trend of a decline in biodiversity continues (Kleijn *et al.* 2011; Scheper *et al.* 2013). With billions of Euros being spent annually on AESs and at least €40billion having been spent since their implementation (Donald & Evans 2006; Kleijn *et al.* 2011; European Commission 2013), the need for long-term, large scale monitoring is essential if biodiversity management decisions are to be effective and beneficial to the environment (Memmott *et al.* 2010).

Certification schemes are more recent than agri-environment schemes and are usually industry led market-driven initiatives. In exchange for a certified product with an eco-label and higher market value, businesses that choose to be certified must meet standards and criteria with regards to management of their land/estates (van Kooten, Nelson & Vertinsky 2005). The Forest Stewardship Council (FSC), established in 1993, is perhaps one of the best known certification schemes , whose standards and criteria are used by many other certification schemes globally (Auld, Gulbrandsen & McDermott 2008). It is generally accepted that forest certification has positive impacts on biodiversity, but Angelstam *et al.* (2013) discovered that the FSC approach to monitoring ecological sustainability poorly reflected quantitative evidence-based knowledge in Sweden. This is unsurprising as the guidelines for monitoring biodiversity within the FSC Principles and Criteria are generic and open to interpretation (Robinson *et al.* 2009; Forest Stewardship Council 2015). This approach to monitoring is mirrored in other certification schemes such as the Roundtable on Sustainable Palm Oil (RSPO) and the Roundtable for Responsible Soy (RTRS). The needs, goals and monetary means of different land-owners and landscapes is often cited as a reason for this approach to monitoring (Guynn *et al.* 2004; Robinson *et al.* 2009), especially as the scheme participants are responsible for carrying out the monitoring themselves (Forest Stewardship Council 2015). Community based monitoring projects are a way of reducing costs (Sheil & Lawrence 2004; Danielsen *et al.* 2011) but they can be susceptible to high variability and reduced accuracy (Palmer Fry 2011). If certification schemes are going to halt or reverse the current trends of declines in biodiversity, ecological management decisions need to be informed more effectively than they currently are being (Memmott *et al.* 2010).

1.1 Bioacoustics

Bioacoustics has largely been a species-centred discipline (Towsey, Parsons & Sueur 2014), studying the acoustic communication pathways between individuals, focussing on signal emission, propagation and reception (Sueur *et al.* 2014b). This approach is extremely useful for understanding aspects of animal behaviour (Marten *et al.* 1977; Favaro, Briefer & McElligott 2014) and evolution/speciation (Kirschel *et al.* 2009a; Tobias *et al.* 2010) but as a discipline has not played a significant role in applied ecological research (Laiolo 2010). Recent advances in recording and storage technology have encouraged ecologists to explore how a habitat's acoustics can help us to better understand ecosystem processes. Identifying species from their vocalisations in the field, such as the point-count method for birds, is a traditional and widely accepted ecological census technique (Sutherland 2006). Perhaps unsurprisingly, given the trend of global declines in biodiversity, attention is turning to improving the scale and efficiency of biodiversity monitoring for conservation.

The use of passive field recordings has been proposed as being more accurate for species identification than active listening/point-count methods due to the ability to stop and rewind recordings and to have a permanent record of the survey that can be re-analysed by more observers (Brandes 2005; Acevedo & Villanueva-rivera 2006). Automated digital recording units (ADRUs) that can be placed in the field for weeks, even months, at a time, offer a unique efficient means of sampling biodiversity at a scale not previously possible. With this, the challenge facing ecologists is matching the technological advances in data collection methods with efficient accurate analysis methods (Sueur *et al.* 2012; Towsey, Parsons & Sueur 2014).

The majority of studies that analyse recorded animal vocalisations use spectrograms to visualise calls. Introduced in the 1950's, the spectrogram revolutionized the field of bioacoustics. The ability to examine calls visually enabled researchers to measure spectral and temporal characteristics of vocalisations and to determine how these features differ between and within species. In ecology and biodiversity surveys the use of spectrograms greatly reduces the amount of time needed to manually process recordings if surveying for one or a few known species with distinct spectral calls (Sutherland 2006). However, manually processing large numbers of field recordings remains a time consuming method which is a major limiting factor when planning a study (Somervuo, Härmä & Fagerlund 2006). It stands to reason then, that a growing field in bioacoustics is the development of automated call recognition using pattern recognition software and machine learning.

1.2 Machine Learning

Automated recognition of species calls using machine learning algorithms has great potential in conservation management and biodiversity monitoring (Gaston & O'Neill 2004). Although this has long been recognised (Riede 1993), its application is becoming more widespread in recent years (Acevedo & Villanueva-rivera 2006; Brandes 2008), likely due to the recent developments in affordable, robust hardware. Research into artificial intelligence and speech therapy (for humans) has led to the development of pattern recognition software that can be used to identify or recognise patterns in acoustic data. These computer algorithms are referred to as Artificial Neural Networks (ANNs) and can either be supervised to recognise patterns, or unsupervised to identify patterns.

1.2.1 Supervised Learning

Supervised learning ANN algorithms are trained, using identified patterns such as known animal calls, to classify patterns within an unknown dataset/recording (Deecke & Janik 2006). This approach is largely based on Automated Speech Recognition (ASR) systems for voice recognition in humans, which use supervised learning algorithms that are mostly based on Hidden Markov Models (HMMs) (Gales & Young 2007). The application of HMMs to identifying non-human species-calls has seen varying levels of success (Towsey *et al.* 2012). Kogan & Margoliash, (1998) demonstrated the potential for HMMs in identifying calls that were recorded from birds in a laboratory, but subsequent studies have found HMMs to be less suitable when applied to ‘noisy’ acoustic environments (Towsey *et al.* 2012). This is largely because they have been developed for situations where background noise can be controlled (i.e. a telephone channel) so when applied to field recordings it is necessary to build further models to detect unpredictable noise events (Towsey *et al.* 2012). However, (Trifa *et al.* 2008) reported higher success at recognising antbirds in field recordings when ‘noisier’ training data was used to develop recognisers.

Other supervised call recognition tasks such as *discriminant function analysis* and *fuzzy logic*, have been shown to perform better than HMMs when using smaller training sets (Kirschel *et al.* 2009b). But Walters et al., (2012) suggest that using ensembles of ANNs is more effective than using single classifiers as long as the accuracy of each exceeds 50%. ANNs have been used to effectively sample targeted communities of species and have been successfully applied to sample bat communities (Parsons & Jones 2000; Wickramasinghe *et al.* 2003), primates (Mielke & Zuberbühler 2013) and birds (Potamitis 2014; Potamitis *et al.* 2014). They can also be used to identify individuals, enabling researchers to investigate social interactions within groups in more detail than previously possible (Favaro, Briefer & McElligott 2014). Terry & McGregor, (2002) displayed the effectiveness of using supervised ANNs to accurately identify up to 30 individual corncrakes in simulated population playback experiments. Individuals can also be detected if recordings are made with multiple microphones (i.e. a microphone array). Used in conjunction with ANNs for detecting the species of interest, one can determine the number of individuals using spatial information by triangulating the position of individual calls (Blumstein *et al.* 2011; Mennill *et al.* 2012). This approach is also being used to monitor illegal logging activities in rainforests using acoustic sensors (in this case, solar-powered smart phones), to detect (using a relatively simple ANN) and triangulate the position of chainsaw sounds and relay this positional information to rangers on the ground (Butler 2014).

Aside from the potential pitfalls of using supervised ANNs in noisy acoustic environments, they require lots of training in order to build suitable call-specific recognisers. Their poor performance in field studies is often attributed to insufficient training data (Kirschel *et al.* 2009b; Towsey *et al.* 2012). This is unsurprising considering the similarities between some species' call structures. For instance, bat species belonging to the *Myotis* genus share very similar spectral and temporal call attributes (Parsons & Jones 2000) and automated recognition of their calls is more accurate when grouping several species together and performing further manual identification to determine species (Walters *et al.* 2012). Furthermore, the expression of regional "accents" within species is a common occurrence that is not restricted to humans. Such regional variations in the calls of conspecifics has been observed in chimpanzees (Mitani, Hunley & Murdoch 1999), geckos (Yu *et al.* 2011), frogs (Wycherley, Doran & Beebee 2002) and a number of bird species (Brandes 2008). Such similarities of different species and variation within species highlight some of the difficulties of building recognisers for large-scale studies that might encompass numerous geographic locations.

Although there are many promising studies out there, supervised learning methods are unlikely to be suitable for large-scale biodiversity monitoring in the near future due to the need to develop reliable species classifiers. This is not possible for many rare species or species that call infrequently due to insufficient training data being available(Sutherland 2006).

1.2.2 Unsupervised Learning

Unsupervised learning methods do not require training and so identify, as opposed to recognise, patterns within complex data and are sometimes referred to as clustering methods. A benefit of using unsupervised neural networks is that they are less constrained by human bias and may pick up patterns not previously predicted (Sathya & Abraham 2013). Self-Organising Maps (SOMs) are perhaps the most widely used unsupervised learning algorithms used in ecology and can be used in data-mining (Kohonen 1998), image-analysis (Purser *et al.* 2009) and bioacoustics (Bormpoudakis, Sueur & Pantis 2013). SOMs are a means of reducing high-dimensional data to a two-dimensional visual display by performing unsupervised clustering (Kohonen 1998). They have been proven to be effective at identifying the calls of multiple species (Somervuo & Harma 2003; Escobar *et al.* 2007; Ranjard & Ross 2008). Kirschel *et al.* (2009) found them to be less effective at classifying calls down to individuals but this may only be echoing the difficulties previously encountered with supervised ANNs for species-call and voice-recognition.

Stowell & Plumbley (2014) introduced the use of *spherical k-means* algorithms for unsupervised species identification with great success. Most automated call-recognition algorithms use acoustic measures based on spectrogram data that have traditionally been converted using a time or frequency warping procedure (Anderson, Dave & Margoliash 1996; Kogan & Margoliash 1998). One of the most common transformations used is the Mel-frequency cepstral coefficient (MFCC). MFCCs undergo frequency-warping to produce a logarithmic spectral scale which is designed to better mimic human-hearing processes. This is a logical thing to do in human speech-recognition software but may be unsuitable when approaching non-human call-recognition. Transforming or warping the data will lead to a reduction or change in the information held within it. In their study, Stowell & Plumbley (2014) did not use any manually-designed feature transformation procedures and allowed their algorithm to search for patterns in the raw audio data. Furthermore, supervised call-recognition methods have a tendency to focus on one or a few species and so inherent in their use is the rejection of all other sounds present in the habitat.

Unsupervised learning algorithms are particularly suited to identifying habitat characteristics through their acoustic properties. De & Chakraborty (2009) demonstrated the use of SOMs to acoustically characterize seafloor sediments using echo waveform data. Bormpoudakis, Sueur & Pantis (2013) used SOMs to identify patterns in the ambient sounds of several different habitats which mirrored patterns in the physical attributes of these habitats. They found that the SOMs clustered recordings of habitats with similar physical characteristics together – i.e. oak forests sound like oak forest, pine forests sound like pine forest, grasslands sound like grasslands and so on. Furthermore, Eldridge *et al.* (2016a) suggest that sparse-coding techniques (another form of unsupervised learning algorithm) may provide ecologically meaningful estimates of species-richness due to the flexibility of these algorithms with regard to time-frequency trade-offs. Using such methods to represent sound recordings will retain more signal information than when using the more common Fourier transform. This highlights the potential for using such algorithms for monitoring ecosystems as a whole. Given the complexities of identifying suitable indicator species and then building suitable call recognisers for them, designing algorithms that explore soundscape recordings in their entirety may provide a more comprehensive means of monitoring landscapes. Encouragingly there are a number of computational tools available for exploring and quantifying soundscape recordings which have been developed in the field of soundscape ecology.

1.3 The Soundscape

A soundscape can be defined as the collection of sounds that are present within a landscape (Pijanowski *et al.* 2011a). Three groups of sounds make up a soundscape: the **biophony** (sounds produced by biological organisms), **geophony** (sounds produced from geophysical processes), and **anthrophony** (sounds produced by anthropological activities) (Krause 1987; Pijanowski *et al.* 2011b). Soundscape recordings are a growing source of data within the world of ecology. A traditional approach of analysing these recordings is to identify one or a few species of interest within them to determine presence/absence, activity-levels and/or species-composition (Miller 2001; Sutherland 2006; Waldon, Miller & Miller 2011; Jung *et al.* 2012). Although there are some relatively efficient techniques for automatically identifying species of interest there is still a lot of information that is often not considered in the analyses. This approach is restrictive with respect to understanding ecosystem dynamics, and is a short-coming that the field of soundscape ecology is aiming to address. Considering all information present within a recording is important for a number of reasons and could prove to be a useful indicator of ecosystem health.

1.3.1 Why is the soundscape important?

Animal communication can be viewed as niche competition, since vocal species must compete for acoustic space in order to effectively exchange information with conspecifics (Villanueva-Rivera 2014). In complex communities with high levels of biodiversity, it is expected that vocal species may exhibit temporal avoidance or spectral partitioning (Planqué & Slabbekoorn 2008). This acoustic signal partitioning in multi-species communities has been observed in birds (Planqué & Slabbekoorn 2008; Luther 2009), insects (Sueur, Windmill & Robert 2010) and frogs (Chek, Bogart & Lougheed 2003; Villanueva-Rivera 2014).The level of signal partitioning within a habitat is thought to indicate how healthy that habitat is in terms of disturbance events it may have experienced. The acoustic niche hypothesis, first suggested by sound recordist Bernie Krause (Krause 1987), suggests that as a habitat is disturbed or degraded the acoustic partitioning of the vocal community will breakdown. This is especially important when considering the potential role that the ambient sounds and acoustic properties of different habitats may play in a number of ecological and evolutionary processes. For example, Slabbekoorn (2004) suggests that the ambient noise conditions of a habitat may drive evolutionary changes in animal signals therefore contribute to divergent evolutionary processes. And Kirschel *et al.* (2009a) illustrated how the physical characteristics of a habitat contributed to variation in the song of the green hylia (*Hylia prasina)*.

Just as climatic conditions may constrain a species' distribution (Thomas *et al.* 2004), the ambient sounds and/or acoustic properties (as determined by habitat structural complexity) of a landscape may also place constraints on dispersal. A number of studies highlight the potential importance of ambient sounds in guiding pelagic larval reef species to coastal reef settlement habitats (Radford et al., 2011, 2010; Stanley et al., 2009; Tolimieri et al., 2002; Vermeij et al., 2010). For example, the ambient sounds of a coral reef have been shown to induce metamorphosis in crab larvae (Stanley, Radford & Jeffs 2009). Vermeij et al (2010) demonstrated that coral larvae navigate towards the ambient sounds of coral reef habitat, a behaviour that has also been observed in coral reef fish (Radford *et al.* 2011). In terrestrial habitats there may be similar constraints on species based on the acoustic properties of the environment. Some bat species are largely restricted to cluttered environments, such as a rainforest understory. These restrictions may be due to their wing morphology but could also be linked to their highly specialized echolocation calls. Insectivorous bats can typically be placed into four functional groups, each of which displays certain echo-location call characteristics that determine the type of environment in which they are best suited to foraging (Schnitzler & Kalko 2001). However, some species such as the greater mouse-eared bat (*Myotis myotis*), can adapt its call to suit different environments, from open space/edge habitats to more cluttered spaces in a forest understory so is more suited to a mosaic landscape (Schnitzler, Moss & Denzinger 2003).

Aside from the acoustic properties of habitats, the soundscape is a natural resource that is often over-looked and under-valued (Dumyahn & Pijanowski 2011b). The conservation of natural sounds within landscapes can be considered an important factor in public health and human-welfare (Farina, Scozzafava & Napoletano 2007). In Japan, forests are recognised as a public health resource for the practice of 'Shinrin-yoku' (or 'forest bathing') to relieve the stresses of modern living (Li 2010; Mao *et al.* 2012). 'Bathing' in a forest (i.e. visiting a forest) is a multi-sensory experience, of which sound plays a large part. Natural sounds have been shown to facilitate recovery from stressful situations in human volunteers (Alvarsson, Wiens & Nilsson 2010), and reduce anxiety and agitation in coma patients (Saadatmand *et al.* 2013). A number of studies have illustrated a human preference for more natural soundscapes and suggest it is an important consideration when planning and protecting urban green space areas (Zhang & Kang 2007; Irvine *et al.* 2009; Lam *et al.* 2010). This cultural importance is not only limited to human-beings. As mentioned previously, the prevalence of regional "accents" in many animal species can be viewed as a more discreet form of biodiversity which is perhaps overlooked in its importance to conservation. Laiolo & Tella (2007) suggest that these regional accents be viewed as cultural elements within a species and that as landscapes become more fragmented and disturbed, much of this hidden diversity is lost. Furthermore, the impacts of anthropogenic noise disturbance is considered a threat to biodiversity (Barber et al. 2010; Slabbekoorn et al. 2010) as it can alter the behaviour and productivity of some species (Fuller, Warren & Gaston 2007; Francis, Ortega & Cruz 2009; Francis *et al.* 2011). So disturbing a soundscape with noise pollution can have negative impacts on the biodiversity present, just as disturbing a landscape with agricultural or urban development can.

1.3.2 Measuring the Biophony

The use of taxonomic groups, such as bats or birds, as indicators of ecosystem disturbance is a widely accepted practise. However, choosing suitable indicators is hotly debated (Noss 1999) and it is considered to be more informative to use multiple taxonomic groups (Gardner *et al.* 2012). Soundscape ecology may provide a means of integrating multiple taxonomic groups into one succinct and easily repeatable measure. There is an increasing amount of research highlighting the distinct acoustic signatures of different habitats including marine (McWilliam and Hawkins, 2013; Radford et al., 2010; Staaterman et al., 2013), freshwater/aquatic (Tonolla *et al.* 2010) and terrestrial (Slabbekoorn 2004; Bormpoudakis, Sueur & Pantis 2013). There have also been some encouraging studies showing the relationship between physical structure of a habitat and its associated acoustic complexity. Pekin et al., (2012) showed that the acoustic diversity of Costa Rican rainforest soundscapes was correlated with canopy height. Differences in the soundscape in a Mediterranean Maquis habitat were also correlated with vegetation height and density (Farina and Pieretti 2014). Furthermore, an inverse correlation between biophony and anthrophony was observed along an urban-rural gradient in Michigan, US (Joo, Gage & Kasten 2011). These studies highlight the potential for using acoustic sensors in monitoring and managing landscapes for biodiversity and reducing the impacts of human activities including noise pollution.

The biophony is the largest contributor to the distinctive acoustic signature that a natural landscape may produce. It is representative of the vocal community of species present in an environment and so its complexity can act as a proxy for the complexity of the species community (i.e. species-richness). Soundscape recordings can be analysed using a number of indices that summarize the structure and distribution of the acoustic energy encapsulated within them (Towsey *et al.* 2014; Sueur *et al.* 2014b). An acoustic index measures some aspect of the spectrogram to give an output that may be indicative of the level of biodiversity present within a landscape (Towsey, Parsons & Sueur 2014). There is an increasing body of evidence outlining the effectiveness of acoustic indices as proxies for biodiversity/species-richness (Towsey, Parsons & Sueur 2014; Sueur *et al.* 2014b). Most of these studies highlight the effectiveness of acoustic indices at determining the species-richness of bird communities (Sueur *et al.* 2008; Pieretti, Farina & Morri 2011; Depraetere *et al.* 2012; Gasc *et al.* 2013; Towsey *et al.* 2014) but have so far yet to determine how the soundscape may be related to other organisms in the environment and how these indices could be used to measure the condition of a habitat in terms of disturbance.

1.3.2.1 Acoustic Indices

There have been a number of indices developed to measure the complexity of the soundscape. Many are openly available using R software tools, such as *Seewave* (Sueur, Aubin & Simonis 2008) and *Soundecology* (Villanueva-Rivera & Pijanowski 2014). Within these packages are a set of tools to calculate several acoustic indices. Amongst those available indices are the following:

Bioacoustic Index

As described by Boelman et al., (2007), the Bioacoustic index (BAI) calculates the association of sound intensity with biological frequency bands in a spectrogram (in Boelman et al., (2007) it was 2KHz-8KHz to correspond with bird calls). Sound intensity is plotted against frequency and the area under the curve is calculated (Boelman et al., 2007). This area essentially represents the vocal activity within the set frequency band range and so acts as a measure of abundance of sound. Higher dB values across a large frequency range would therefore generate a greater BAI value

Acoustic Entropy Index

One of the first indices described to indicate species-richness measured acoustic entropy (Sueur *et al.* 2008). Acoustic entropy (H) can be defined as:

$H = H_t \times H_f$ with $H \epsilon [0,1]$

Where temporal entropy is H_t and spectral entropy is H_f. Scores closer to 1 will be indicative of more acoustic complexity and 0 would be a single pure tone. Acoustic entropy uses a very complex algorithm compared to other available indices (Villanueva-Rivera *et al.* 2011) but it is one of the most consistent indices available in terms of estimating bird species-richness (Towsey *et al.* 2014). It is possible to calculate *H* using both *Seewave* and *Soundecology*. However, it is very demanding in terms of computing power and may be less suitable than other available indices if it is to be used in monitoring projects where access to high-spec computers is limited.

Acoustic complexity Index

The acoustic complexity index (ACI) was developed based on the observation that biotic sounds are characterized by having variable intensities, whereas mechanical sounds tend to present constant intensity values (Pieretti, Farina & Morri 2011). The ACI extrapolates a matrix of intensity values from a spectrogram, which is divided into user-defined frequency bins and temporal steps. It then calculates the difference between adjacent values of intensity within each frequency bin and temporal step. The final ACI value is derived using a series of simple steps to sum up the different values present in a given recording (see Pieretti et al., 2011). As a standalone index, ACI performs well at estimating species-richness. When compared to 13 other indices it was in the top three (Towsey *et al.* 2014). ACI can be calculated using the R software package *Soundecology* (Villanueva-Rivera & Pijanowski 2014) or by using the *Soundscapemeter1.0* plugin for the WaveSurfer sound analysis freeware (Farina *et al.* 2012).

Acoustic Diversity Index

The Acoustic Diversity Index (ADI) is a form of frequency band analysis based on the Shannon's Index (Villanueva-Rivera *et al.* 2011; Pekin *et al.* 2012). The value of this approach is that it first calculates the proportion of sound occurring in each frequency band (i.e. 1-2 KHz, 2-3 KHz, 3-4 KHz etc) of a spectrogram. This allows each band to represent a "species", and the proportion of sound within that band the occupancy of said species. This is used to calculate Shannon's Diversity. A further benefit of this approach is that this index can be used to determine which frequency bands are contributing most to the soundscape, which can offer further insights as to the composition of the vocal community. For example, Villanueva-Rivera et al., (2011) showed that night-time recordings were dominated by frequencies between 1-4 KHz, which were mostly frog calls, whilst the morning soundscapes ranged from 0-6 KHz, which corresponded with an increase in bird activity. The ability to investigate the composition of a soundscape in this manner highlights the flexibility of this approach with regards to developing targets for monitoring.

Acoustic Evenness Index

Based on the Gini coefficient, the Acoustic Evenness Index (AEI) calculates the evenness of sound energy across all frequency bands within a recording (Villanueva-Rivera *et al.* 2011). Values closer to 1.0 indicate high inequality, where sounds mostly occur in one frequency band. Sounds closer to 0 indicate high equality, where sounds occur equally across all bands. AEI is complimentary to the ADI and when used in conjunction offers greater insight into the complexity of a soundscape.

Normalized Difference Soundscape Index

The Normalized difference soundscape index (NDSI) is a little cruder than the previously mentioned indices but it offers a means of measuring anthropogenic noise disturbance within a soundscape. It computes the ratio of anthrophony to biophony (Kasten *et al.* 2012). Most mechanical or technophonic sounds (i.e. anthrophony) are prevalent between 1-2 KHz and biological sounds are mostly represented between 2-8 KHz. The NDSI is essentially a form of frequency band analysis that computes the ratio of these parts of the spectrum with each other, and is calculated as follows:

$\mathrm{NDSI} = (\beta - \alpha) / (\beta + \alpha)$

Where β is the total estimated power spectral density (PSD) for the largest 1 KHz biophony bin (i.e. frequency band) and α the PSD for the anthrophony bin. The output ranges from -1 to +1, where +1 indicates a total biophonic soundscape, with no anthropogenic noise/pollution. However, there are some species that have calls that fall within the "anthrophony" bin so care must be taken when planning to use this index. This index is not a standalone means of measuring the acoustic properties of a soundscape but it can be useful for categorising recordings for further investigation (Kasten *et al.* 2012).

Acoustic Dissimilarity Index

A useful tool for comparing soundscapes as opposed to measuring absolute complexity is the acoustic dissimilarity index (*D*) (Sueur et al., 2008). This index measures the distance between the *H* values of two sites and uses a complex algorithm that requires high-specification computing equipment. This is a barrier to its widespread use but is unlikely to be a long-term obstacle considering the pace of advancement in this field. Gasc et al., (2013) also tested Kolmogorov-Smirnov distance (KS), Symmetric Kullback-Leibler distance (KL) and the similarity RV correlation coefficient and found that each performed well, with the RV calculation being better than *D* but required extra processing time making it unsuitable for handling large datasets. However, in another study several acoustic dissimilarity indices failed to accurately track changes in the composition of three temperate woodland bird communities (Lellouch *et al.* (2014) suggesting that more research is needed before these indices can be applied effectively to biodiversity monitoring.

1.4 Ecoacoustics in Conservation Monitoring

With recent advances in hardware and software, the emerging fields of soundscape ecology and ecoacoustics offer a new and exciting approach to monitoring and understanding landscapes. The principles of both fields are intuitive and potentially offer a highly repeatable method of surveying landscapes that minimise observer-bias. Some key challenges facing the use of such methods in biodiversity monitoring are:

1. Understanding the relevant spatial scales at which one should monitor. Farina & Pieretti, (2014) found that soundscape characteristics change over very small spatial scales in their study of a grid with recording points spaced just 25m apart. This is unlikely to be a feasible sampling scale for most monitoring schemes but it highlights the fine-scale at which soundscape patterns can be observed.
2. Understanding relevant temporal scales for informative monitoring. It may not be possible to deploy recording units 24/7 in all areas so determining suitable

monitoring time-scales can be considered a priority. The level of variability within a given soundscape would need to be determined before any management targets could be made (Rodriguez *et al.* 2014).

3. Selecting the right acoustic analysis methods to contribute to better adaptive management. Considerations here include analysis processing times and data storage capabilities. Towsey, Wimmer, Williamson, & Roe, (2014), suggest that using a combination of acoustic indices is more effective at measuring species-richness than using a single index.
4. Accessibility of recording equipment. Although automated digital recording units have improved vastly over the past five years, most still remain off-limits to grassroots organisations due to their costs. However, the use of the Raspberry Pi computer in a number of creative DIY solutions, from security cameras to weather stations and bat detectors, offers the potential for developing a low-cost, open-source hardware to mirror the open-nature of the available analysis tools.

There is a need for highly repeatable, low-cost methods for monitoring habitats and soundscape ecology has the potential to fulfil this requirement. Studies have already indicated that acoustic indices can act as proxy measures of species richness and that different habitats produce different soundscapes. One of the main benefits of using acoustic monitoring is that there is a permanent record of a survey (Acevedo & Villanueva-rivera 2006; Towsey, Parsons & Sueur 2014). One that has been subject to almost no observer bias and assuming recording units that capture this data are used in accordance with a set protocol, the method is highly repeatable (Waldon, Miller & Miller 2011). This approach potentially offers a much more informative baseline upon which to develop management strategies. Ethically speaking, the non-invasive approach to sampling is less likely to inflict undue stress and suffering on individual animals (Jewell 2013). However, to determine the suitability of using such methods for monitoring in certification schemes and other conservation initiatives it is necessary to investigate their ability to detect differences not only between habitats but within them as well. In order to feed into adaptive management strategies, an effective monitoring system should be aware of detecting gradients within habitats. For example, to improve the chances of success in a woodland restoration initiative, developing an understanding of habitat characteristics along an age-gradient can help to produce achievable and realistic targets (Pryor, Curtis & Peterken 2002). Similarly, monitoring the effects of, and recovery from, disturbance (such as logging) requires an understanding of acoustic patterns before, during and after the disturbance event. Although they are not natural ecosystems, plantation forests are an important refuge for biodiversity (Brockerhoff *et al.* 2008) and offer a unique system for investigating the efficacy of soundscape-based survey methods at detecting gradients.

In the UK, the Forestry Commission widely practises clear-fell silviculture creating mosaic landscapes comprising different-aged even-age forest stands. Within forests there may be several different types of woodland including coniferous, semi-natural lowland deciduous and coppiced stands. The National Forest Inventory (Forestry Commission 2017a) generates up to date GIS data about each forest stand. This wealth of data offers a great opportunity to investigate acoustic patterns in relation to habitat types, habitat age, landscape composition and management history. By combining field-based measures of vegetation structure with this landscape data it may be possible to uncover patterns in the soundscape and determine whether acoustic indices can be used to detect structural and age-based gradients. This thesis investigates the soundscape in relation to these factors. It explores the use of low-cost recording equipment in two different UK forests and in different types of forest.

1.5 Aims and Objectives

This PhD provides a significant contribution to the field of soundscape ecology through achieving the following aims.

1. It investigates the relationship between acoustic diversity and vegetation structure in two different types of plantation forest – non-native coniferous woodland and sweet-chestnut coppiced woodland.
2. It compares acoustic diversity between two different coniferous plantation forests with different landscape-configurations and management histories.
3. It investigates the role that landscape heterogeneity plays in contributing to acoustic diversity.

4. It sheds light on the impact that roads have on the soundscape and highlights a relationship that might be used in noise mitigation/landscape-planning.
5. It designed and built a low-cost automated acoustic recording unit (ARU). The instructions are freely and openly available and were published online in September 2015. These units are potentially the first field-based ARU that uses the raspberry pi computer as a platform.

1.6 Thesis Structure

In order to explore these aims, this thesis presents three data-chapters:

- **Chapter two** maps the soundscape in part of the UK's largest lowland conifer plantation, Thetford Forest. Using a handheld recording unit and a more traditional approach to conducting an ecological census it investigates the relationship between forest stand age, vegetation structure and acoustic diversity in two consecutive years.
- **Chapter three** compares the soundscape of two parts of Thetford Forest with similar aged coniferous stands in Bedgebury forest - a plantation on ancient woodland site. It aims to determine whether the relationships observed in chapter one are evident in a coniferous forest with a different management history that is situated in a more heterogeneous landscape.
- **Chapter four** uses an automated recording unit called the ARUPI, which was designed specifically for this study. It was deployed in coppiced woodland stands in Bedgebury forest to investigate temporal and spatial patterns in the soundscape and to determine whether acoustic diversity reflects vegetation structure and landscape composition.
- **Chapters two to four** all investigate the relationship between the soundscape and proximity to roads and offer insights into the effects of anthropogenic noise disturbance on the soundscape.
- **Chapter five** presents the ARUPI. An automated recording unit that utilizes the Raspberry Pi single board computer and several off-the-shelf components to

produce a piece of equipment that costs a quarter of the price of the leading market alternative.

- **Synthesis and discussion**. Outlines the key findings from this study and offers suggestions for future directions of research in the fields of soundscape ecology and ecoacoustics.

Chapter 2 - Sound-mapping a coniferous forest – perspectives for biodiversity monitoring and noise mitigation.

2.0 Summary

Acoustic diversity indices have been proposed as low-cost biodiversity monitoring tools. The acoustic diversity of a soundscape can be indicative of the richness of an acoustic community and the structural/vegetation characteristics of a habitat. There is a need to apply these methods to landscapes that are ecologically and/or economically important. We investigate the relationship between the acoustic properties of a coniferous forest with stand-age and structure. We sampled a 73 point grid in part of the UK's largest man-made lowland coniferous plantation forest, covering a 320ha mosaic of different aged stands. Forest stands ranged from 0-85 years old providing an age-gradient. Short soundscape recordings were collected from each grid point on multiple mornings (between 6am-11am) to capture the dawn chorus. We repeated the study during July/August in 2014 and again in 2015. Five acoustic indices were calculated for a total of 889 two minute samples. Moderate relationships between acoustic diversity with forest stand-age and vegetation characteristics (canopy height; canopy cover) were observed. Ordinations suggest that as structural complexity and forest age increases, the higher frequency bands (4-10KHz) become more represented in the soundscape. A strong linear relationship was observed between distance to the nearest road and the ratio of anthropogenic noise to biological sounds within the soundscape. Similar acoustic patterns were observed in both years, though acoustic diversity was generally lower in 2014, which was likely due to differences in wind conditions between years. Our results suggest that developing these relatively low-cost acoustic monitoring methods to inform adaptive management of production landscapes, may lead to improved biodiversity monitoring. The methods may also prove useful for modelling road noise, landscape planning and noise mitigation.

2.1 Introduction

The global landscape is increasingly being modified by anthropogenic activities. Unsustainable forestry and intensive agricultural practises, and the resulting habitat fragmentation, degradation and loss, are recognised as one of the greatest threats to biodiversity worldwide (Kleijn *et al.* 2011; Laurance, Sayer & Cassman 2014). This has led to the development of commodity certification schemes, eco-labelling and agri-environment schemes that aim to redress the balance between economic viability, social equality and environmental destruction(Edwards & Laurance 2012). Integral to the success of these schemes is the effective monitoring of biodiversity to enable comparative assessments within and between scheme participants. However, due to the complexities associated with monitoring biodiversity, in terms of selecting suitable methods, monetary costs and time-constraints, few schemes offer quantitative evidence-based protocols on how to monitor biodiversity within participating landscapes (Kleijn & Sutherland 2003; Angelstam *et al.* 2013). Without suitable monitoring of biodiversity, the efficiency of management practises can be misinterpreted and misunderstood (Kleijn & Sutherland 2003; Guynn *et al.* 2004).

Selecting suitable indicators for monitoring biodiversity is notoriously difficult. The term 'biodiversity' can be used to describe many aspects of nature, including genetic diversity, species diversity, species distributions, community composition, functional diversity, the diversity of habitats within a landscape, landscapes within a region and regions globally (Noss 1990). Species-richness and diversity and other associated composite indices are perhaps the most traditional and often considered the simplest way to describe biodiversity (Buckland *et al.* 2005). As such, the use of taxonomic communities as indicators (such as birds, beetles, ants or plants) can be considered cost-effective in some circumstances (Gardner *et al.* 2008). However, the need for expert knowledge in species-identification and survey methods is one of the greatest drawbacks of any multi-taxa approach (Sueur *et al.* 2012). Since habitat heterogeneity and complexity has long been recognised as an indicator of bird diversity (MacArthur & MacArthur 1961; James & Wamer 1982; Goetz *et al.* 2007), alternative biodiversity indicators use habitat features (such as patch density, canopy openness and forest area) as metrics, from which habitat health and biodiversity values can be inferred (Noss 1999). This kind of indicator can be extended to include the use of remote sensing methods. However, although remote-sensing methods can be used to predict potential areas of species-richness (Leyequien *et al.* 2007; Goetz *et* *al.* 2007; Müller & Brandl 2009; Jung *et al.* 2012) and have been used to assess the effectiveness of certifications schemes (Takahashi & Todo 2014), they cannot give actual biodiversity values (Bradley *et al.* 2012). The wealth of literature on selecting suitable indicators highlights a further obstacle to effective monitoring, whereby the global biodiversity dataset can be regarded as disaggregated, in part due to the non-standardised nature of data collection and lack of cohesion between different data-collecting groups (Roberts & Moritz 2011; Han *et al.* 2014). Waldon et al. [22] suggest that a model protocol for biodiversity monitoring should be repeatable, robust against observer bias and require little training or equipment.

An acoustic community is defined as an aggregation of sound-producing species and as such can be considered an appropriate measure of biodiversity within a habitat (Farina & James 2016). The use of acoustic monitoring is emerging as a valuable tool in conservation. Acoustic surveys are considered to be a cost and time-efficient method for reliably sampling vocal communities (Brandes 2005). However, processing recordings to identify species can be extremely time-consuming and susceptible to observer-bias. Research into automated species identification is growing but identifying species within variably noisy environmental recordings is problematic and not currently considered a suitable replacement for human processing (Towsey, Parsons & Sueur 2014). Aside from these challenges, identifying species or groups of species is exclusive to other components of the soundscape which may be important for understanding the health of an ecosystem. The field of soundscape ecology is the study of the soundscape as a unit of measurement in and of its self (Pijanowski *et al.* 2011a). It aims to understand the composition of sound energy in the context of the environment from which it emanates. The soundscape can be considered as the interaction between the biophony (sounds from animal sources); geophony (sounds such as wind and rain) and anthrophony/technophony (man-made noise pollution from machinery- typically between 1-2KHz) (Pijanowski *et al.* 2011a).

Within the biophony, there are three broad types of acoustic communities – infrasonic (eg. whales <20Hz); “ordinary” (20-20,000Hz eg.mostly within the human hearing range); and ultrasonic (eg. microchiropterans >20,000Hz) (Farina & James

2016). Within each of these acoustic communities there is further partitioning, which may be frequency or temporally bound. The niche hypothesis, first introduced by Bernie Krause (Krause 1993), suggests that such frequency partitioning is a necessary evolutionary process that enables species to co-exist within acoustic space. Recent studies have shown that the diversity and composition of a soundscape can be indicative of the richness of an acoustic community (Sueur *et al.* 2008; Pieretti, Farina & Morri 2011) and can offer insights into functional and phylogenetic diversity (Gasc *et al.* 2013). If used in conjunction with environmental data they may provide insights into habitat type (Bormpoudakis, Sueur & Pantis 2013) and of structural/vegetation characteristics within a habitat (Pekin *et al.* 2012; Farina & Pieretti 2014).

Aside from monitoring the biophony, the technophony is of key importance to biodiversity conservation. Noise pollution is known to have drastic impacts on faunal communities, including altering species communities (Francis, Ortega & Cruz 2009); masking acoustic signals in fish (Holt & Johnston 2015); and causing birds to alter their song (Slabbekoorn, Peet & Grier 2003). One study suggests that noise from machinery may alter the temporal dynamics and patterns of animal sounds within a soundscape indicating significant shifts in animal behaviours (Duarte *et al.* 2015). Perhaps one of the biggest contributors to the global technophony is road noise. The ecological effects of roads range from fairly obvious things such as increased mortality through traffic collisions (i.e. road kill) (Coffin 2007) to more obscure and sinister effects including increased habitat fragmentation and its associated effects (Spellerberg *et al.* 1998); and the accumulation of heavy metals and salts in roadside habitats, which can have consequences for terrestrial and aquatic wildlife (Trombulak & Frissell 2000). Roads can also alter animal behaviours and road noise was shown to alter survival behaviours in the North American prairie dog *Cynomys ludovicianus* (Shannon *et al.* 2014) and cause birds to change their calls to suit noisier city-habitats (Slabbekoorn, Peet & Grier 2003). Understanding the dispersion of road noise through different habitats and how that contributes to the acoustic properties of a landscape is of key importance to furthering the field of soundscape ecology.

Several acoustic indices, which aim to quantify the soundscape, such as: the acoustic diversity index (ADI) and acoustic evenness index (AEI) (Villanueva-Rivera *et al.* 2011); the normalized difference soundscape index (NDSI) (Kasten *et al.* 2012); the acoustic complexity index (ACI) (Pieretti, Farina & Morri 2011); and the bioacoustic index (BAI) (Boelman *et al.* 2007) have been developed in recent years. The use of these indices has been proposed as a low-cost, long term biodiversity monitoring strategy (Sueur *et al.* 2014b), which highlights the need to assess the suitability of these methods in a range of habitats. Plantation forests have become increasingly important refuges for biodiversity throughout the world (Coote *et al.* 2013). There are 2.9 million hectares of woodland in Great Britain, and around 47% of it is coniferous plantations (Forestry Commission 2011). The majority of coniferous woodland is managed by clear-felling and replanting, thus creating mosaics of even-aged, mostly uniform, forest stands (Mason *et al.* 1999). The resulting patchwork landscape offers opportunities to investigate species-assemblages within different aged stands and presents itself as a good model for studying soundscapes.

This is the first study to explore the relationship between the soundscape and physical properties of a coniferous plantation forest in the UK and it is structured around four objectives. Firstly, we explore how the soundscape changes with forest age, hypothesising that acoustic diversity would increase with age. Forests become more structurally complex with age (Humphrey 2005), offering more resources and niches for bird species (MacArthur & MacArthur 1961), which should in turn lead to a more complex acoustic community (Sueur *et al.* 2014b). Secondly, we assessed the temporal variation of the soundscape (within and between years) in order to determine the potential suitability of these methods as a long-term monitoring tool. Thirdly as soundscape conservation is an important consideration both to ecosystem health and human health (Dumyahn & Pijanowski 2011b), we investigated how the acoustic signature of the forest changes with increasing distance from two moderately busy roads.

2.2 Methods

Covering 18,730ha, Thetford Forest in East Anglia is the largest man-made forest in lowland UK (Armour-Chelu, Riley & Brooke 2014). Planted during the first half of the 20th century on poor agricultural soils and heathland, it is a somewhat young forest, with forest stands ranging from 1 year to >100years, and is managed by the UK government Forestry Commission. Around 76% of the plantation comprises a mosaic of even-aged coniferous forest stands (of which 74% is Corsican Pine; 19% Scots Pine; and 7% other conifers), ranging in size from <1ha to 18ha, which are managed by clear felling and replanting on a 55-70 year rotation cycle. The remaining parts of Thetford forest comprise 12% broadleaf woodland (beech; oak; birch and mixed) and a mixture of open habitats including grassland, heathland, bracken and farmland habitats. The forest is divided by a number of roads, including three major ones (A1065; A134; A11) as well as a number of smaller ones. The forest is open to the public but vehicular access is restricted to Forestry Commission personnel and those with permits. It is a popular recreational area and much of the forest is used by dog-walkers, cyclists, walkers and equestrians. There is a large deer population within the forest which is mostly managed by the Forestry Commission (Wäber, Spencer & Dolman 2013). It is a designated Special Protection Area for the ground-nesting birds, the Woodlark and the Nightjar. It is also an important area for a number of scarce and rare fauna and flora in the UK and Europe and 94% of the forest (17,653ha) has been designated for national and international conservation interests (Armour-Chelu, Riley & Brooke 2014).

This study took place near Santon Downham in the Central Thetford Forest block, which is managed by the Forestry Commission (52°28'2.1828''N, 0°39'53.2872''E) (Figure 2.1). Permission to conduct the study was obtained from the Forestry Commission and we liaised with them to ensure we did not interrupt any felling operations or deer management activities. Sampling points (N=73) were predominantly classified as coniferous woodland (N=65) of which 70% was Corsican Pine, 20% Scots Pine, 4% clear-felled and 6% other coniferous species; other habitats included broadleaved and lowland mixed deciduous woodland (n=7) and grassland (n=1).

Figure 2.1 A) United Kingdom coastline. Thetford Forest (black dot) is situated in East Anglia. B) Map of the main central Thetford Forest block. Thick dark lines indicate busy A-roads. Thinner dark lines indicate minor roads. Black dots represent study grid. C) Study grid. Dots represent sampling points (n=73), which are spaced 250m apart. Polygons represent different forest stands. The thick dark line on the Western edge of the grid is the A1065 and the thick dark line to the North East of the Grid is the A134 – two busy main roads.

2.2.1 Recording methods and sampling design

To explore spatial variation in the forest soundscape, a systematic grid was used. Other soundscape studies have used sampling grids of 50m (Farina & Pieretti 2014) and 100m (Pieretti, Farina & Morri 2011). In this study, a 250m grid was used (Figure 2.1), as one of the key objectives was to explore the relationship between forest stand age and acoustic diversity and a larger grid was necessary to represent a meaningful age-gradient of forest stands (table 2.1). Soundscape recordings (44.1KHz; 24Bit; Stereo) were made using a Roland R-05 digital audio recorder and a DIY stereo microphone using Primo EM-172 electret condenser capsules, powered by a 5V phantom power battery box. Although the Primo EM172 capsules are omnidirectional, this stereo microphone was made to enable bi-directional recording for other purposes – a single Primo EM-172 capsule can be used to build a mono microphone and give suitable recordings for a study of this kind. The Primo EM-172 was selected as it is a favoured microphone for DIY nature sound recordists due to its low self-noise. Acoustic analysis of recordings was conducted on both channels and scores used in statistical tests were taken as the average value of both channels. The recording unit was mounted on a tripod 1.5m from the ground. To minimise handling noise, the observer stood 8m from the unit and remained quiet throughout recordings. Since the presence of an observer may affect the vocal activity of any animals, upon arriving at a site there was a one minute quiet interval before commencing recording. However, since Thetford Forest is a popular recreational area it was assumed that the observer did not have a drastic effect on the vocal fauna.

Table 2.1 Survey effort showing the age and type of forest stands sampled. CCA label column refers to the key for the Canonical Correspondence Analysis.

WOODLAND TYPE	AGE (YRS)	NO. SITES 2014	2015	CCA LABELS
Coniferous	0-5	7	8	CF1
Coniferous	5-10	7	7	CF2
Coniferous	15-20	9	9	CF3
Coniferous	20-30	6	6	CF4
Coniferous	30-35	9	9	CF5
Coniferous	35-45	13	11	CF6
Coniferous	45-50	8	10	CF7
Coniferous	50+	6	5	CF8
Broadleaf	15-20	1	1	BLM3
Broadleaf	50+	6	6	BLM8
Lowland Acid Grassland (n=1 both years)				*LAG*

Three minute recordings were made at each grid point during the morning (6am-11am). Although this is a relatively short snapshot of a soundscape, it is possible to capture and categorise different habitats using as little as 80 seconds of recording (Bormpoudakis, Sueur & Pantis 2013). Furthermore, our aims were to investigate the role that snapshot soundscape recordings might have in large-scale monitoring so shorter recordings and more sites were deemed a suitable logistical trade-off. On average, it was possible to visit 21 sites during the 6-11am sampling window. To ensure each site was sampled earlier and later during this period, it was further split into two separate sampling periods (6am-08:30am and 08:30am-11am). The temporal variation of the soundscape between different years was explored by sampling the grid in two consecutive years during the summertime: between 21st July - 20th August 2014; and 29th July - 28th August 2015. Due to logistical limitations it was not possible to sample all sites equally but most sites were sampled at least six times in each year, with each site being sampled at least three times in one or both sampling periods. During 2014, two sites were sampled five times, 61 sites sampled six times, and ten sites were sampled seven times (N=446). In 2015 three sites were sampled five times, 64 sites sampled six times, four sites sampled seven times and two sites were sampled eight times (N=443).

Percentage cloud cover was recorded for each recording by estimating what portion of the sky directly above the observers head and in the observers field of view was taken up with cloud (0-20%; 20-40%; 40-60%; 60-80%; 80-100%). This was done from the closest track from each recording point since in some sites it was not possible to see a representative portion of the sky. Recordings were not made if it was raining or in very windy conditions. Due to logistical constraints an anemometer was not available for the study but the wind levels were estimated for each recording as 1=still; 2=light breeze; 3=strong breeze; 4=windy. However, for analysis purposes this was condensed to whether it was still or if there was any breeze (1=no wind; 2=some wind). The final “wind” score for each site was calculated as the percentage of “windy” recordings. To assess the suitability of this, we also obtained hourly wind-speed records from the nearest UK Met-Office weather station at RAF Marham (14miles north of study site). Although this is quite a distance, we make the assumption that the weather will have been similar at our study grid, largely due to the (flat) topography of East Anglia.

2.2.2 Vegetation Structure and Landscape Variables

Field-based observations and GIS data were used to identify habitat structure and landscape characteristics. Canopy height was estimated using an ordinal scale of: 0m; 1-5m; 5-10m; 10-15m; 15-20m; 20-25m; >25m. Canopy cover was estimated using an ordinal scale of: 0% cover; 1-20%; 20-40%; 40-60%; 60-80%; 80-100%. Tree density was measured by counting the number of trees above head height (ca. 2m) in an 8m radius of the recording position. The number of different tree species (referred to as TRSP from here on) and types of ground vegetation were noted down for the same 8m radius. Average ground vegetation height was estimated using an ordinal scale of: 0; 0-10cm; 10-40cm 40-80cm; 80-130cm; >130cm). Vegetation surveys were conducted in both years. GIS data obtained from the Forestry Commission was used to determine the age of each forest stand on the grid and the number of species planted in each stand (from here on referred to as ‘stand diversity’). The distance of recording points to the nearest road (50m bands) and the nearest forest stand edge (10m bands) were measured using the multiple ring buffer and intersect functions in ArcGIS (ESRI 2014).

2.2.3 Calculation of acoustic indices

In order to improve processing time in R, each three minute recording was split into ten second segments using WAV Splitter v.1.31 (DigitByte Studio software).Unwanted noises (i.e. footsteps, handling noise) were removed from subsequent analyses by removing relevant segments (generally 30s from the beginning and 30s from the end). For each recording, acoustic indices values were calculated for 12, ten second segments (equating to two minutes in total). The average value of these 12 segments was then used for that particular recording. Recordings from both sampling periods (early morning and late morning) were pooled. In the site comparison analyses, the average acoustic indices values were used. (ca. 12 minutes audio per site). There were a total of 453 soundscape recordings from 2014 and 445 soundscape recordings from 2015. This equates to 889 two minute samples (2014 N=446; 2015 N=443). As Thetford Forest is a recreational area, popular with dog-walkers and cyclists, some recordings were interrupted when the observer was approached by other forest users. In these instances, if the full three minute recording had not been collected the observer returned to that point within 15 minutes and collected the remaining recording period required. The usable parts of the two recordings were considered as one repetition for analysis purposes. A total of 29.6 hours of recordings (2014=14.9hours; 2015=14.7hours) from 73 locations were considered in the analyses.

Five acoustic indices were calculated for each soundscape recording using the *soundecology* package (Villanueva-Rivera & Pijanowski 2014) in the R (ver3.1.3) statistical analysis environment (R Core Team 2015). The acoustic diversity index (ADI) and acoustic evenness index (AEI) were calculated using values derived from the proportion of sounds above -50dbfs (decibels) in ten 1 KHz frequency bands across the 0-10 KHz frequency range (Villanueva-Rivera *et al.* 2011). The normalized difference soundscape index (NDSI), which calculates the ratio between anthrophony and biophony (Kasten *et al.* 2012), was calculated using default bandwidth values (i.e. anthrophony = 1-2KHz; biophony = 2-11KHz). The acoustic complexity index (ACI) was developed to sample avian communites and essentially divides the recording into frequency bins (i.e. bands) and temporal steps and then calculates the sound intensities within this matrix, giving a measure of the number of sound events and their relationship to one another (Pieretti, Farina & Morri 2011). In this study it was calculated using the default parameters (Fast Fourier Transform window length = 512; cluster size (J)=5). The bioacoustic index (BAI) measures the amount of sound intensity (y axis) across a specified frequency range (x axis) and the index value is essentially the area under the curve for any given recording. It was calculated for sounds between 2-8 KHz and thus serves as a function of the sound levels and frequency bands used by the majority of avifauna (Boelman *et al.* 2007).

2.2.4 Data Analysis

To investigate the relationship between the soundscape and environmental variables in coniferous forest stands only (N=65) a Spearman Rank correlation matrix was created using SPSS v.23 (IBM Corp. 2015). This matrix was used to identify and interpret the nature of the relationships between indices and environmental variables and to guide subsequent analyses.

We tested our variables for normality using Shapiro-Wilk tests and Q-Q plots and applied square-root transformations to achieve normality where appropriate (indicated with sqrt in results section). In cases where transformations did not achieve normality, we used non-parametric equivalent tests. To address the hypothesis that acoustic diversity would increase with stand-age we grouped forest stands based on age and conducted one-way ANOVAs with Gabriel post-hoc tests using SPSS v.23. Gabriel post-hoc tests are recommended where samples sizes are unequal (Field

2009). Homogeneity of variance was tested using the Levene test. The Kruskall-Wallis test was performed on ACI values from 2014 and 2015 as these data failed the Levene test.

Canonical correspondence analysis (Ter Braak 1986), using PC-Ord v.6 (MjM Software, Oregon, USA), explored the correlation between sounds occurring in different frequency bands with habitat variables and stand age. The frequency band values used represent the proportion of sounds above -50dbfs (decibels) in ten 1 KHz frequency bands (0-10KHz). CCA is often used in ecological studies to investigate the associations of different species with habitat features and types. Here, we enter the frequency band values as we would with species count data, (N=10) since we were interested in determining where these frequencies lie within the physical landscape. Because species' calls span different frequencies, ordinations can be used to determine which frequencies are most associated with particular habitat features and shed light on the acoustic community present (Pekin *et al.* 2012; Farina & Pieretti 2014). All sites (N=73) were included in the CCA and were split into 11 categories based on stand-age and habitat-type (table 2.1). Habitat structure metrics were averaged for each category and each category classed as a site. To investigate how the anthrophony/biophony ratio (i.e. NDSI) changes with increasing distance from roads, linear regression was used. The impact of road noise on the landscape was visualised using interpolation maps created in ArcGIS (ESRI 2014).

To assess whether acoustic indices values from each site (N=73) were similar between years, parametric (i.e. Pearson) (ADI, AEI, NDSI, BAI) and non-parametric (i.e. Spearman–rank) correlations (ACI) were used. To determine whether indices values per site were significantly different between years, we used paired-samples t-tests (ADI, AEI, NDSI, BAI) and Wilcoxon signed-rank tests (ACI). To investigate correlations between weather data (personal observations and weather station data) and acoustic indices scores we used a spearman rank correlation matrix. To investigate differences in the soundscape between the two recording periods (i.e period one = 06:00-08:30am and period two = 08:30-11:00am), paired samples t-tests were performed where appropriate and a Wilcoxon Signed-rank test was used for non-normally distributed data.

2.3 Results

2.3.1 Relationships between the soundscape and environmental variables

Spearman correlations between acoustic indices and environmental data in coniferous forest stands (table 2.2) suggest that ADI was higher in older forest stands with a taller, more closed canopy. These stands were more likely to have a higher diversity of tree species and lower ground cover diversity. Inversely, AEI was lower in these taller, more closed stands. ACI was higher in stands with a more open canopy/no canopy and higher ground cover diversity. These stands tended to be younger, with a shorter canopy and lower tree density. ACI was the only index to display a relationship with distance to the forest stand edge, indicating that ACI tended to be higher in more open areas. NDSI increased with increasing distance from the nearest road in both years. In 2014, NDSI also bore a relationship with stand age though this relationship was not observed in 2015. In 2014 BAI bore a relationship with canopy height and had a similar strength relationship to stand age as ACI displayed. However, in 2015 these relationships were not observed.

2.3.2 Stand Age

One-way ANOVAs reveal significant differences in ADI/AEI and NDSI in different aged forest stands (Figure 2.2). ADI was higher in older forest stands and lowest in the youngest, more open stands. There appears to be a non-linear relationship, which shows two stages of increase in acoustic diversity, which is corroborated with Gabriel Post Hoc test – showing three (2014 data) and four (2015) groupings of sites based on mean values (Figure 2.2). AEI displays the inverse relationship to that of ADI. Groupings based on NDSI values are less clear, which is likely due to the effect road noise at different sites. Since NDSI calculates the ratio between biophony and technophony, the weaker observed relationships with stand age were somewhat expected. ACI was significantly different in different aged forest-stands (Kruskal-

Wallis; 2014, $X^2 = 20.932$; $p<0.005$; 2015 $X^2 = 20.327$; $p=0.005$) and visual inspection of the data indicate that this is largely driven by high ACI values in the youngest forest stands. There were no significant relationships observed between BAI and different age-groups of forest. However, plotting the mean values from 2014 revealed a similar relationship to that observed between ADI and stand age but this relationship was not as clear in 2015 (Figure 2.2).

Table 2.2. Spearman rho correlation matrix of acoustic indices and environmental variables for coniferous woodland (N=65). Non-significant results are displayed as ns. Significant correlations are marked in bold **(**=p<0.01; *=p<0.05)**. GIS data: Age = forest stand age; RdDst=distance to nearest road; EdgeDST=distance to edge of forest stand; STDV=stand diversity – no. species planted by the Forestry Commission. Field data: TRDN=tree density; TRSP=no. of different tree species; CNHT=canopy height; CCVR=canopy cover; GCDV=number of different types of ground vegetation; GCHT=ground vegetation height.

		Age	RdDist	EdgeDist	STDV	TRDN	TRSp	CNHT	CCVR	GCDV	GCHT
2014	ADI	**.570****	.038	.151	.225	.034	**.485****	**.570****	**.503****	-.014	-.087
	AEI	**-.559****	-.080	-.109	-.206	-.039	**-.470****	**-.555****	**-.482****	-.034	.096
	NDSI	**.374****	**.659****	-.239	.109	-.177	**.275***	.151	.150	.243	.102
	ACI	**-.274***	.108	**-.367****	-.047	**-.309***	-.128	**-.344****	**-.536****	**.282***	**.291***
	BAI	**.321****	-.111	.077	.010	-.078	.215	**.421****	**.264***	.047	.153
2015	ADI	**.659****	**.283***	.121	**.446****	.233	**.346****	**.646****	**.665****	**-.307***	-.084
	AEI	**-.643****	**-.309***	-.082	**-.463****	-.215	**-.373****	**-.656****	**-.601****	**.261***	.034
	NDSI	.213	**.640****	-.212	.210	-.141	.207	**.248***	.041	.033	-.066
	ACI	**-.321****	.046	**-.320****	-.023	**-.430****	.148	-.237	**-.525****	**.376****	.021
	BAI	-.005	-.199	-.063	.027	-.047	.125	.089	.122	-.068	-.046

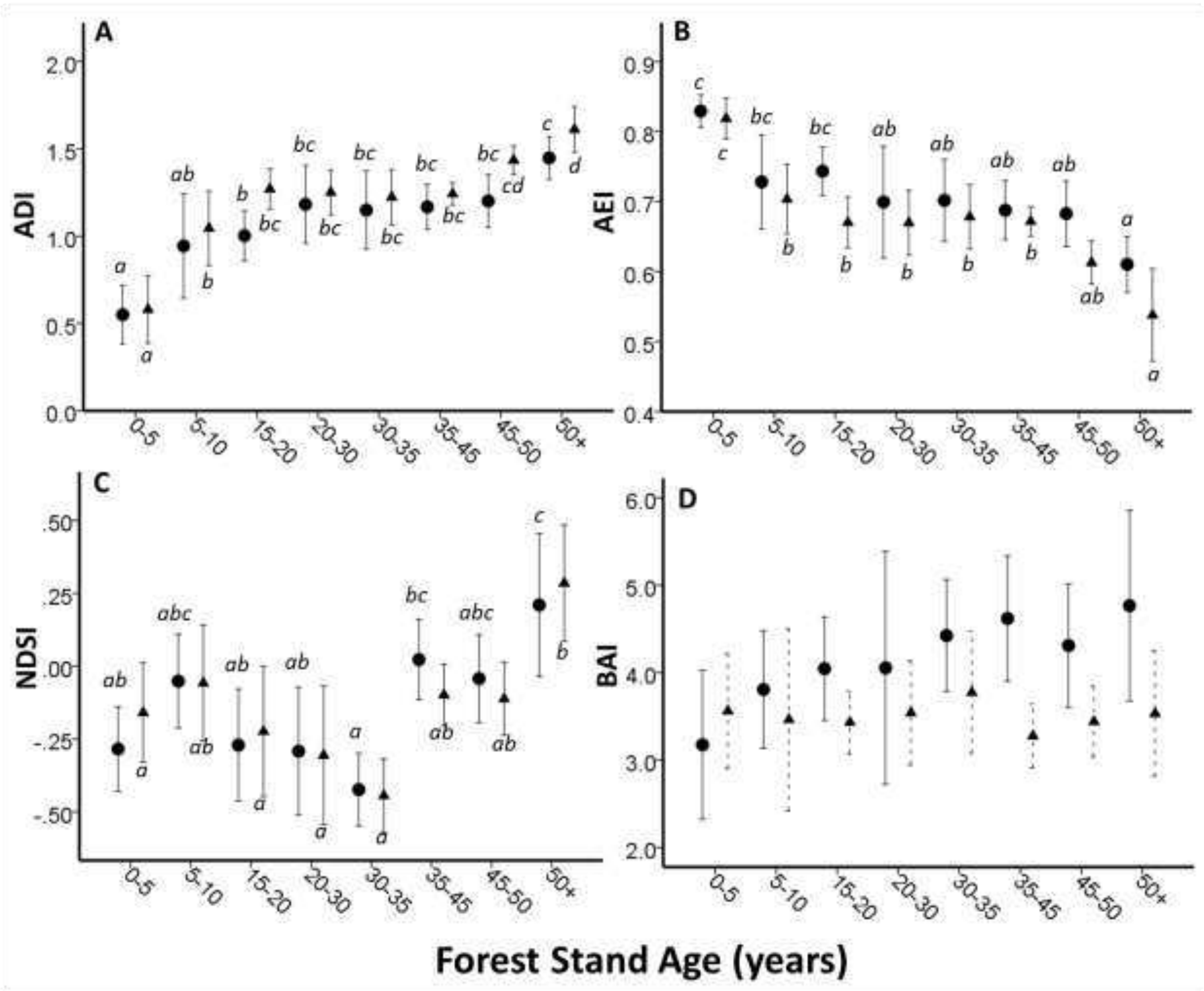


Figure 2.2 Relationships between acoustic indices with coniferous forest stand age (N=65) from each year (dots = 2014 data; triangles = 2015 data). Letters represent mean groupings from the Gabriel post-hoc test ($p<0.05$). A) Mean ADI (+/-2 SE). 2014, $F_{7,57}=6.896$, $p<0.001$; 2015, $F_{7,57}=18.772$, $p<0.001$. B) Mean AEI (+/-2 SE) 2014, $F_{7,57}=5.417$, $p<0.001$; 2015, $F_{7,57}=14.359$, $p<0.001$. C) Mean NDSI (+/-2 SE) 2014, $F_{7,57}=5.827$, $p<0.001$ (*abc*); 2015: $F_{7,57}=5.010$, $p<0.001$. D) Mean BAI – there were no significant differences between age-groups but the plotted means indicate that in 2014 the mean BAI values were higher in older stands.

2.3.3 Canonical correspondence analysis

The ordinations reveal that there were three approximate frequency band clusters: 0-2KHz (associated with more open habitat types), 4-7KHz (associated with broadleaf woodland), and 7-10KHz (older coniferous woodland) (Figure 2.3). They also suggest that acoustic diversity would increase with habitat structural complexity. Axis 1 in both ordinations was strongly associated with the biophony (3-10KHz), which was higher in stands with greater structural diversity. Axis 2 reveals that older coniferous sites (>35 years) were most associated with the highest frequency bands (7-10KHz) in 2014, but only the oldest group (>50 years) was associated with this bandwidth in 2015. Open areas were also associated with these high frequency bands (CF1 in 2014 and LAG in 2015). Across all axes, sites aged 15-35years (CF4, CF5, CF6) were largely similar to one another in their regression scores, which may partly explain the ‘plateau’ in acoustic diversity revealed in earlier analyses.

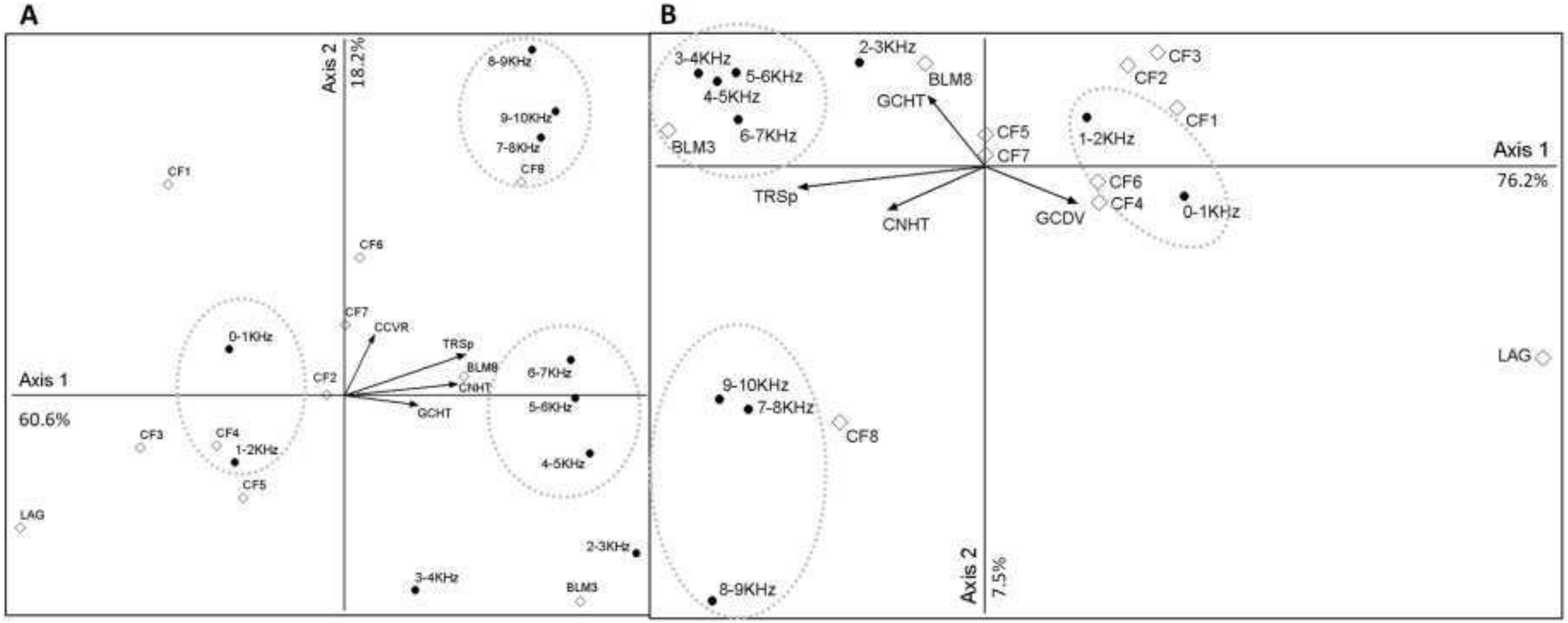


Figure 2.3 Canonical correspondence analysis exploring the relationship between habitat type habitat features and ten 1KHz frequency bands. (see table 2.1 for key to category labels; R^2 cut-offs for environmental variables = 0.1; TRSp = no. of tree species; CNHT=Canopy Height; GCHT=ground vegetation height; GCDV=ground vegetation diversity). A) 2014 data. Strong associations between axis 1 with CNHT and TRSp (Appendix 2.1) indicate that as structural complexity increases, the higher frequency bands become more apparent in the soundscape. B) 2015 data. Similar relationships between axis 1 and habitat structural metrics (Appendix 2.1) show fairly similar distribution of sites in relation to frequency bands. See results section for explanation of key findings.

2.3.4 Anthropogenic disturbance

The strongest predictor of NDSI in both years was the distance to the nearest road (Figure 2.4). The sampling grid was sandwiched between two busy roads, the A1065 (running along the Eastern edge of the grid) and the A134 (ca. 500m West of the grid). NDSI values reached '0' (i.e. an equal amount of anthrophony/biophony in the soundscape) at approximately 1km from the nearest road. ADI and AEI were also significantly correlated with distance to nearest road but the strength of the relationship is somewhat lower. This is likely due to the way the indices are calculated (see methods section), making NDSI a more suitable measure of road noise/anthropogenic disturbance.

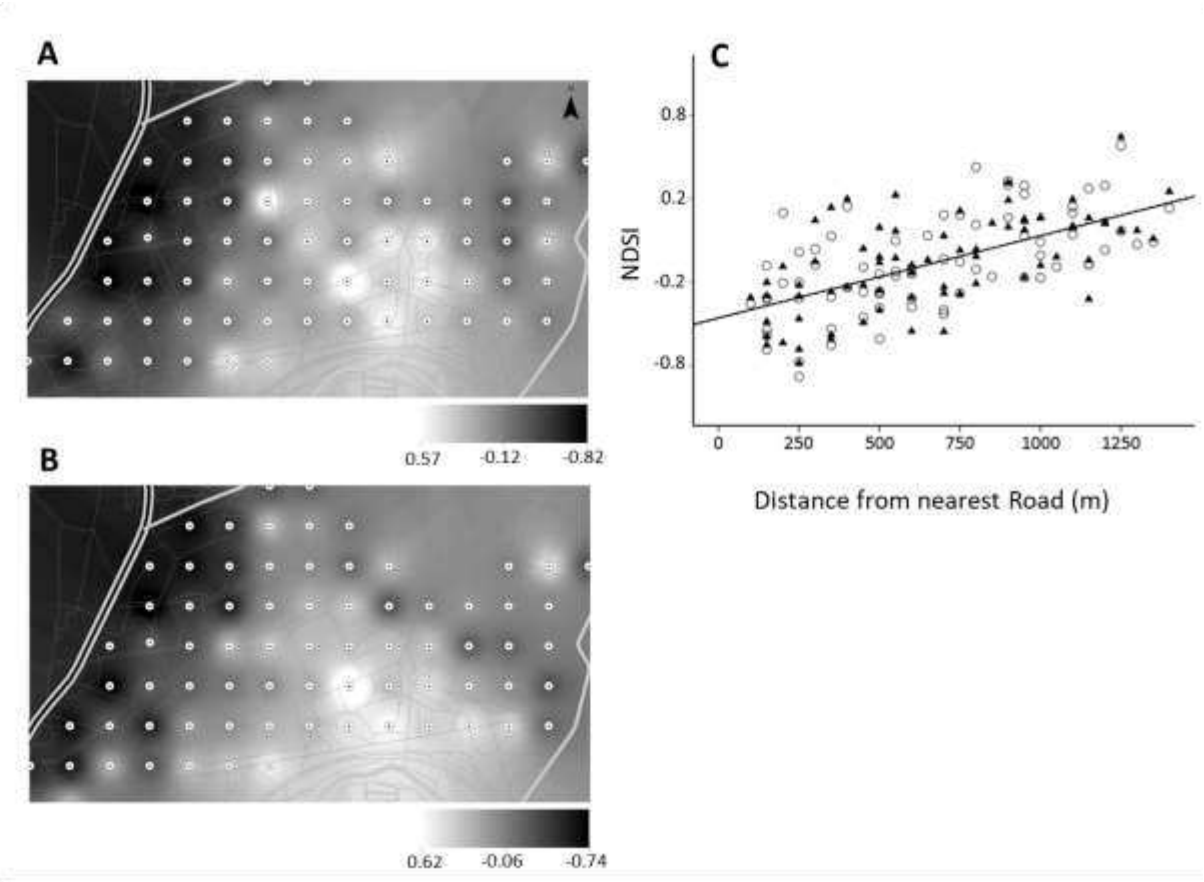


Figure 2.4 Interpolation maps of average normalised difference soundscape index (NDSI) scores from each sampling point from 2014 (A) and 2015 (B) (points are 250m apart). Darker shading indicates higher levels of anthropogenic/technophonic sounds (i.e. from machinery) in the soundscape. Lighter shades indicate higher levels of biological/biophonic sounds. The grey and black striped line on the left of each map is the A1065, a busy main road. The lighter grey lines indicate smaller connecting roads. The lighter grey lines indicate smaller connecting roads. C) Strong positive relationship between NDSI and distance to nearest road 2014 data ($r2=0.373$, $p<0.001$, $N=73$) displayed as circles; 2015 data ($r2=0.397$, $p<0.001$) displayed as black triangles. The lines of best fit for both datasets overlap so are not distinguishable from one another.

2.3.5 Temporal changes in the soundscape

Pearson correlations reveal that ADI, AEI and NDSI values from 2014 were strongly related to 2015 values for ADI $r=0.709$; AEI $r=0.646$; and NDSI $r=0.810$, but only displayed a moderately weak correlation for BAI(sqrt) $r = 0.381$, $p<0.001$, N=72 for all correlations). ACI values from 2014 were related to 2015 values (Spearman Rho $r_s=0.428$, $p<0.001$, N=72). Paired-samples t-tests reveal that mean ADI per site was higher in 2015 ($t_{71}= 4.78$ $p<0.01$), whilst AEI was lower ($t_{71}=-4.93$, $p<0.01$). BAI (sqrt) was significantly higher in 2014 than 2015 ($t_{71}= 4.742$ $p<0.01$). Neither NDSI or ACI were significantly different between years.

The number of “windy” recordings was considerably higher in 2014 (N=264) than 2015 (N=165). The proportion of windy recordings (from here referred to as %WND) was significantly correlated to mean windspeed (kn) data obtained from the met-office (Spearman Rho, 2014 $r_s= 0.279$, $p<0.05$; 2015 $r_s= 0.48$, $p<0.001$), indicating that our rough measures of “wind” reflected that of the observed windspeeds at RAF Marham. Relationships between %WND and acoustic indices were stronger in 2015 than 2014. ADI was lower when %WND was high (2014, Spearman Rho $r_s=-0.247$, $p<0.05$; 2015, $r_s=-0.475$ $p<0.001$) and in 2015 AEI was higher when %WND was high ($r_s= 0.427$ $p<0.001$). Similarly ACI bore a significant correlation to %WND in 2015 only (Spearman Rho $r_s= 0.493$, $p<0.001$), indicating that ACI is higher during “windy” recordings.

Acoustic activity was significantly higher during the first recording period (06:00-08:30) (ADI 2014, $t_{72}=5.233$, $p<0.001$; 2015, $t_{72}=2.025$, $p < 0.05$; and BAI 2014, $t_{72}=4.874$ $p<0.001$; 2015, $t_{72}= 2.850$, $p<0.01$). AEI and NDSI were higher during the second period (08:30–11:00) in 2014 ($t_{72}=-2.929$, $p<0.005$ and $t_{72}=-2.076$, $p<0.05$ respectively). NDSI was also higher during the second period in 2015 ($t_{72}= -2.001$, $p<0.05$), which may be related to an easing of traffic after morning “rush hour”. ACI was not significantly different between different recording periods.

2.4 Discussion

2.4.1 Relationships between the soundscape and environmental variables

The relationships between ADI and AEI with canopy characteristics and forest stand age echo the findings of Pekin et al. (2012), who observed a similar relationship in a Costa Rican rainforest. The relationship in this study perhaps reflects the management strategy of the Forestry Commission. Trees in the newly established stands were planted in rows ca. 2m apart, with trees spaced ca. 1m from one another. Stands aged between 10-35 years were typically very dense due to natural establishment of new trees, and often had little or no ground vegetation cover. From around 20 years old, stands are progressively thinned every five years until the remaining timber reaches economic maturity between 55-70 years (Armour-Chelu, Riley & Brooke 2014). Thinning opens up the forest and allows light to reach the forest floor, enabling a more complex ground vegetation to establish itself (Kerr & Haufe 2011).

It has long been understood that as habitat structural complexity increases, so too does bird diversity (MacArthur & MacArthur 1961). Mean number of individuals (birds) increases linearly with woodland age for winter-bird communities in UK plantation forests but community composition is more dependent upon structural characteristics (Donald, Haycock & Fuller 1997). Calladine et al. (2015) found that bird assemblages in young UK coniferous forest stands (<10years) were typically distinct from older stands (15-30years). Although we have no biodiversity values for our study grid, our results indicate that different aged stands comprise different compositions of sound energy and older stands generally have higher levels of acoustic diversity. This may be caused by higher levels of bird vocal activity (i.e. one bird/species with a large vocal repertoire) or higher levels of bird diversity (i.e. more vocal species). Upon further investigation, the ordinations suggest that as structural complexity increases, the higher frequency bands (4-10KHz) become more represented in the soundscape - the majority of UK woodland bird calls range between 3-8KHz. Visual inspection of spectrograms highlight the contributions of different bird calls to the soundscape (Figure 2.5). In the oldest coniferous stands (>50years), the highest bandwidths (7-10KHz) become particularly noticeable within the soundscape. The goldcrest (*Regulus regulus*), which has one of the highest frequency calls in the UK (peak frequency ca. 7KHz, with contact calls peaking higher still) is more associated with older coniferous woodland than other habitats in the UK (Donald, Haycock & Fuller 1997) and so may have been a key contributor to the soundscapes of the oldest coniferous stands in this study (Figure 2.5).

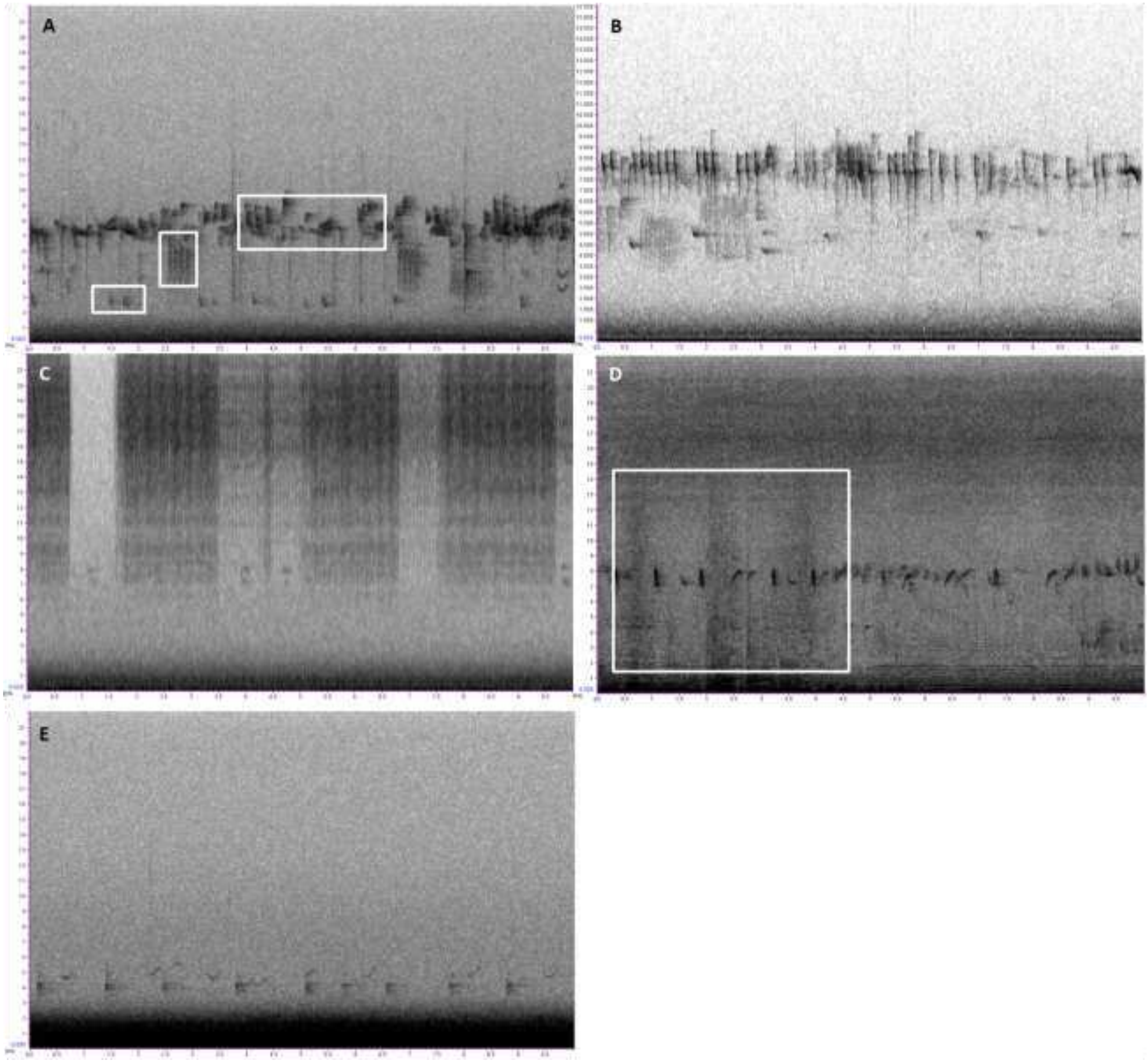


Figure 2.5 Ten second spectrograms illustrating different contributors to the soundscape. A) An example of a recording with high ADI, BAI and NDSI values. Three separate bird species calls are highlighted by white squares. This kind of frequency partitioning is one of the key concepts in soundscape ecology and ecoacoustics. B) Recording from an older coniferous stand (>45yrs) capturing what appear to be contact calls of *Regulus regulus* (goldcrest). C) Highlighting the presence of Orthoptera within our recordings. Although we only utilised audio data up to 11KHz in our statistical analyses, this recording shows that the Orthopterans in our recordings are occupying higher frequencies (up to 22KHz). D) Another recording with high values in the 0-10KHz range. The three darker vertical patches highlight the sound of a flying insect (potentially Syrphidae) passing the microphone. This kind of frequency modulated pattern might be a useful indicator of winged-insect (i.e. pollinator) activity. E) Recording displaying very low NDSI values (-0.95 – i.e. high road noise) which is evident from the thick black band filling the 0-2KHz frequency range.

Another contributor to the high frequency bandwidths is likely to be the wing beats of Dipterans, in particular the Syrphids (hoverflies), and flying Hymenopterans (bees and wasps). Syrphid diversity is generally greater where there is greater ground vegetation cover (Humphrey *et al.* 1999). Hoverflies were present in many of the older forest stands during the study, and the ambient background noise in some stands was a gentle buzzing sound (pers. observation). This buzzing sound can increase the overall proportion of sound within a recording and when a flying insect passes close to the microphone the buzzing sound can occupy the entire bandwidth of the recording (0KHz-22.5KHz) and is strong at 10KHz (Figure 2.5). In areas with greater ground vegetation complexity and flower diversity, there are likely to be a higher number of flying invertebrates which may explain why some of the more open areas had similar sound profiles to the older forest stands with regards to the higher frequency bands (8-10KHz). Orthopterans (crickets and grasshoppers) were also more abundant in the open areas (pers. observation) and their songs can occupy a wide range of frequencies, including 10KHz (Robinson & Hall 2002) (Figure 2.5). The grassland site (LAG) was more strongly associated with the higher frequency bands in 2015 than in 2014, which may be due to the grass being cut by the Forestry Commission during the 2014 field season and subsequently disturbing the invertebrate communities there. Mowing events cause major Orthopteran population declines (Weiss, Zucchi & Hochkirch 2013) with diversity and abundance recovering over time (Chisté *et al.* 2016). However, due to the relatively short period of time we were sampling, it is unlikely that the Orthopteran communities re-established themselves during the remaining sampling period. Our findings with regards to ACI were in contrast to those found in a study by Farina and Pieretti (2014), who found that ACI was typically higher in sites with denser vegetation. This study observed the opposite pattern, where ACI was generally higher in more open areas. This may be explained by the strong effect that the wind had on ACI. However, it may also have been partly driven by the presence of invertebrate communities in the more open areas since ACI was calculated for the whole bandwidth of the recordings. The lack of strong relationships between BAI and any habitat characteristics could perhaps be explained by the relatively broad way in which BAI characterises the soundscape. It was developed to detect differences in bird communities in rich bird-diverse rainforests on Hawaii (Boelman *et al.* 2007). This may explain strong differences in BAI between recordings made during the dawn chorus and those made shortly afterwards. But perhaps due to Thetford Forest being relatively species-poor poor when compared to Hawaiian rainforests, BAI was not acute enough to detect changes in the soundscape along the age-gradient.

2.4.2 Anthropogenic disturbance

Anthropogenic noise disturbance is recognized as a threat to terrestrial wildlife (Barber, Crooks & Fristrup 2010). At high levels it can cause birds (Slabbekoorn & Ripmeester 2008) and frogs (Parris, Velik-Lord & North 2009) to alter their song characteristics to reduce signal-masking. Bats will avoid crossing roads where vehicle noise reaches a certain level (Bennett & Zurcher 2013). Mcclure et al. (2013) created a phantom road (using loud speakers in an otherwise road-free area) and observed that bird abundance declined by over 25% during periods of road-noise and that two species completely avoided the phantom road. The negative impacts that anthropogenic noise can have on humans is also well documented (Goines & Hagler 2007). Indeed the practise of forest bathing (or *Shinrinyoku* in Japanese) is a means of escaping the stresses of city-living and can have measurable health benefits to humans (Li 2010), part of which could be due to being immersed in a natural soundscape. Natural sounds have been shown to speed up recovery from stressful situations in humans (Alvarsson, Wiens & Nilsson 2010), and to reduce stress-levels in coma patients (Saadatmand *et al.* 2013).

Recognising the negative impacts that anthropogenic noise has, and the positive benefits that natural soundscapes can have, on biodiversity and on human health, Dumyahn and Pijanowski (2011b) suggest that soundscapes should be viewed as a common pool-resource and be managed as such. Other studies have documented ‘user’ perceptions of soundscapes in national parks (Iglesias Merchan, Diaz-Balteiro & Soliño 2014) and urban green space (Irvine *et al.* 2009) to identify management and mitigation needs. Using the NDSI, this study demonstrates how noise from a busy road leaches into the forest (Figures 2.4 and 2.5), with a balance between anthrophony and biophony (i.e. NDSI = 0) being reached at ca. 1km from the nearest busy road. This distance echoes findings from a 2010 meta-analysis of road-impact studies which found that bird communities were affected over a distance of up to 1km (Benítez-López, Alkemade & Verweij 2010). This distance may differ depending on the size of the road and how busy it is, the type of surrounding habitat and time of day. However, we demonstrate the potential for NDSI to be used as a tool for modelling and predicting areas of 'acoustic tranquillity', and for managing soundscapes and mitigating noise disturbance.

2.4.3 Temporal changes in the soundscape

Interpolation maps help to visualise the relationship between both sampling years in terms of the acoustic signature (Appendix 2.2). The soundscape on the grid did change between years but the general patterns of acoustic diversity remained largely similar with regards to stand structure. Changes in bird assemblage structure due to migration and/or breeding season success may account for some of these differences. Since bird communities were not sampled as part of this study, it is not possible to determine whether a change in bird communities was the main driver of the observed differences. However, the ordination techniques do offer some evidence that differences in ADI/AEI were potentially being driven by changes in bird communities. Furthermore, changes in ADI/AEI over the five hour sampling period also indicate that these indices were detecting changes in bird activity. ADI was higher between 6-8am, which corresponds with the 'dawn chorus' peak of bird activity.

Perhaps a more likely explanation for the observed differences in ADI/AEI between sampling years was the differences in wind conditions in each year. It is clear that the wind affects the performance of some acoustic indices as proxies for species-richness (Towsey *et al.* 2014). All of the acoustic indices used in this study were strongly affected by the wind conditions. With the proliferation of studies using automated recording units (ARUs), understanding the relationship between the geophysical properties of a soundscape and the performance of acoustic indices will become even more important for ensuring accurate predictions about biodiversity can be made using unattended field recordings. Deploying low-cost weather stations alongside ARUs in the field may help to disentangle the geophony from the biophony and anthrophony. They may also prove useful for understanding the geophonic properties of different habitat-types, since the wind-profile of a forested landscape is shaped by canopy structure and tree density (Boudreault *et al.* 2015). In the very least, they would help to speed up the processing of large numbers of recordings by allowing researchers to rule out windy/rainy/stormy recordings more efficiently.

Our study was conducted by one observer using one recording unit on a minimal budget. This is important to note as the FSC principles and criteria state that scheme participants should conduct biodiversity monitoring that is relevant to the scale of their operation (Forest Stewardship Council 2015). This presents a challenge as the monetary resources and expertise of those collecting data will vary greatly. The observer bias of using a soundscape approach would mostly rest on the type of recording equipment used. This bias could be minimised by using the same equipment; or by calibrating different types of equipment to enable comparisons of data collected with different units. Farina *et al.* (2014) demonstrated that low cost recording units detected similar patterns in acoustic complexity to more expensive recording equipment, though overall resolution was reduced. The use of automated recording units (ARUs) is becoming more common in the field of soundscape ecology. However, ARUs are relatively expensive and typically do not provide data on weather conditions, although some units are now available with on board sensors for light, humidity, temperature and pressure (Farina *et al.* 2016) , which can greatly affect the interpretation of data. Using handheld recording units and a more traditional on-foot approach may be more suitable for wider monitoring applications.

2.5 Conclusion

The relative low-cost of the recording equipment used in this study would enable regular assessment of forests to inform adaptive management strategies. The need for a relatively high-powered computer is the main logistical barrier to this kind of monitoring being used for certification schemes or other environmental initiatives. However, having a centralised data processing location as part of a monitoring initiative may reduce the monetary pressure on scheme participants (such as in the FSC) and enable for better data management protocols to be put in place (Waldon, Miller & Miller 2011). Our results indicate that older forest stands have higher acoustic diversity, which could be explained by changes in the vocal community. This relationship could be used to measure the progress and impacts of management decisions on biodiversity. The suite of acoustic indices currently available offers a number of ways to characterise the acoustic landscape. For example, the NDSI could be used to produce dispersion models of road-noise. Used in conjunction with species-distribution data such information could feed into landscape planning and noise mitigation strategies. Interpolation maps of both NDSI (Figure 2.4) and ADI (appendix 2.2) demonstrate how such soundscapes can be visualised to aide interpretation and highlight areas of interest. Methods from soundscape ecology clearly have great potential for the conservation and management of forests and biodiversity. Collaborations between soundscape ecologists and species-focussed research will likely add another string to the bow of our understanding of how anthropogenic activities impact on nature.

Chapter 3 – A comparison of the soundscapes of two UK coniferous woodlands.

3.0 Summary

There are around 3.17 million hectares of woodland in Great Britain, of which 44% is currently certified and 17.5% is classified as ancient woodland. Of the ancient woodland sites around 40% is planted on ancient woodland (PAWS), so has been continually wooded for ca. 400 years but has been converted into plantation forest during this period. The Convention on Biological Diversity places great emphasis on the restoration of forest biodiversity and restoration of PAWS sites to more natural woodland is part of the UK Forestry Standard. As with certification schemes, restoration schemes require monitoring. The performance of certification schemes in delivering biodiversity targets has been questioned echoing questions raised about the efficacy of agri-environment schemes. One of the key concerns relates to adequate monitoring protocols and procedures. Selecting suitable indicators is notoriously difficult but methods in soundscape ecology have shown promise in numerous studies. This chapter investigates the relationship between vegetation structure and acoustic diversity in two UK coniferous forests, Thetford forest and Bedgebury forest. It investigates temporal differences in the soundscape and further investigates the relationship between road proximity and NDSI. Acoustic indices were more strongly related to vegetation structure in Thetford forest with canopy height bearing the strongest relationships. The acoustic complexity index (ACI) displayed significant relationships with canopy cover and tree density in all sites. The only acoustic measure to bear a relationship with stand age in all sites was the subjective, Observer Index (O_I). Acoustic diversity was greater in Bedgebury forest than Thetford forest, which is likely due to the differences in management histories and landscape composition between the two sites. Cluster analysis and canonical correspondence analysis shows that although vegetation structure was similar in the two forests, their acoustic signatures (based on 10 one KHz frequency band values) were relatively unique from one another. Strong relationships between the normalized difference soundscape index (NDSI) and road proximity were observed in all sites. Spearman correlations indicate that sound levels in five frequency bands, between 3-8 KHz, increase with greater distance from the nearest road. This frequency range is most represented by bird vocalisations so this relationship suggests an element of road avoidance in the biophony, though this may not be driven by road noise per se. This chapter also reveals that relationships between

acoustic indices are different depending on the study site, suggesting that the use of multiple indices to characterise the soundscape may be more meaningful than using a single index. Importantly, this chapter indicates that the relationships between soundscape and landscape are not consistent between different sites with the same habitat, suggesting that landscape composition plays an important role in contributing to acoustic diversity. Finally, this chapter further highlights that low-cost survey methods may be a useful tool in furthering the field of soundscape ecology.

3.1 Introduction

There are around 3.17 million hectares of woodland in Great Britain, which covers 13% of total land area (Forestry Commission 2017b). This area represents a 277% increase in forest cover in the UK since 1905 (Forestry Commission 2017b), which is largely due to the industrialisation of Britain's forestry following the 1919 Forestry Act (Raum 2017). Currently around 51% of woodland is coniferous woodland (mostly comprising of the native Scots pine and non-native Corsican pine), the remaining 49% is broadleaf woodland. Just 17.5% of total woodland cover is classified as ancient woodland, so-called as it has been continuously wooded since 1600 (Rackham 2008). Between 1919 and the 1970s the government policy on forestry resulted in the conversion of many ancient woods into plantations (Brown, Curtis & Adams 2015), which mostly comprise of native and non-native conifers. Today, around 60% of ancient woodland is designated ancient and semi-natural woodland (ASNW) and 40% is planted on ancient woodland sites (PAWS) (Atkinson & Townsend 2011). The Convention on Biological Diversity places great emphasis on the restoration of forest biodiversity (Dudley *et al.* 2005) and restoration of PAWS sites is part of the UK Forestry Standard (Forestry Commission 2017c). As with sustainable forest management, woodland restoration requires monitoring. There is a plethora of research into biodiversity indicators of forest health and sustainable forest management (Franc, Laroussinie & Kafjalainen 2001; Marchetti 2004), which feeds into developing certification criteria for schemes such as the Forest Stewardship Council.

Of the total UK woodland area, 44% is currently certified. The performance of certification schemes in delivering biodiversity targets has been questioned (Angelstam *et al.*

2013) which echo questions raised about the efficacy of agri-environment schemes (Kleijn & Sutherland 2003). One of the key concerns raised relates to adequate monitoring protocols and procedures. There appears to be an opportunity to integrate soundscape methods into large-scale monitoring but there must first be an evidence-base on which to build such an initiative. The Forestry Commission guidelines on monitoring restoration projects focus mainly on monitoring native flora development and suggests keeping a photographic record to document the process (Thompson *et al.* 2003). There seems to be a great opportunity to incorporate soundscape methods into these fairly recent monitoring initiatives, which could contain important information relating to other aspects of forest health, often missed through focussing solely on vegetation.

Since the 1970s UK bird populations have been in decline (Hayhow *et al.* 2015). The data obtained through large-scale citizen science initiatives was integral to identifying this alarming population trend (Greenwood 2007; Jiguet *et al.* 2012). Using data from the Breeding Bird Survey (BBS) collected from 1994-2012, Sullivan, Newson & Pearce-Higgins (2015) identified that population declines were most evident in woodland-birds and urban habitats. They suggest that research and conservation efforts should be focused on those habitats if declines are to be reversed. Birds deliver a number of ecosystem services (Whelan, Wenny & Marquis 2008) including seed dispersal (Loiselle & Blake 2002) and pest control (Bereczki *et al.* 2014) that are essential to the maintenance of healthy forests. The use of acoustic indices to monitor bird species-richness has been a focus of soundscape ecology with varying degrees of success being reported. Initial studies indicated that bird-diversity was strongly correlated with different diversity indices, notably the Bioacoustic Index (Kasten *et al.* 2012); the Acoustic Diversity Index (Sueur *et al.* 2008); and the Acoustic Complexity Index (Pieretti, Farina & Morri 2011). Though there is clearly a need to develop the performance of these acoustic indices if they are to be used as proxy-measures for biodiversity, there is also a need to understand how the soundscape connects with the landscape.

There is a growing body of evidence to suggest that soundscape analysis methods can be indicative of the landscape structure, with particular reference to forest fragment-size and connectivity (Tucker *et al.* 2014; Fuller *et al.* 2015). Other studies have focussed on describing spatial and temporal patterns in the soundscape and investigating their connection to the landscape. Rodriguez *et al.* (2014) observed clear differences between canopy and understory soundscapes in a Neotropical forest, whilst also shedding light on distinct temporal patterns. In South-Central Alaska there are clear patterns between landscape variables and the composition of the soundscape indicating that proximity to wetlands and rivers was strongly associated with the biophony. Bormpoudakis, Sueur & Pantis (2013) were able to demonstrate that distinct habitat types produce distinct soundscapes. There are fewer studies that investigate the connection between vegetation structure and the soundscape. Using remote-sensing methods such as LiDAR (Pekin *et al.* 2012) and the Normalized Difference Vegetation Index (Machado, Aguiar & Jones 2017), clear relationships between vegetation structure and the acoustic diversity index (ADI) have been demonstrated. Using field-based measures, (Farina & Pieretti 2014) and a combination of remote sensing and field-measures (Farina *et al.* 2015) relationships between the acoustic complexity index (ACI) and vegetation structure have been demonstrated. Understanding the relationship between vegetation structure and acoustic diversity at the habitat-level could be particularly useful for monitoring the progress of restoration and certification initiatives, whilst also providing insights into bird diversity and activity.

In this chapter I aim to further build on the findings in chapter two. Ultimately it compares soundscapes in forest stands comprised of the same species and similar age-gradients at two different forests in the UK.

3.2 Aims and Objectives

1. Determine whether there is a relationship between vegetation structure and acoustic diversity in Bedgebury Forest - a non-native PAWS conifer plantation. There was a clear relationship between canopy height and acoustic diversity at Thetford Forest sites and so I will test the same hypothesis: that acoustic diversity will be higher in older forest stands with higher degrees of structural complexity.
2. Compare the soundscape between two forest sites with different landscape-scale attributes and management histories, testing the hypothesis that acoustic diversity will be higher

in Bedgebury Forest than Thetford forest. The landscape composition surrounding both sites differs significantly, with Bedgebury forest being surrounded primarily by ancient woodland.

3. Compare the soundscape between two temporal sampling periods, testing the hypothesis that acoustic diversity will be higher in early summer than late summer. Birds are generally more vocally active earlier in the summer due to the breeding season.
4. Further discuss the nature of road-noise disturbance and investigate the relationship between the soundscape and distance to main roads to build on the observations from chapter two.
5. Investigate the relationship between acoustic indices across the different sites to determine whether the relationships between indices vary depending on site.

3.3 Methods

3.3.1 Study Sites

Bedgebury forest (N 51.071882, E 0.462425°) is situated in the High Weald Area of Outstanding Natural Beauty (AONB), in South East England, UK (figure 3.1). The South East is England's most wooded region having twice the national average at 15% cover and has the highest concentration of ancient woodland in the country. The area surrounding Bedgebury forest is a mosaic of different types of, primarily privately owned, woodland under varying degrees of management (figure 3.2), along with swathes of agricultural land and grasslands. Managed by the Forestry Commission, Bedgebury forest is a planted on ancient woodland site (PAWS) covering an area of approximately 900 hectares. Comprising 55% coniferous woodland; 32% Broadleaf, Mixed/Yew Woodland (55% of which is worked coppice); and 12% lowland mixed deciduous woodland (the remaining 1% is open water and gardens), Bedgebury forest is under a long-term management initiative to restore native broadleaf woodland across the site. In contrast, Thetford forest is the largest man-made forest in lowland UK (Armour-Chelu et al. 2014). Situated in East Anglia it covers 18,730ha and comprises a mosaic of even-aged, primarily coniferous, forest stands (figure 3.1). The forest was created in response to the great demands for timber during the First World War to provide an extensive timber reserve on land that was not suitable for agriculture. The Forestry Commission began afforestation of the area in the 1920s making Thetford forest relatively young. The plantation is managed by clear-felling and replanting on a 60-80year rotation cycle. Around 76% of the plantation comprises a mosaic of even-aged coniferous forest; 10% Broadleaf, Mixed/Yew Woodland; and 2% lowland mixed deciduous woodland; and the remaining area is a mixture of open habitats including grassland, heathland, bracken and farmland habitats.

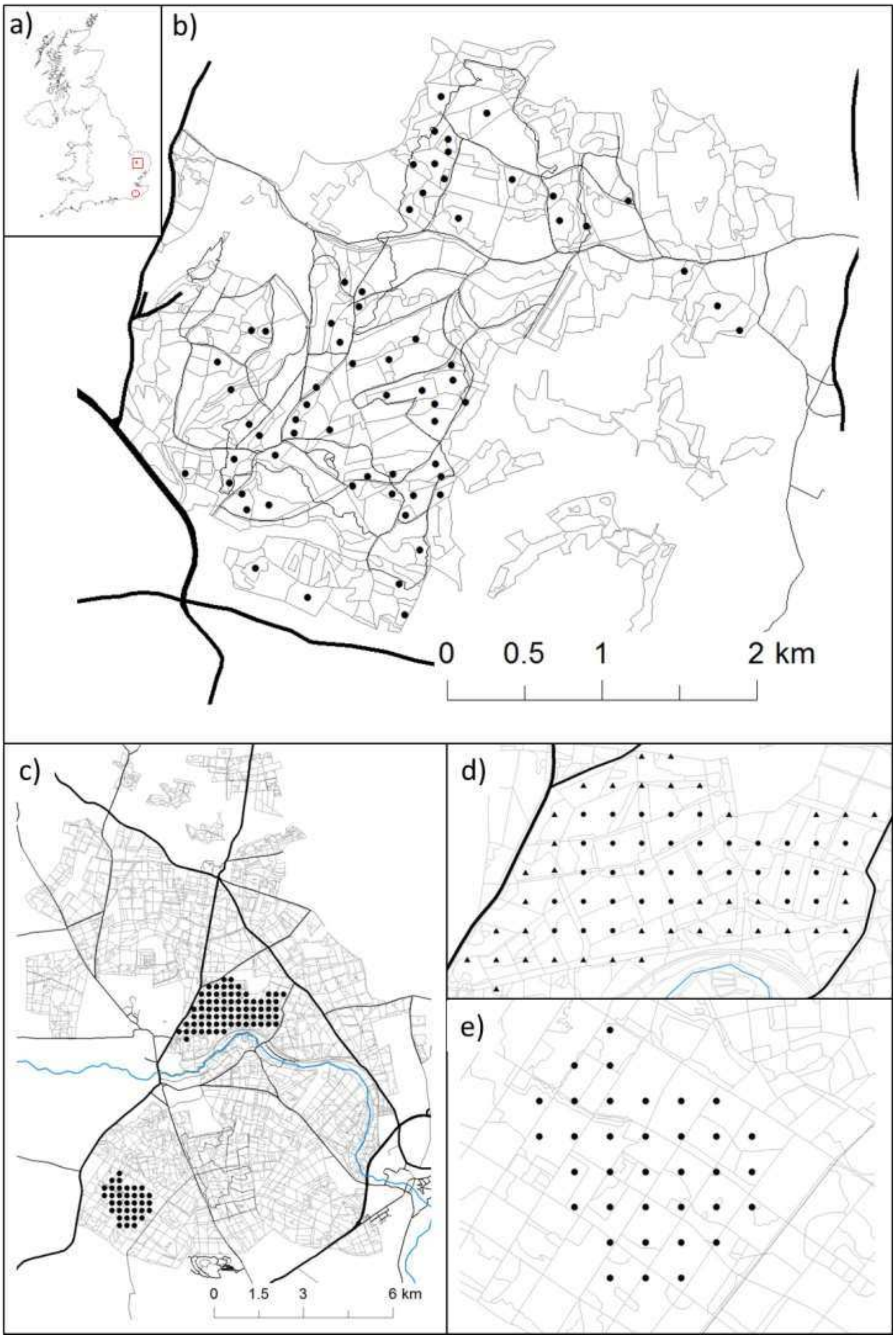


Figure 3.1. a) Map of the UK. The red square indicates the location of Thetford Forest in East Anglia and the red circle highlights location of Bedgebury Forest in the High Weald AONB. b) Map of Bedgebury Forest. Black dots are sampling locations, which represent a gradient of different aged coniferous woodland stands. c) Map of central Thetford Forest block. Black dots show the two sampling grids used in this study. d) Northern sampling grid. Black dots were sampled for the Thetford forest early summer (TFES) and Thetford forest late summer (TFLS) data and black triangles indicate sites sampled only in the TFLS data. e) Southern sampling grid. Black dots indicate sites sampled in TFES data. Sampling points in d and e are spaced 250m apart.

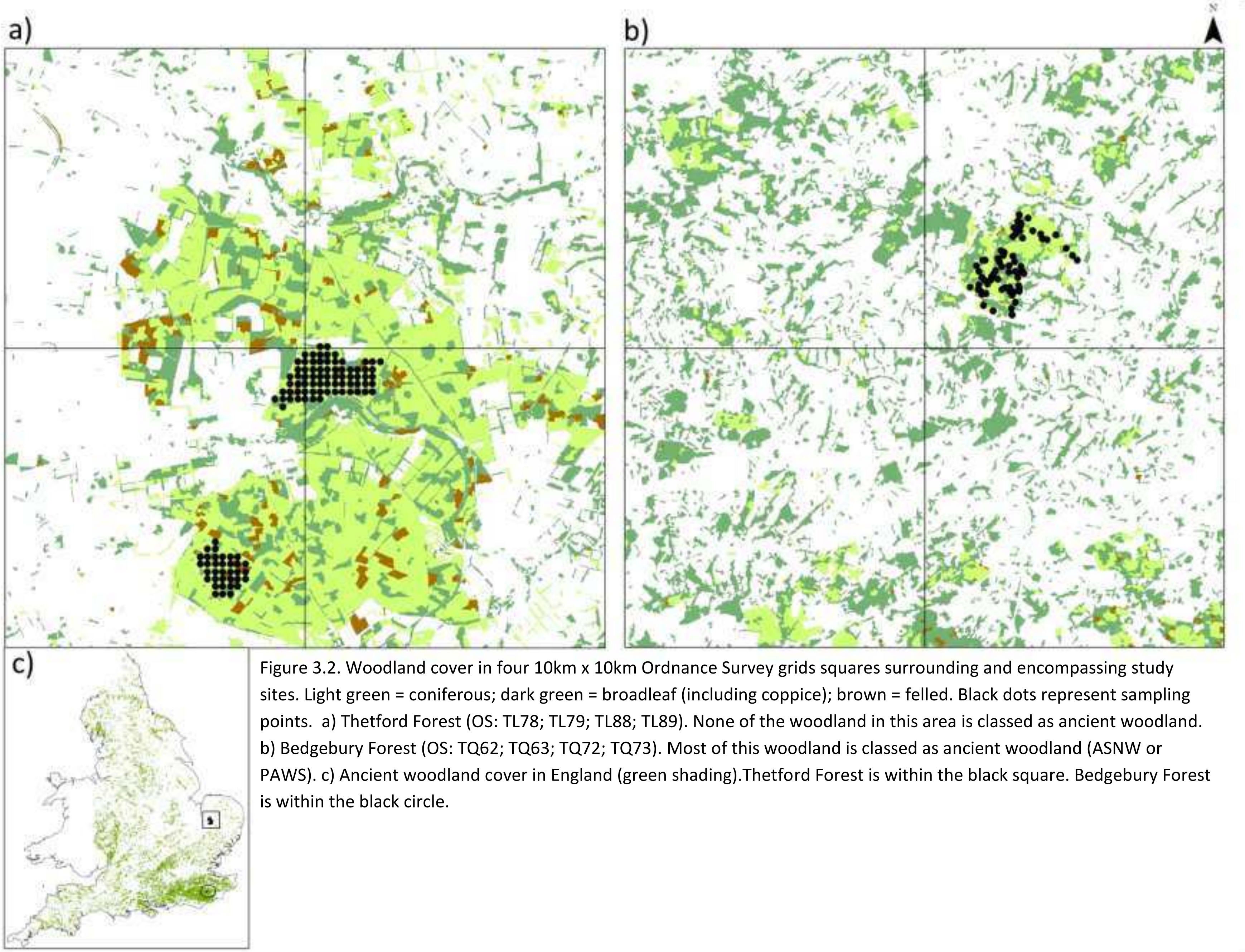


Figure 3.2. Woodland cover in four 10km x 10km Ordnance Survey grids squares surrounding and encompassing study sites. Light green = coniferous; dark green = broadleaf (including coppice); brown = felled. Black dots represent sampling points. a) Thetford Forest (OS: TL78; TL79; TL88; TL89). None of the woodland in this area is classed as ancient woodland. b) Bedgebury Forest (OS: TQ62; TQ63; TQ72; TQ73). Most of this woodland is classed as ancient woodland (ASNW or PAWS). c) Ancient woodland cover in England (green shading).Thetford Forest is within the black square. Bedgebury Forest is within the black circle.

Although the area surrounding the Thetford Forest study grid contains more overall continuous forest cover (figure 3.2), the areas surrounding Bedgebury forest contain a significantly greater proportion of broadleaf woodland (table 3.1), the majority of which is classed as ancient woodland. This offers an opportunity to compare one habitat-type (i.e. non-native coniferous woodland) in two very different landscapes.

Table 3.1. Total area by woodland type and the percentage cover within 10km x 10km OS grid squares (i.e. 40,000ha) surrounding and including study sites.

Woodland Type	Bedgebury Forest		Thetford Forest	
	Area	% of grid	Area	% of grid
Broadleaved	8262.8	20.66	2949.1	7.37
Conifer	2098.2	5.25	9351.5	23.38
Coppice	18.1	0.05	2.2	0.01
Felled	78.7	0.2	927.1	2.32
Mixed mainly broadleaved	16	0.04	106.7	0.27
Mixed mainly conifer	62.8	0.16	136.2	0.34
Young trees	214.1	0.54	1058.8	2.65
TOTAL	***10750.7***	***26.9***	***14531.5***	***36.34***
% Ancient Woodland Cover	76.50%		0%	

3.3.2 Sampling Design

Thetford Forest Early Summer (TFES)

Two separate grids were sampled in Thetford Forest between 16th June and 1st July in 2014 (figure 3.1). Sampling points were arranged 250m apart as in (Turner, Fischer & Tzanopoulos 2018). One 33 point grid was situated in the southern part of the forest in the Elveden estate (52.413128, 0.618907); and a 29 point grid was located 7km northeast of that grid, close to the Forestry Commission headquarters in Santon Downham (52.468089, 0.665853). These data (N=62) are considered as one treatment in the analyses and are referred to as Thetford Forest Early Summer (TFES). These grids comprised Corsican pine (45); Scots pine (10); clear-felled/newly planted (4); other conifers (3).

Bedgebury Forest Early Summer (BFES)

Bedgebury forest early summer (BFES) sites were samples between 17th June and 12th July, 2015. Due to logistical issues, it was not possible to sample both Thetford and Bedgebury at the same time. Although this is not ideal for making direct comparisons between sites, data from chapter two indicate that patterns in the soundscape at Thetford Forest were largely similar in two consecutive years. As such I make the assumption that the soundscape in Bedgebury forest is relatively stable from year to year and will mostly change in localised areas in response to disturbance events.. In order to capture a similar age-gradient in Bedgebury Forest, it was necessary to stratify the sampling approach. Coniferous stands (N = 67) were selected to represent an age-gradient (13-87years) and ranged in size from less than 1ha to 9ha. Due to this range in stand sizes, centroids were used as sampling points - meaning that the area surrounding some sites was more heterogeneous than others. This somewhat reflected the variation in heterogeneity of sites on the systematic grid at Thetford forest. Due to the PAWS restoration initiative, there were only four stands that were less than 15 years old. In order to capture more data from this younger age-class, three of these stands contributed two separate sampling points, each spaced at least 90m apart. Although this distance is significantly less than that the 250m used in Thetford Forest it was not deemed unsuitable since (Farina & Pieretti 2014) found soundscape heterogeneity at 25m resolution in Mediterranean maqui habitat. The dense shrub layer and low canopy in young conifer stands results in considerable variation in terms of plant species composition when compared to older more uniform stands so the distances between these sampling points was considered appropriate. Most other sampling points throughout Bedgebury forest were at least 100m from another.

Thetford Forest Late Summer

In 2015 it was not possible to return to the Elveden grid due to commercial hunting activity. Therefore, the northern grid near Santon Downham was revisited in 2015 and sampled between 29th July and 28th August (referred to from here as TFLS – Thetford Forest Late Summer). The grid was extended to cover a larger area (N=65). Sites comprised

Corsican pine (40); Scots pine (16); clear-felled/newly planted (3); other conifers (6). On both grids, points were 250m apart from one another (figure 3.1) and were representative of forest stands aged between 0-89 years old.

3.3.3 Recording Methods

Sampling points were visited on multiple mornings between the hours of 6-11am to capture morning avian activity. BFES and TFLS sampling points were each visited on six different mornings. Due to logistical constraints TFES sites were only visited on three different mornings. Three minute soundscape recordings (44.1 KHz; 24Bit; Stereo) were made at each grid point using a Roland R-05 digital audio recorder and a Primo EM-172 electret condenser stereo microphone with a 5V phantom power battery box. The recording unit was mounted on a tripod 1.5m from the ground. To minimise handling noise, the observer stood 8m from the unit and remained quiet during throughout. Wind conditions were noted down as either no wind/still=0; or windy=1 as the wind can have a large effect on acoustic indices.

3.3.4 Vegetation Structure and Landscape Variables

Field-based observations and GIS data were used to identify habitat structure and landscape characteristics (table 3.2). Canopy height was estimated using an ordinal scale of: 0m; 1-5m; 5-10m; 10-15m; 15-20m; 20-25m; >25m. Canopy cover was estimated using an ordinal scale of: 0% cover; 1-20%; 20-40%; 40-60%; 60-80%; 80-100%. Tree density was measured by counting the number of trees above head height (ca. 2m) in an 8m radius of the recording position. The number of different tree species (referred to as TRSP from here on) and types of ground vegetation were noted down for the same 8m radius (VS). Average ground vegetation height was estimated using an ordinal scale of: 0; 0-10cm; 10-40cm 40-80cm; 80-130cm; >130cm) (NB: ground vegetation data was not collected for TFES so this data will only be included in BFES site-level analyses). GIS data obtained from the Forestry Commission was used to determine the age of each forest stand on the grid and the number of tree species planted in each stand (from here on referred to as 'stand diversity' or STDV).

The distance of recording points to the nearest road (RdDist) was measured using 50m bands; and the nearest forest stand edge (EDs) measured using 10m bands using the multiple ring buffer function and intersect function in ArcGIS.

3.3.5 Measures of Landscape Heterogeneity and Elevation

Four measures of landscape heterogeneity were determined using ArcGIS software. Buffer zones of 50m radius were created around each sampling point. The number of different stands within that radius was considered as a crude measure of heterogeneity. To investigate further, new areas and perimeters were calculated for each polygon within the buffer zone. The primary tree species/land-use type for each polygon was determined using GIS data obtained from the Forestry Commission. Simpson's Diversity Index was calculated using this data to give an indication of stand-based heterogeneity (SH). A further index was calculated based on the age of the forest stands within the buffer zones (AH), where Simpson's Diversity Index was calculated using 9 age-groups of forest and the respective area of each group. Edge density (EDn) was calculated by dividing the total length of perimeter with the total area of the buffer zone (Katayama *et al.* 2014). A digital elevation model (DEM) was produced using the OS contour lines for Bedgebury Forest. Elevation values of each sampling point were determined using the DEM.

Table 3.2. Environmental data codes and descriptions.

Data Type	Code	Description
Vegetation structure from field-based measures.	VH	Average height of ground vegetation along transects.
	VS	Total number of ground vegetation species.
	CC	Estimate of canopy cover (0m; 1-5m; 5-10m; 10-15m; 15-20m; 20-25m; >25m).
	CH	Estimate of canopy height.
	TRSP	Number of tree species in 8m radius of recording point.
	TRDN	Number of trees in 8m radius of recording point.
	SD	Structural Diversity based on different size trees (including saplings – dbh <5cm).
GIS data and landscape heterogeneity measures.	Age	Age of forest stand.
	Edn	Density of forest stand edges/different habitat edges within 100m buffer zone.
	SH	Stand-based heterogeneity within 100m buffer zone.
	AH	Forest stand-age heterogeneity within 100m buffer zone.
	Eds	Distance of recording unit to nearest stand edge.
	RD	Distance to nearest road (including A and B roads as well as all minor public access roads).
	Elevation	DEM derived elevation of recording point.

3.3.6 Calculation of acoustic indices

The following acoustic indices were calculated for all recordings: the acoustic diversity index (ADI) and acoustic evenness index (AEI) (Villanueva-Rivera *et al.* 2011), Acoustic Entropy (*H*) (Sueur *et al.* 2008), the normalised difference soundscape index (NDSI) (Kasten *et al.* 2012), the bioacoustic Index (BAI) (Boelman *et al.* 2007)and the acoustic complexity index (ACI) (Pieretti, Farina & Morri 2011). All indices were calculated using default values with the multiple_sounds function in the R statistical package ‘soundecology’. Recordings were split into ten second segments using WAV Splitter v.1.31 (DigitByte Studio 2007) and the first and last 30 seconds of each recording were removed to ensure there were no unwanted noises (i.e. footsteps and handling noise). A total of 772 two minute soundscape recordings (25.7 hours) were used in the analyses (TFES = 194, NB: some sites were recorded 4-5 times, but 12 recordings were lost due to a corrupt sd card meaning 12 sites were only sampled twice: BFES = 383, NB: nineteen recordings were lost due to a corrupt sd card meaning 19 sites were only sampled five times: TFLS = 195 NB: only three recordings per site are considered in the analysis of this chapter as a more in depth look at TFLS data is in chapter two). Acoustic indices values were taken as the average value per sampling point.

Additionally, during each recording, an observer acoustic-diversity index (O-I) was estimated to give an indication of the activity and diversity of bird calls in the soundscape. The observer scored the soundscape in-situ on an ordinal 1-5 scale (1=Rare/no vocalisations; 2=Occasional vocalisations; 3=Frequent vocalisations by one species/occasional vocalisations by more than one species; 4= numerous vocalisations by a few species/several different call types; 5= many vocalisations by numerous species/many different call-types). The O_I, therefore, acts as a rough measure of acoustic biodiversity since it was solely scored on the vocalisations of birds. Since sites were visited multiple times, the average value of all visits to each site was used in subsequent analyses, and the resulting O_I values were treated as ratio data.

3.3.7 Data Analysis

SPSS Statistics 23 (IBM Corp. 2015) was used for all data analysis unless otherwise stated. Normality of data was checked visually using histograms and PP-plots, and numerically using Skewness and Kurtosis values and Kolmogorov-Smirnov tests. Where ANOVAs were used, the Levene's test was used to check for homogeneity of variance. Data that failed to meet assumptions for parametric tests were transformed using log10 and square root transformations. For some sites, acoustic indices were not normally distributed even after transformation and so only non-parametric tests were used in their analysis if deemed necessary. T-tests revealed that acoustic indices values did not differ significantly between the two grids sampled in Thetford Forest during 2014 so data from both were pooled as one (i.e. TFES) for analyses.

3.3.7.1 Acoustic indices relationships to habitat/landscape characteristics

Spearman correlations were used to identify relationships between habitat/landscape characteristic and acoustic indices. One-way ANOVAs were used to explore the relationship between NDSI and distance to nearest road for each sampling grid. All three sites were then pooled together in a separate, two-way ANOVA to investigate the effects of distance to nearest road (grouped into eight 250m distance bands) and the sampling grid (BFES; TFES; TFLS) as well as the combination effect of both predictors. Gabriel post-hoc tests were used to identify groups with significant differences to one another. Gabriel tests are recommended where group sizes are unequal (Field 2009). The relationship between the acoustic activity levels (i.e. the proportion of sounds above -50 dBFS) in ten, 1 KHz frequency bands (0-10KHz) with distance to the nearest road was investigated using Spearman Rank correlations.

3.3.7.2 Between Site Comparisons

In order to standardise survey effort across sites, acoustic indices values for BFES were taken as the average of three recordings per site. Furthermore, time of year was somewhat controlled for by only using recordings made between 16th June and 1st July, 2015 in the BFES data (collected in 2015) and TFES data (collected in 2014). Site means and ranges were explored visually for all indices to give an idea of how sites differed from one another. For indices that were normally distributed within each treatment/site, one-way ANOVAs were used to determine how much sites differed from one another. As such only AEI, BAI and O_I were suitable for ANOVAs.

PC-Ord v6 (McCune & Mefford 2011) was used to conduct CCA and cluster analysis. Canonical correspondence analysis (CCA) (Ter Braak 1986) was used to explore the relationship between habitat structure with the acoustic properties of all sampling points (N=194). CCA is an ordination technique that is widely used to explore the relationships between species-communities at different sites in relation to environmental measures/variables (Laiolo, Rolando & Valsania 2004; Zalewski & Ulrich 2006; Jung *et al.* 2012). Ten 1 KHz frequency bands (used to calculate ADI and AEI) were entered as 'species' (B1 = 0-1 KHz; B2 = 1-2 KHz; B3 = 2-3 KHz; B4 = 3-4 KHz etc) and the acoustic activity levels in each frequency band act as 'abundances'. In this way, it is possible to look for patterns in the physical environment that may be driving key features of the sonic environment. Fourteen environmental variables were included. O_I was included as an environmental variable as it was considered important in characterising the bird-activity levels at each site.

Cluster analyses were used to assess the similarities between sites based on their acoustic composition and their habitat characteristics. Sites were split into 26 categories based on stand age and habitat type (NB: data from broadleaf stands on the Thetford forest grids were included in this analysis). Two separate cluster analyses were run; average values for ten, 1 KHz frequency bands were entered for each category in one; and average values for four habitat structural measures for each category were entered in the other. The Bray-Curtis distance and centroid linkage method was used in both analyses.

3.3.7.3 Acoustic Indices Associations

To explore how acoustic indices were related to each other at different sampling sites we used Spearman correlations. If strong correlations were found and the data were normally distributed, linear regressions were applied to determine the strength of relationships. Relationships between O_I and the acoustic indices were explored as O_I was considered as a rough measure of avian activity.

3.4 Results

3.4.1 Soundscape relationships to habitat/landscape characteristics

3.4.1.1 Bedgebury Forest (6 reps per site)

Spearman correlations (table 3.3) show that ACI was higher where the canopy was more open (r_s=-0.598, $p<0.01$) and tree density lower (r_s= -0.396, $p<0.001$) and where ground vegetation was taller (r_s= 0.370; $p<0.001$) and more diverse (r_s= 0.349; $p<0.001$). BAI decreased as tree density increased (r_s= -0.301, p=0.013) indicating that acoustic activity, which could be attributed to bird calls (3-11KHz), was higher in less dense forest stands. There were also weak negative correlations between AEI with stand diversity (r_s= -0.260, p=0.024), TRSP (r_s= -0.276, p=0.024) and canopy height (r_s= -0.275, p=0.024) indicating that acoustic evenness was slightly lower in mixed-species stands, with a taller canopy comprising a higher number of different tree species. Conversely ADI was slightly higher in mixed-species stands with a higher number of different tree species. There were several correlations between O_I and various habitat characteristics and this was the only acoustic measure to display a significant relationship with forest stand age (r_s=0.295, $p<0.05$) and edge density (r_s=-0.285, $p<0.05$), indicating that older, larger stands had higher O_I. Negative correlations between O_I with tree density and canopy cover and a positive correlation with canopy height indicate that O_I was higher in stands with fewer, but larger trees. ADI, H and NDSI all increased with greater distance from main roads, whilst AEI increased with proximity to roads.

3.4.1.2 Thetford Forest

Spearman correlations (table 3.3) indicate that for TFES data, ADI and H were higher in older forest stands whilst AEI was higher in younger stands. Importantly, this relationship was being driven by the Santon Downham grid (ADI r_s= 0.563; H r_s= 0.604; and AEI r_s= -0.617, $p<0.01$) as there were no significant relationships observed in the Elveden grid. TFES had the weakest relationship between NDSI and distance to nearest road of all three sites (table 3.3), which may be due to the Elveden grid being situated further from any main road than the other sampling areas. In the TFLS data, Spearman correlations (table 3.3) indicate that acoustic diversity tended to be higher in older, more structurally complex forest stands. Canopy height was the strongest predictor of ADI/AEI/H, followed by stand-age, then canopy cover (table 3.3).

3.4.2 Between Site Comparisons

Average O_I/ADI/H and BAI values were highest and AEI the lowest in BFES (table 3.4) suggesting that BFES was the most acoustically diverse of all sites. ACI was lowest in BFES and highest in TFES. One-way ANOVAs show that BAI differed significantly between different sites ($F_{2,191}$=289.78, p<0.001) and Tukey post hoc analysis show that all three sites were distinct from one another with BFES having the highest BAI values and TFLS the lowest. AEI was significantly lower at Bedgebury Forest than Thetford Forest ($F_{2,191}$=41.74, p<0.001) but Tukey post hoc analysis indicate that TFES and TFLS were not significantly different to one another. O_I was highest at BFES and lowest in TFLS ($F_{2,191}$=13.88, p<0.001); Tukey post hoc tests reveal that BFES and TFES were not significantly different to each other. These findings suggest that acoustic bird activity was greatest at BFES then TFES and was lowest at TFLS. Mean ADI, H and BAI values were higher in the Elveden grid than the Santon Downham grid though these differences were not statistically significant.

Table 3.3. Spearman correlation coefficients between acoustic indices and O_I with landscape and habitat variables for all sites. See table 3.2 for variable codes.

Dataset	Variable	ADI	AEI	H	NDSI	BAI	ACI	O_I
BFES	Age	.203	-.221	.148	.163	.204	.024	**.295***
	STDV	**.256***	**-.260***	.192	.156	.048	-.070	.091
	EDn	-.026	.033	-.056	.023	-.240	-.158	**-.285***
	RdDst	**.481****	**-.546****	**.452****	**.581****	.055	.064	.133
	TRDN	-.036	.042	-.095	-.145	**-.301***	**-.396****	**-.293***
	TRSP	**.262***	**-.276***	.225	.083	.122	-.122	.161
	CH	.240	**-.275***	.170	.210	.208	-.043	**.325****
	CC	.132	-.085	-.051	-.137	-.239	**-.598****	-
	VS	-.086	.036	.034	.141	.118	**.349****	.066
	VH	.012	-.017	.104	.104	.155	**.370****	.213
TFES	*Age*	**.361****	**-.379****	**.392****	.117	.046	-.219	**.266***
	STDV	.187	-.186	**.256***	.074	-.023	-.124	-.023
	Elevation	.151	-.205	.133	**.263***	.060	.022	**.264***
	RdDist	**.332****	**-.372****	**.265***	**.293***	.203	.033	**.378****
	TRDN	.006	.012	-.003	-.193	-.099	**-.358****	-.042
	TRSP	**.364****	**-.377****	**.359****	.080	.058	-.229	**.337****
	CH	.147	-.149	.207	-.091	-.150	**-.420****	-.036
	CC	.161	-.169	.208	-.113	-.153	**-.587****	-.013
TFLS	*Age*	**.579****	**-.610****	**.492****	**.252***	-.216	**-.257***	**.413****
	STDV	**.384****	**-.408****	**.324****	.138	-.191	-.017	.241
	SH	-.060	.061	-.012	**.285***	-.012	.189	.131
	EDn	.075	-.092	.181	**.252***	-.012	**.283***	.160
	Elevation	-.077	.062	-.163	**.473****	**-.273***	-.178	-.124
	RdDist	.223	**-.248***	.150	**.659****	-.197	-.056	.170
	EDs	-.073	.082	-.221	-.190	-.024	**-.283***	-.148
	TRDN	.162	-.112	.069	**-.291***	-.133	**-.369****	.014
	TRSP	**.342****	**-.384****	**.303***	.207	-.084	.085	**.350****
	CH	**.603****	**-.639****	**.587****	**.265***	-.122	-.158	**.486****
	CC	**.574****	**-.527****	**.376****	.009	-.040	**-.418****	**.313***

Table 3.4. Average acoustic indices and observer index values for each site.

Index	BFES			TFES			TFLS		
	N	Mean	S.E.	N	Mean	S.E.	N	Mean	S.E.
O_I	67	2.77	0.09	62	2.54	0.10	65	2.12	0.07
ADI	67	1.86	0.02	62	1.57	0.04	65	1.42	0.05
AEI	67	0.44	0.01	62	0.56	0.01	65	0.60	0.01
H	67	0.68	0.00	62	0.61	0.01	65	0.63	0.01
NDSI	67	0.53	0.04	62	0.58	0.03	65	-0.07	0.04
BAI	67	13.31	0.40	62	8.60	0.27	65	3.32	0.12
ACI	67	309.13	0.48	62	315.14	1.07	65	309.93	1.06

3.4.3 Canonical Correspondence Analysis (CCA) and Cluster Analysis (all three sites)

Fourteen explanatory variables were included (table 3.5). The observer acoustic-diversity index (O_I) was included as it was considered to be important in characterising stands in terms of avian vocalisations. CCA explained 45.8% variance in three axes (table 3.5). Axis 1 had strong positive associations with distance to nearest road and O_I and was moderately associated with age and elevation. Axis 2 shows moderate associations with field-based habitat structure data and forest stand age. Axis 3 only accounted for 2.5% variation in the data but was mostly associated with the measures of landscape heterogeneity. Frequencies between 3KHz to 8KHz were closely related to one another and all have a strong positive relationship with axis 1 (figure 3.3). Many UK bird calls are within this frequency range, which is an indication that Bedgebury Forest had higher levels of bird activity than Thetford Forest. The CCA shows that BFES, TFES and TFLS general had distinct acoustic signatures from one another. The strongest environmental predictors were distance to nearest road, O_I and tree diversity.

Table 3.5. CCA axis associations with fourteen environmental variables. See table 3.2 for variable codes.

Independent Variable	AxIs (45.8%)		
	1 (34.7%)	2 (9.0%)	3 (2.1%)
Age	**0.349**	**0.239**	0.045
O-I	**0.62**	-0.006	-0.008
W	0.003	**0.278**	0
TRDN	-0.031	**0.232**	-0.13
TRSP	**0.295**	**0.406**	-0.104
CH	**0.26**	**0.264**	0.133
CC	0.171	**0.296**	-0.063
Elevation	**0.387**	0.094	**-0.281**
RdDist	**0.627**	-0.065	0.115
EDs	0.013	-0.175	-0.083
STDV	0.113	0.19	0.128
EDn	0.043	0.142	0.129
SH	0.032	0.127	0.157
Age_D	0.069	0.16	0.135

Cluster analysis reveals that when grouping sites based on the acoustic activity in ten frequency bands, Bedgebury Forest sites were largely distinct from Thetford Forest sites, and the TFES sites were distinct from the TFLS sites (figure 3.4). And broadleaf stands in TFES and TFLS, aged 55-65 years old, were most similar to BFES sites than any other. However, cluster analysis based on habitat characteristics indicates three groupings which correlate with different age-groups: 0-5years old; 5-35 years; and 35-90 years old, regardless of site (figure 3.4). The youngest sites (0-5years: TFES_1, TFLS_1) were distinct from all other sites in both cluster analyses. These sites were newly planted or recently felled coniferous forest, so were essentially open areas with relatively little structural complexity or avian activity. This indicates that habitat structure was similar at BFES, TFES and TFLS, suggesting that differences in acoustic measures were likely being driven by other factors.

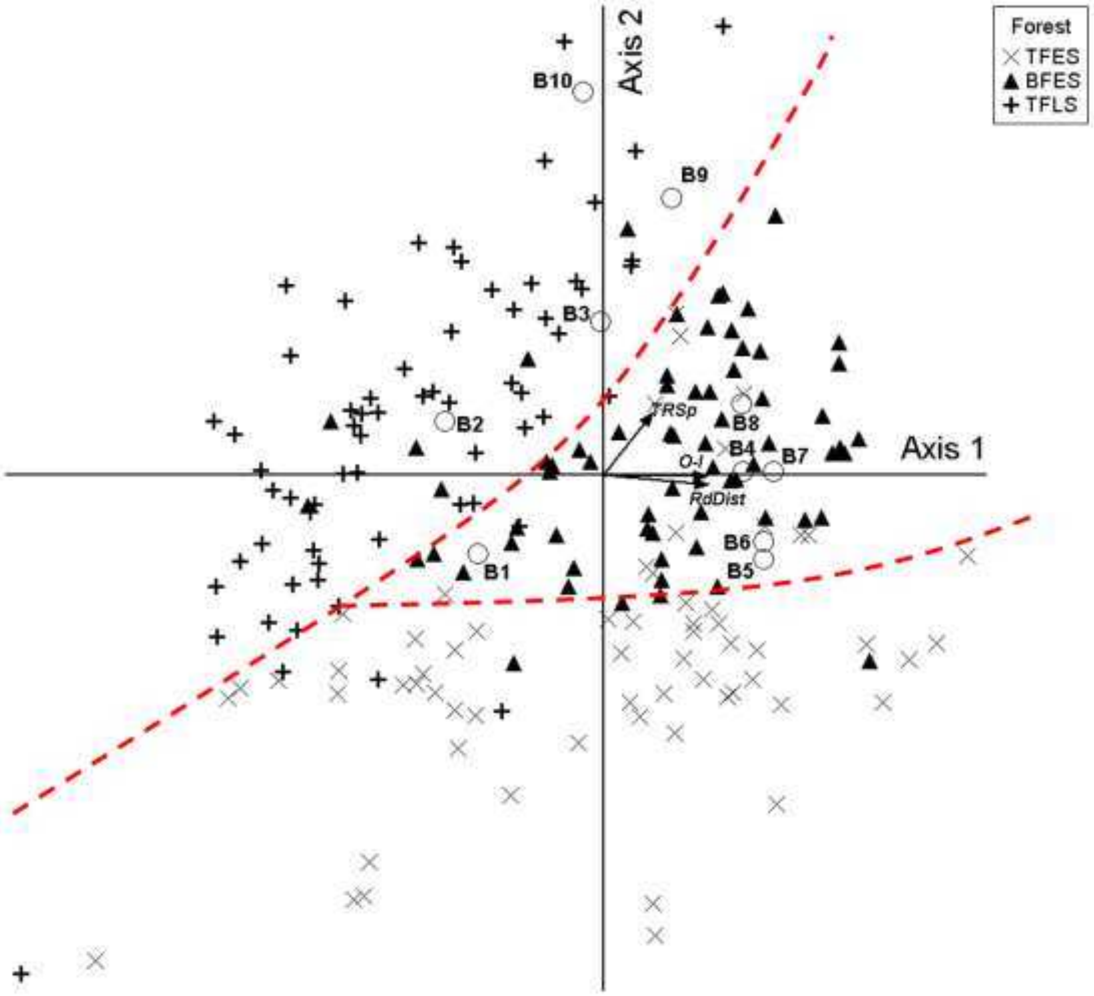


Figure 3.3. Canonical Correspondence Analysis showing relationships between recording locations at three sites (N=194). Fourteen environmental variables were included and frequency band values inputted as species. R^2 cutoff for environmental variables = 0.2. Bedgebury Forest (BFES) soundscapes were more closely associated with the frequency bands B4-B8 (3-8KHz) than Thetford Forest sites (TFES/TFLS). TFLS was more associated with B2 and B3 (1-3KHz), and B10 (9-10KHz) than TFES and BFES. NB: TFES and BFES data are from the same time of year (mid-June – early July) but in different years (TFES =2014; BFES = 2015). TFLS data are from 2015 (mid-July to mid-August).

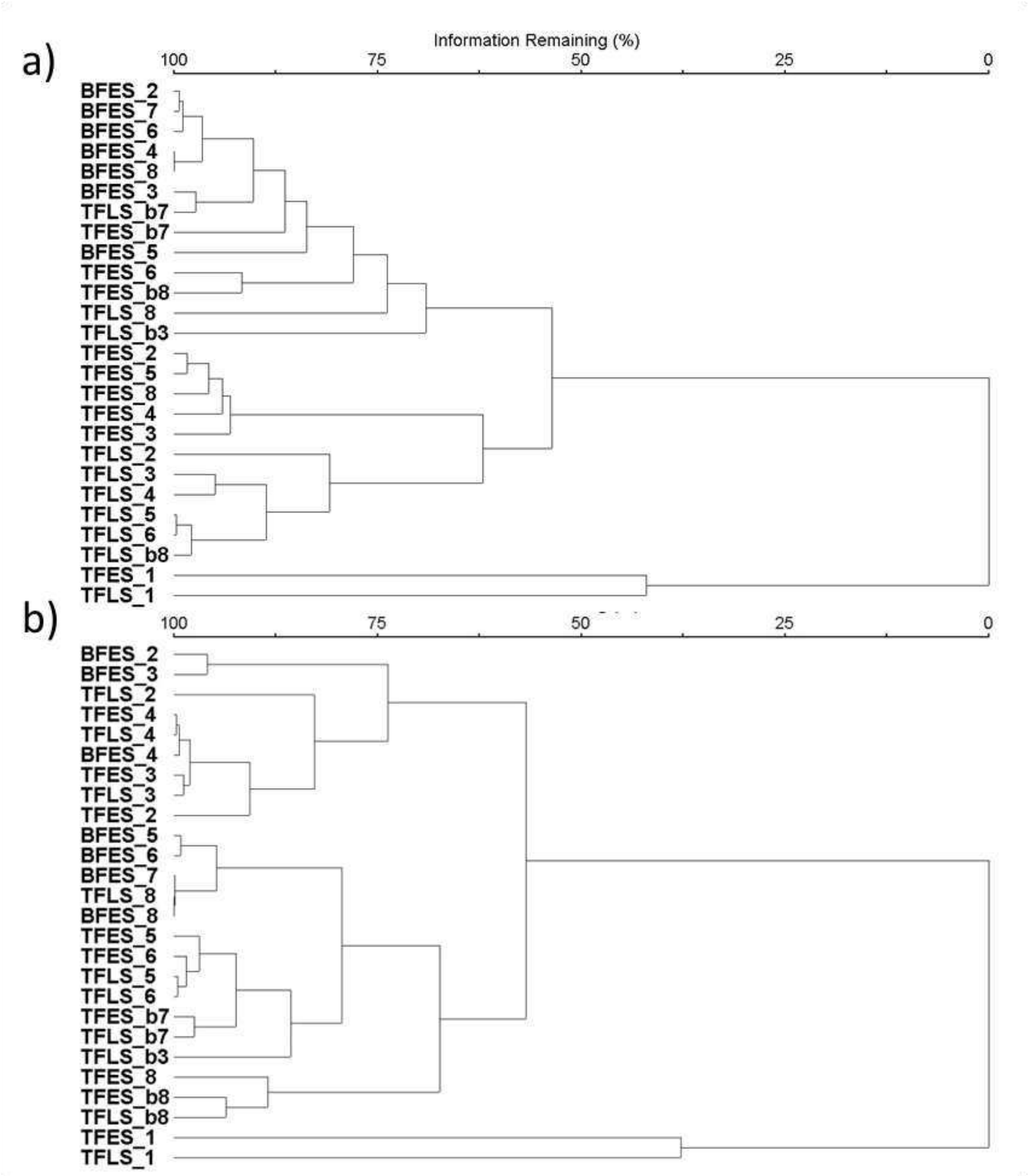


Figure 3.4 a) Cluster dendrogram showing groupings of sites based on ten 1KHz acoustic frequency band activity values. b) Cluster dendrogram showing groupings of the same sites based on measures of habitat structure (canopy height, canopy cover, tree density and tree diversity).

3.4.4 Effect of roads on soundscape

One-way ANOVAs revealed significant differences in NDSI at different distances to the nearest road in BFES ($F_{6,60}$=7.160, p<0.001) and TFLS ($F_{5,59}$=10.289, p<0.001) but no significant differences in TFES data. Means plots reveal the nature of the relationship with distance to road whereby NDSI generally increases with increasing distance from roads in all 3 sites (figure 3.5). Two-way ANOVA reveals significant differences in NDSI values between sites and between different distance bands but that there was no significant interaction effect between distance to road and the study grid (table 3.6). Gabriel post-hoc tests indicate that BFES and TFES were not significantly different between one another but they were both significantly different to TFLS (table 3.7).

Table 3.6. Two-way ANOVA showing differences in NDSI values between sites and at different distances from the nearest road and showing there was no interaction effect between site and road distance.

Source	D.F.	Mean Square	F	Sig.
Corrected Model	20	1.193	19.372	<0.001
Intercept	1	12.843	208.544	<0.001
Site	2	1.964	31.885	<0.001
RdDist_G	7	.745	12.090	<0.001
Site * RdDist_G	11	.069	1.128	.342

Table 3.7. Gabriel Post-hoc test results indicating that TFLS had significantly lower mean NDSI values than BFES and TFES (which were not significantly different to one another).

(I) Site	(J) Site	Mean Difference (I-J)	Std. Error	Sig.
BFES	TFES	-0.053	.0437	.536
	TFLS	**0.601**	.0432	**<0.001**
TFES	BFES	0.053	.0437	.536
	TFLS	**0.655**	.0440	**<0.001**
TFLS	BFES	**-0.602**	.0432	**<0.001**
	TFES	**-0.655**	.0440	**<0.001**

Spearman correlations ($p<0.01$) show that sounds between 3-8 KHz tend to increase with distance from roads (3-4 KHz, $R_s = 0.480$; 4-5 KHz, $R_s = 0.522$; 5-6 KHz, $R_s = 0.507$; 6-7 KHz, $R_s = 0.474$; 7-8 KHz, $R_s = 0.413$) and sounds between 0-2 KHz decrease with distance from roads (0-1 KHz, $R_s = -0.276$; 1-2 KHz, $R_s = -0.322$). These results suggest that the relationship between NDSI and distance to nearest roads is not solely being driven by the dispersion of road noise (i.e. technophonic noise between 1-2 KHz), but that road avoidance of bird species may also be a contributing factor. There were no significant correlations between technophonic noise (i.e. 1-2 KHz) with frequencies associated with bird vocalisations (i.e. 3-8 KHz) suggesting that noise may not be driving these relationships. We also observed strong relationships between ADI, AEI and H with distance to the nearest road in BFES and TFES which were not as strong or evident in TFLS (table 3.3).

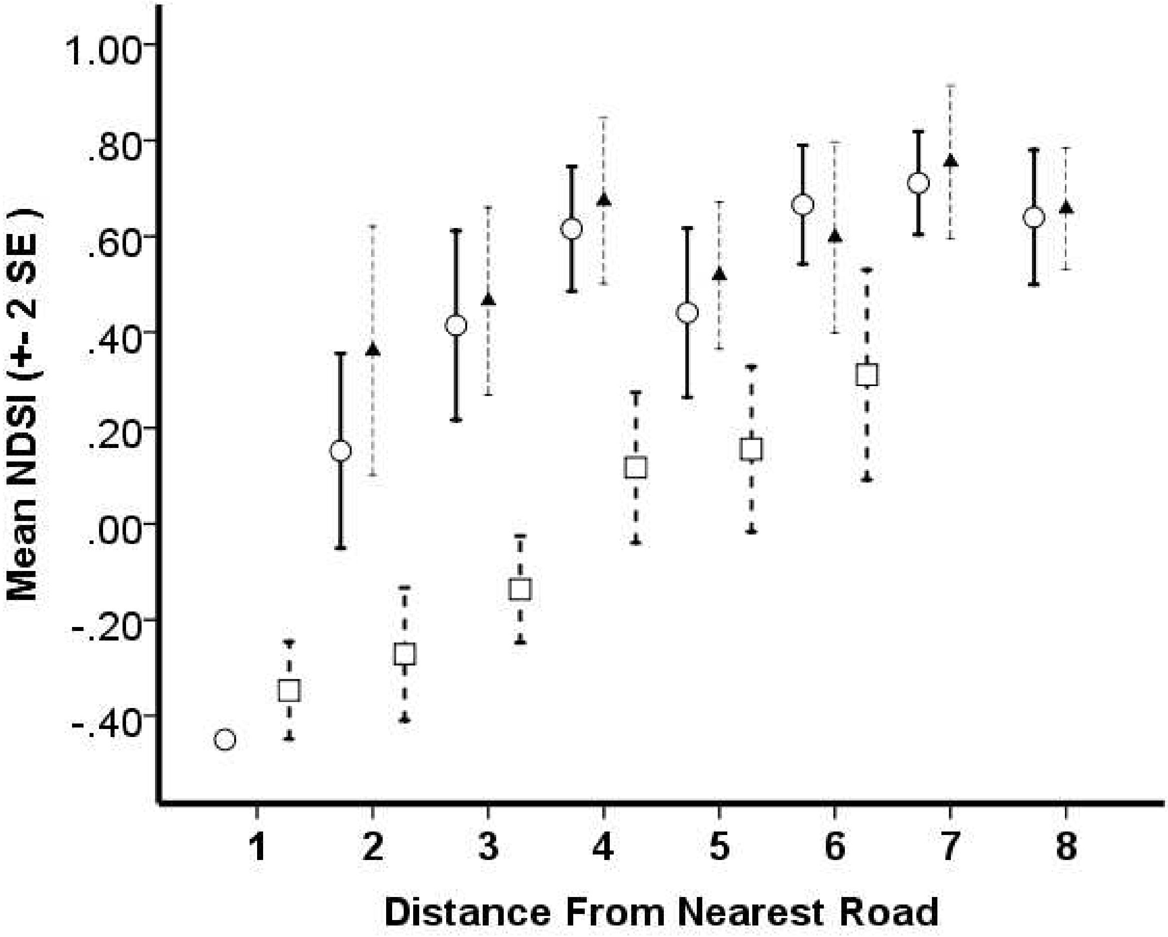


Figure 3.5. Error bar plot showing the relationship between NDSI and distance to the nearest road. BFES=circles; TFES=triangles; TFLS=squares. The relationship was strongest in the TFLS data.

3.4.5 Acoustic Indices Associations

O_I was square root transformed (sqrtO_I) for some of the following analyses. Relationships between acoustic indices were not constant across sites indicating that seasonal changes and differences in acoustic communities affect how indices correlate with one another (table 3.8). O_I was correlated with all the acoustic indices (except ACI in the TFLS data) suggesting that the indices values were related to acoustic biodiversity to some degree. BAI was most strongly related to sqrtO_I (r^2=0.325, p<0.001, N=194) and in the BFES dataset the relationship between BAI and O_I was very strong (r^2 = 0.719, p<0.001, N=67). The weakest relationship between BAI and O_I was in the TFLS data when bird-activity was notably lower. ACI was most closely correlated with BAI in the BFES data but again this relationship was weakest in the TFLS data. Similarly O_I, ADI, AEI, H, ACI and BAI were all strongly correlated to NDSI in the BFES and TFES sites but these strong relationships disappear in the TFLS data. The relationship between BAI and ADI was strongest in the TFES data (linear r^2=0.373, p<0.001) and was fairly strong in the BFES data but this relationship also disappeared in TFLS data. The relationships between ADI/AEI/H all remained fairly similar across the three sites, which is due to the similar methods used for calculating these indices. These results indicate that time of year may play an important role in how these indices perform in terms of capturing surrogate measures of biodiversity. It is evident that the two indices that focus mostly on total bird activity (BAI and O_I) were higher during early summer, which is what one might expect.

Table 3.8. Spearman correlation coefficients showing relationships between six acoustic indices and the observer-estimate of bird-diversity (O_I). * p<0.05; ** p <0.01

		O_I	ADI	AEI	H	NDSI	BAI
Bedgebury Forest Early Summer (2015) N=67	O_I	1					
	ADI	$.374^{**}$	1				
	AEI	$-.410^{**}$	$-.976^{**}$	1			
	H	$.487^{**}$	$.892^{**}$	$-.923^{**}$	1		
	NDSI	$.635^{**}$	$.612^{**}$	$-.654^{**}$	$.720^{**}$	1	
	BAI	$.843^{**}$	$.366^{**}$	$-.374^{**}$	$.482^{**}$	$.621^{**}$	1
	ACI	$.584^{**}$	0.01	-0.06	$.276^{*}$	$.454^{**}$	$.648^{**}$
Thetford Forest Early Summer (2014) N=62	O_I	1					
	ADI	$.577^{**}$	1				
	AEI	$-.600^{**}$	$-.977^{**}$	1			
	H	$.464^{**}$	$.930^{**}$	$-.946^{**}$	1		
	NDSI	$.477^{**}$	$.768^{**}$	$-.756^{**}$	$.704^{**}$	1	
	BAI	$.477^{**}$	$.635^{**}$	$-.608^{**}$	$.513^{**}$	$.682^{**}$	1
	ACI	$.324^{*}$	0.08	-0.09	-0.04	$.384^{**}$	$.567^{**}$
Thetford Forest Late Summer (2015) N=65	O_I	1					
	ADI	$.417^{**}$	1				
	AEI	$-.438^{**}$	$-.982^{**}$	1			
	H	$.372^{**}$	$.860^{**}$	$-.879^{**}$	1		
	NDSI	$.284^{*}$	0.22	$-.274^{*}$	0.15	1	
	BAI	$.423^{**}$	0.12	-0.08	0.14	-0.04	1
	ACI	0.20	-0.14	0.12	0.04	0.19	$.375^{**}$
All Sites N=194	O_I	1					
	ADI	$.502^{**}$	1				
	AEI	$-.515^{**}$	$-.983^{**}$	1			
	H	$.421^{**}$	$.866^{**}$	$-.888^{**}$	1		
	NDSI	$.566^{**}$	$.573^{**}$	$-.571^{**}$	$.425^{**}$	1	
	BAI	$.554^{**}$	$.594^{**}$	$-.565^{**}$	$.425^{**}$	$.700^{**}$	1
	ACI	$.326^{**}$	-0.04	0.05	-0.01	$.403^{**}$	$.276^{**}$

3.5 Discussion

3.5.1 Acoustic indices relationships to habitat/landscape characteristics

The relationship between habitat structure and the soundscape was not consistent across the sampling sites. The hypothesis that older forest stands would be more acoustically diverse was only true in the TFLS data. The only index/acoustic measure to bear a significant relationship with forest stand age in all sites was O_I. However, O_I was only included in this study as a rough measure of audible bird activity and cannot be considered an objective measure of acoustic diversity. Observer-estimates in other facets of habitat surveys are open to bias and variability depending on both environmental conditions and the actual and perceived skill level of the observer (Farmer *et al.* 2009; Campbell & Francis 2011). In this study there was only one observer and the parameters were quite crude so the level of variation within the data may be somewhat reduced but this kind of measure would be unsuitable for a large-scale monitoring initiative involving numerous observers.

Of the computer-based indices ACI appears to have the most consistent relationship to habitat structure. In all three sites it showed relatively strong negative correlations with canopy cover and tree density indicating that ACI tended to be higher in more open areas. ACI can be particularly sensitive to random noise events, such as wind (Sueur *et al.* 2012), which may explain these consistent findings across all three sites. The strongest relationships between habitat structure and acoustic indices were observed in the TFLS data, which echoes the findings of Pekin *et al.* (2012) and may be being driven by greater species-richness in older, taller stands. However, the relationship does not appear in the BFES data and is much weaker in the TFES data. When separating TFES data into two separate grids (Elveden Forest and Santon Downham) it is apparent that the Santon Downham grid is driving the relationship between habitat structure and the acoustic indices. The fact that these strong relationships are not evident in the BFES data or on the Elveden grid (TFES) may be indicative that the Santon Downham grid has a particular landscape composition that lends itself to such a relationship. Landscape composition is a driver of biodiversity in woodland and agricultural landscapes (Kroll *et al.* 2014; Neumann *et al.* 2016). Further study grids in Thetford forest and across other coniferous plantations in the UK may shed light on the effect that landscape composition has on the soundscape.

The relationship between habitat structure and acoustic diversity may also be linked to anthropogenic noise. ADI, AEI and H bore relatively strong relationships with distance to the nearest road in the BFES and TFES data. The same relationship was not observed in the TFLS data. Sites in the TFLS grid were generally closer to roads because the grid was bordered on the east and west by busy A-roads. It might therefore be possible that these roads are affecting both the abundance and diversity of birds or their behaviour (Trombulak & Frissell 2000; Slabbekoorn & Halfwerk 2009) which could have skewed the results. Road avoidance is common amongst bird species (Brotons & Herrando 2001; Husby 2017) and road noise can affect the health, and survival, of some birds (Halfwerk *et al.* 2011; McClure *et al.* 2017) so it may be that the vocal community throughout the TFLS study is not what one would expect in a less-disturbed site. However, other sites were subject to anthropogenic noise disturbance too. Half of the TFES data (Elveden grid, N=35) was collected between 0.5-3km from RAF Lakenheath. As such there were often bursts of loud engine noise that permeated through the grid as planes were taking off and landing so anthropogenic noise was often a dominant feature of the soundscape. Studies have shown how birds living close to airports, or other sources of anthropogenic noise disturbance, alter their singing behaviour to avoid overlapping with the noise(Gil *et al.* 2015). Further studies throughout Thetford Forest would need to be conducted in order to determine whether proximity to RAF Lakenheath does alter the temporal and spatial patterns of acoustic diversity.

3.5.2 Effects of Roads on the Soundscape

Proximity to roads bore the strongest relationship to the soundscape (particularly NDSI) across all sites. Roads are known to have negative effects on terrestrial and aquatic ecosystems (Forman & Alexander 1998). Our results are consistent with findings from previous studies that indicate that species richness/abundance increase with increasing distance from roads (Brotons & Herrando 2001; Forman, Reineking & Hersperger 2002; Husby 2017; Yip *et al.* 2017). We found strong correlations between indicators of bird activity (i.e. acoustic activity in the 3-8 KHz bandwidth) and distance to road which remained strong when only considering sites over 500m from a road. There is debate over the cause of biodiversity decline with proximity to roads. Roads are a source of anthropogenic noise disturbance, which can cause birds to change their vocalisations (Slabbekoorn, Peet & Grier 2003; Nemeth *et al.* 2013; Grade & Sieving 2016) and even disrupt the breeding success of freshwater fish (Holt & Johnston 2015). It is well documented that anthropogenic noise is a source of environmental pollution that can have surprising and far-reaching effects on wildlife (Slabbekoorn & Ripmeester 2008). However, a number of studies have concluded that noise is not the main driver of reductions in biodiversity with proximity to roads. Berthinussen & Altringham (2012) found that bat foraging activity increased dramatically with increasing distance from a busy motorway (between 0-1600m) but found no evidence to suggest that noise-levels were driving this relationship and instead suggested habitat degradation and collisions with vehicles as being more important. Likewise, (Summers, Cunnington & Fahrig 2011) suggest that traffic mortality is the main driving factor in the relationship between species diversity/abundance and proximity to roads. However, these studies have only focussed on noise levels, which often dissipate rapidly over a relatively short distance. This study demonstrates that road-noise is the most dominant feature in the soundscape for distance of at least 1km in a wooded area (and even beyond this it is still clearly audible). Other studies have shown that birds do avoid road traffic noise (McClure *et al.* 2013). With this in mind, studying the effects of road noise on wildlife might be slightly more nuanced than simply measuring noise levels. Regardless of the causes of apparent biodiversity declines due to the presence of roads, this study demonstrates a simple, low-cost method for mapping road-noise and audible biodiversity and highlights the level of information available within a single recording.

3.5.4 Between Site Comparisons

As expected Bedgebury forest had the highest acoustic diversity values followed by early summer and then the late summer recordings from Thetford forest. These differences are particularly clear when taking into consideration BAI and ADI values. Both of these indexes have been linked to bird species richness in previous studies (Boelman *et al.* 2007; Machado, Aguiar & Jones 2017). Aside from absolute differences in acoustic index values, the composition of the soundscape (as determined by activity levels in ten 1 KHz frequency bands) was distinct at the three sites. There are several factors that may be driving these results.

Bedgebury forest is relatively small and forms part of a mosaic landscape comprising pockets of ancient and plantation woodland, farmland and, improved and unimproved grassland. Landscape heterogeneity is often considered a key driver of biodiversity and is especially important for bird diversity (Báldi 2008; Cerezo, Conde & Poggio 2011; Neumann *et al.* 2016) though it is acknowledged that different species respond differently to landscape composition (Katayama *et al.* 2014). Forest stands at Bedgebury forest were on average much smaller and comprised greater variety (i.e. coniferous, coppiced and other broadleaf stands) than those sampled in Thetford Forest, leading to greater heterogeneity and higher availability of different niches. Furthermore, the average age of forest stands in Bedgebury forest is much older than Thetford Forest. Older forest stands can act as refuges for wildlife in UK woodlands and creating old-growth stands within plantations is becoming a standard of best forestry practise in the UK (Humphrey 2005). Additionally, Bedgebury forest has been undergoing a long-term restoration to ancient semi-natural (broadleaf) woodland since 2005. Although there is limited data on species-recovery rates during ancient woodland restoration it is likely that the impact of such restoration initiatives may be detectable after ten years of progress.

In contrast to BFES, the TFLS sampling grid, situated at the heart of Thetford Forest, is bordered by two busy A-roads with a quiet road to the north and a relatively quiet railway to the south. The Elveden grid (N=35 in TFES data) is located in a corner of Thetford Forest (figure 3.2) and so may be more susceptible to edge effects that may affect the relationship between forest structure and acoustic diversity, though it does still comprise large, even-aged forest stands. Bird diversity is often higher closer to forest edges as different habitats and their respective vegetation combine to provide opportunities for multiple species (Reino *et al.* 2009). Although not significant, both BAI and ADI were higher in the Elveden Grid than the Santon Downham grid which suggests that bird activity may have been slightly higher there. Another possible explanation for this is the proximity of the Elveden grid to RAF Lakenheath and so was subject to extreme-noise events when aeroplanes were taking off and landing. Birds have been shown to sing at a higher pitch in areas where anthropogenic noise is high (Slabbekoorn & Ripmeester 2008) so it is possible that birds living in closer proximity to RAF Lakenheath sing louder than those situated in Santon Downham. Another explanation could be due to potential differences in deer populations between the two sites. The Elveden grid, although part of Thetford Forest, is privately owned and deer populations are managed by the landowners. There were several well maintained deer “hunting” platforms situated around this grid, compared to only one on the Santon Downham grid. Speaking with a deer-stalker from Elveden estates it became clear that they take bookings of private hunting parties during the hunting season, which is why I was not allowed access to the site later in the summer.

3.5.5 Temporal Variations in the Soundscape

Temporal differences in the soundscape may also be important. The results indicate that early summer recordings generated higher acoustic values, in particular for the BAI and ADI. Most birds are still breeding during June/July in the UK and by August their breeding activity is slowing down. This likely explains the higher acoustic values in the TFES data than TFLS. Soundscape composition also appeared to be different between TFES and TFLS. Higher frequencies (9-10 KHz) were more represented in the TFLS recordings. Thetford Forest comprises lots of grassland and open areas as part of its management for ground-nesting birds (nightjar and woodlark). These areas attract a diverse invertebrate fauna including Orthopterans (crickets and grasshoppers) and Syrphids (hoverflies). However, the lack of strong associations with TFES sites and the higher frequencies indicates that soundscape composition changes depending upon the time of year. Orthopterans and syrphids are typically more abundant later on in the summer (Riede *et al.* 1998) and so are more likely to become a more prominent fixture in the soundscape during these warmer months.

3.5.6 Acoustic Indices Associations

The results indicate that O_I was significantly correlated with all indices. These correlations were the strongest in the early summer recordings (BFES and TFES) which may be suggestive that these indices are more effective at estimating bird abundance/diversity during periods of high activity. BAI was likely the strongest predictor of avian activity since it was most correlated with O_I. The relationships between acoustic indices were different depending on the sampling period. During periods of higher bird activity (i.e. BFES and TFES), all six indices were more correlated with one another than in periods of low bird activity (TFLS). This indicates that using a combination of indices may be more suitable for characterising sites than relying on one index. Towsey *et al.* (2014) found that using combinations of acoustic indices was more appropriate for determining bird-species richness. A similar approach may be useful when determining differences between sites. In this study, the relationship between acoustic indices was not uniform across all sites. For example, ADI/AEI and H were stronger predictors of structural complexity when BAI was low (i.e. TFLS data). Where BAI was high the relationship between canopy structure and ADI/AEI/H was not evident. Further data collected at different times of the year may shed light on this. Bormpoudakis, Sueur & Pantis (2013) were able to classify different habitat types using recordings taken in the afternoon, during the autumn (i.e. when bird singing activity is vastly reduced). The clear relationship between habitat structure and ADI in the TFLS data (where BAI was low) could be indicating that vegetation differences may be more easily detected during periods of relative quiet in the biophony.

3.6 Conclusion

Echoing the findings of chapter two – using soundscape recordings to monitor road noise and its effect on wildlife could be a valuable tool for noise mitigation. Unfortunately the methods of this study do not enable the proper modelling of road noise and further, more targeted studies would need to be done in order to feed into suitable models. Determining the finer relationships between the soundscape, habitat structure and landscape composition is an area of research still in its infancy. If such methods are to be incorporated into monitoring initiatives they first need to be trialled in a variety of habitat types and environmental conditions. It is evident that in some cases there is a clear relationship between habitat structure and acoustic diversity (i.e. TFLS). This relationship, however, may not be a general rule. In chapter two I suggest that this relationship may be due to differences in species communities along the vegetation gradient since several studies have found such relationships (Nikolov 2009; Pekin *et al.* 2012; Calladine *et al.*

2015). However, this chapter indicates that the relationships between soundscape and landscape are not consistent between different sites with the same habitat. Improvements on this study would include conducting some sound-transmission surveys as in Darras *et al.* (2016) to investigate how sounds travel through different forest stands and how forest structure affects sound transmission. Aside from investigating forest structure and its role in sound transmission, the role of landscape heterogeneity is likely important. There are many studies attempting to understand the relationship between the soundscape and the landscape using passive acoustic monitoring equipment and long audio recordings (Krause, Gage & Joo 2011; Gage & Axel 2014; Pieretti *et al.* 2015; Mullet *et al.* 2016). Although useful for creating a detailed acoustic image of an area, the time and resources available for conducting these studies on a wider scale are limited. This study highlights that differences and relationships between the soundscape and landscape can be observed using relatively low-cost methods. Such methods could prove extremely useful if enough data could be generated over a wider variety of landscapes. This kind of data-collection could lend itself well to a large-scale citizen-science initiative along similar lines to the National Bat Monitoring Project, by the Bat Conservation Trust (Barlow *et al.* 2015) or The Breeding Bird Survey, by the British Trust for Ornithology (Sullivan, Newson & Pearce-Higgins 2015). There is one such initiative, the Global Soundscapes Project /Record the Earth but it lacks a standardised protocol and is not focussed on recording outdoor soundscapes. Combining the ecology protocols/ethos of species focussed citizen science projects with the technological advances of Record The Earth may be an extremely useful means of identifying relationships between biodiversity, the landscape and the soundscape.

Chapter 4 – Investigating the soundscape of Sweet Chestnut coppiced woodland.

4.0 Summary

Coppicing is one of the oldest known forms of woodland management. Since the late 19th and early 20th century Europe has seen a huge decline in this form of woodland management, with many stands being abandoned or restored to High Forest. The biodiversity associated with coppice woods is the product of many centuries of management and is distinctive from that of high forest due to a number of features including: short rotation cutting cycles, high woody species diversity, high degrees of spatial heterogeneity and limited amounts of fallen deadwood. The loss of these particular structural phases has been linked to declines in some aspects of biodiversity. Although sweet chestnut coppice in the UK is generally considered to be poor for biodiversity, there are relatively few studies demonstrating this. This study investigates the relationship between the soundscape with vegetation structure and landscape composition in sweet chestnut coppice stands in a UK plantation forest. It uses a low-cost automated recording unit built for the purpose of this study and a suite of acoustic indices to uncover temporal and spatial patterns in the soundscape. A total of 6930 one minute recordings equaling 115 hours and 30 minutes of soundscape recordings were collected in 40 sites. Although there were no particularly strong correlations between acoustic index values and vegetation structure but there were a number of moderately significant findings. Each acoustic index was associated with one or more vegetation structure metrics. There were several significant relationships between acoustic indices and landscape-based heterogeneity measures. Sites with a greater proportion of broadleaf woodland displayed greater acoustic diversity than those with mostly coniferous woodland. The strongest observed relationships in the study were between NDSI and distance to the nearest A-road. NDSI values increased with increasing distance from the nearest busy road following a non-linear relationship. This chapter provides evidence that soundscape-based monitoring techniques could provide useful tools in forest management and best practice guidelines, with particular reference to road-disturbance and landscape heterogeneity. Furthermore it presents a dataset that was collected using the ARUPI – an automated recording unit utilizing the Raspberry Pi single board computer. These units cost a quarter of the price of the leading market alternative

and are customizable to suit different research needs. As such they present the budget-limited researcher with a high-quality, low-cost option for investigating soundscapes.

4.1 Introduction

Coppicing is one of the oldest known forms of woodland management. The practice involves periodically cutting trees to promote new growth to emerge from the cut stumps (termed *stools*). The multiple stems are then harvested on regular short rotations to provide timber in smaller dimensions than traditional, long-term silvicultural methods (Forestry Commission 2015). A great number of broadleaf tree species will coppice readily but amongst the most common are hazel, ash, hornbeam, and sweet chestnut. The time between harvest (or rotation) is different depending on the species. For example, Hazel is usually cut every 7-10 years and sweet chestnut every 12-16 years, though this can be different depending on the desired product (Fuller & Warren 1993). The harvested poles have a variety of uses including as fence palings, posts and planking and firewood (Buckley & Howell 2004). Coppices can be managed as *simple coppice* or *coppice with standards.* Simple coppice is defined as even-aged single storey stands that are clear-cut at the time of harvest leaving stools to regenerate without canopy cover. Coppice with standards involves growing larger trees (aka standards), often oak trees or other important timber species, scattered infrequently around the coppice stand so their crowns do not touch, allowing plenty of light through to the coppice below. Standard trees often span several age-classes to give increased vertical complexity to the overall structure of the stand (Forestry Commission 2015). In this chapter coppiced woodland is referred to as an all-encompassing term for both management practices.

Since the late 19th and early 20th century Europe has seen a huge decline in coppiced woodland, with many stands being abandoned or restored to High Forest (Mairota *et al.* 2016). In the UK, these declines were in part due to the post-war 1919 Forestry Act, which saw a shift towards creating a strategic timber reserve using even-aged silviculture (Mason 2007). Combined with reduced market demand for coppiced products over the past few decades, the loss of coppiced woodland has been drastic. In the UK, although broadleaf forest cover has increased by over 25% in the past 70 years, the area of coppice has declined by around 600%. In 1947 there were 141,698ha of coppiced woodland in the UK, representing around 21% of all broadleaved woodland, and by 2002 that figure stood at 23,523ha, representing just 2.6% of broadleaf woodland cover (Hopkins & Kirby 1947). Indeed, the value of sweet chestnut coppice per hectare of land in Kent dropped by 43% between 1987 and 1999 (Buckley & Howell 2004). In the past two decades, forestry has undergone yet another sea change in management practice and has veered towards restoration of natural forest processes and continuous cover forestry (Angelstam 1998; Mason *et al.* 1999; Humphrey 2005). And more recently there has been a resurgence of interest in reinstating coppice management as a means of sustainable timber production for biofuels (Fuller *et al.* 2007; Fuller 2013) whilst also accommodating the distinctive biodiversity associated with coppiced woodland (Kirby, Buckley & Mills 2017).

The biodiversity associated with coppice woods is the product of many centuries of management and is distinctive from that of high forest due to a number of features including: short rotation cutting cycles, high woody species diversity, high degrees of spatial heterogeneity and limited amounts of fallen deadwood (Kirby, Buckley & Mills 2017). The loss of these particular structural phases has been linked to declines in some aspects of biodiversity. For example, several heath butterfly species (notably the High Brown Fritillary *Argynni adippe*) have shown significant declines since the 1970s (Hopkins & Kirby 2007). The reduction in coppice management practices coupled with a switch towards continuous cover forestry has resulted in a decline in woodland clearings on which many species depend. Similarly, Willow Warbler (*Phylloscopus* trochilus) population decline in the UK has been linked to the loss of coppice management as they prefer sites with a partially closed canopy, where tree density is high but trunk diameter is small (Stostad & Menéndez 2014). As such, different aged stands often display distinct faunal assemblages and it is the maintenance of a mosaic of different aged stands that contributes to maintaining a distinct forest biota. Moth assemblages in young coppice stands are characterized by species typically associated with open habitats, whereas assemblages in older coppice are typically comprised of species associated with closed-canopy woodland (Broome *et al.* 2011). Similar changes in bird assemblages are observed through different aged coppice stands and studies often suggest that management should be geared towards maintaining a mosaic of age-structures in order to maximize biodiversity on the whole (Maccoll, du Feu & Wain 2014). Indeed, younger sweet-chestnut coppice stands are associated with open-ground and migrant bird-species but following canopy closure the balance shifts towards resident woodland species and species richness declines (Fuller & Moreton 1987).

There are studies that suggest that allowing natural regeneration of sweet-chestnut coppice into high forest can yield biodiversity benefits, particularly for tree-cavity and deadwood species (Laiolo, Rolando & Valsania 2004). And although it is generally recognized that in the UK, sweet-chestnut coppice monocultures are relatively poor in terms of their biodiversity, maintaining them with mature standards can improve the habitat for a variety of species, including dormice and several bird species (Buckley & Howell 2004). It is inevitable that forest management practices will continually fluctuate between placing emphasis on different aspects of forestry such as the economy, biodiversity and social well-being. Just as forest management practices evolve, so too can the methods used to inform best practice. The purpose of this study is to investigate the relationship between forest structure and the soundscape within worked coppice woodland and assess the viability of such methods as a monitoring tool. Thus, the key purpose of this study is to identify whether differences in the soundscape relate to differences in vegetation and landscape structure.

4.2 Objectives

1. To explore the temporal patterns of acoustic activity throughout worked coppice stands along an age-gradient to test the hypothesis that acoustic activity will be the highest in the morning during and immediately following the dawn chorus, when bird activity is at its highest.

2. To investigate the relationship between vegetation structure and acoustic diversity to test the hypotheses:

    a. That acoustic diversity will be greater in stands that display higher structural complexity – previous studies suggest that acoustic diversity and structural complexity are intrinsically linked through the Niche Hypothesis (Krause 1993).

    b. And that young stands (<10years) will display high-levels of acoustic diversity as will older stands (aged >40 years). Previous studies have found bird species-richness to be particularly high in very young coppice (Fuller & Henderson 1992) and other studies suggest that when left or abandoned, the biodiversity of sweet chestnut coppice increases (Laiolo, Rolando & Valsania 2004).

3. To explore the relationship between landscape heterogeneity and acoustic diversity testing the hypothesis that stands located in more heterogeneous surroundings will display greater levels of acoustic diversity. Landscape hetereogeneity is known to have a positive influence on species-richness and diversity, particularly in birds so it stands to reason that areas with a greater degree of landscape complexity should produce more diverse soundscapes.

4. To further elaborate on the relationships between road proximity and acoustic diversity to test the hypotheses that:

    a. NDSI values will increase with distance to the nearest road, following a linear relationship - chapters two and three indicated that NDSI values reach '0' at around 1000m from the nearest busy road, therefore it is assumed that a similar pattern will be found in this study particularly in the morning.

    b. Acoustic diversity will be higher at greater distances from roads; there was some evidence in chapters two and three that acoustic diversity increased with distance from the nearest road and the use of automated recording units should improve the interpretation of that finding.

4.3 Methods

4.3.1 Study Site

Bedgebury Forest, situated near Goudhurst, Kent, is managed by the UK government funded body, the Forestry Commission and falls within the High Weald Area of Outstanding Natural Beauty. It is a planted on ancient woodland site (PAWS), meaning it has been continually wooded since 1600. Part of the forest (around 6%) is made up of the National Pinetum, a centre for international conifer conservation, but the rest of the forest is managed for timber and a host of recreational activities. There are over 40km of walking, cycling and horse-riding routes running throughout the forest making it a popular spot for recreational forest users. The forest itself is comprised of around 73% High Forest and 17.6% worked coppice, which is almost exclusively (99.3%) composed of sweet chestnut (*Castanea sativa*) (appendix 4.1). It was selected for this study due to the relatively large number of worked coppice stands (N=107), which span a range of ages from 0-49 years. As such Bedgebury forest offers an opportunity to sample stands that are under "active management" and those that may be considered abandoned or regenerating. Active management can be defined as coppices that undergo cutting cycles of 0-20 years for sweet chestnut (Buckley & Howell 2004) or 5-30 years for coppices in general (Kirby, Buckley & Mills 2017). One limitation that has been noted in previous studies is the omission of older abandoned coppice stands when investigating age-associated bird assemblages (Fuller & Moreton 1987; Maccoll, du Feu & Wain 2014); or the absence of younger, actively managed stands when investigating natural regeneration of coppice (Laiolo, Rolando & Valsania 2004).

4.3.2 Site Selection

Sweet Chestnut worked coppice sites were selected using GIS data obtained from the Forestry Commission (figure 4.1). At the time of the study there were 157 hectares of sweet chestnut coppice in Bedgebury Forest. They ranged from 0.2 - 6.3 ha in size and were aged between 0-49 years (i.e. time since last coppicing event). 48 sites were selected to give a range of different aged stands. In order to select a suitable range of different aged-forest stands, sites were divided into five 10 year age-brackets. Unfortunately it was not possible to select an equal number of sites for different age-categories due to the recent management history of the forest. As such there were only 6 sites aged 0-10 years; 11 sites aged 10-20 years; 11 sites aged 20-30 years; 10 sites aged 30-40 years; and 10 sites aged 40-49 years. Since data analysis with regard to stand age was mostly based on regression or correlation this was considered acceptable as age-groups were not directly compared to one another.

4.3.3 Recording Methods

Recordings were made using the ARUPI (see chapter five) between June 17th and July 18th in 2015. The units were programmed to record one minute of audio (16-bit; Mono; 48 KHz sampling rate) every 15 minutes. Rodriguez *et al.* (2014) used the same recording schedule to investigate the temporal and spatial dynamics in a neotropical forest. Bormpoudakis, Sueur & Pantis (2013) were able to distinguish different habitat types from one another using just 80 seconds worth of recording per site. Furthermore, in Thetford forest meaningful relationships between habitat structure and the soundscape were documented based on several two minute recordings per site (Turner, Fischer & Tzanopoulos 2018). Based on these previous studies it was deemed appropriate to use a schedule of one minute recordings every 15 minutes to characterize the soundscape. The added benefit of using this schedule is that it also minimized energy consumption and data storage, lowering the overall budget considerably than using longer or more frequent recordings. The order of sampling was randomized to ensure that different aged stands, in different parts of the forest were sampled throughout the survey period. ARUPI units were placed as close to the centroid of each forest stand attached to a suitable sized tree using bungee cord at a height of between 2.5-3.5m from the ground. The microphone was angled away from the tree and as far away from any foliage as possible to reduce the sound of leaves rustling in the wind. Units were left at each site for around two days and on average units were left in position for approximately 43 hours (2hours 54 minutes of audio per site on average). Each unit was numbered to help identify if there were any significant differences in recording quality between units. Four units were deployed for this study.

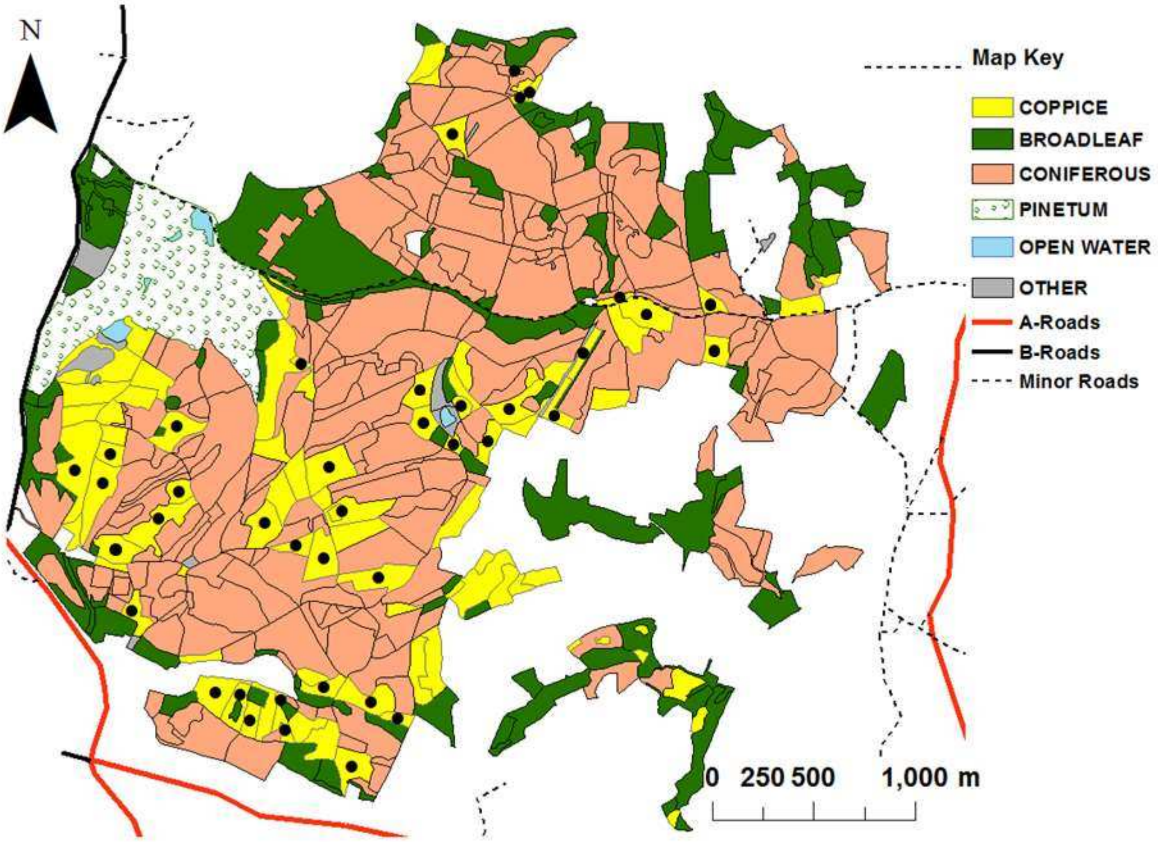


Figure 4.1. Worked coppice ARUPI recording sites in Bedgebury Forest. Black dots indicate survey positions (N=40).

4.3.4 Vegetation Structure and Diversity

Two belt transects (2m x 15m) were surveyed at each recording site. Transects radiated out 15m north and 15m south-east of the recording tree. The purpose of using this v-shape was to better capture spatial heterogeneity and vegetation structure (Shoko, Masocha & Dube 2015). All trees and saplings were identified to species in each transect. Every tree-trunk measuring >5cm diameter at breast height (DBH) was assigned to a size class (1 = 5-10cm; 2 = 10-20cm; 3 = 20-30cm; 4 = 30-40cm; 5 = 40-50cm; 6 = 50-60cm; 7 = 60-70cm; 8 = 70-80cm; 9 = 80-90cm; 10 = 90-100cm; 11 = 100-110cm; 12 = 110-120cm; 13 =120-130cm). An estimate of basal area was calculated using the upper measure for each DBH size-class and multiplied by the number of tree-trunks in that group to give an approximate measure of total basal area (BA) per transect. Deadwood volume was also estimated in this same way – each standing dead trunk was assigned a DBH group and total basal area calculated. Two diversity indices were calculated based on the Simpson's Diversity Index (1-D): tree-species diversity (TD) and tree-size diversity (SD), which was based on the number of individuals in each size-class. SD acts as an approximate measure of structural diversity, based only on living trees as deadwood was calculated separately. Shannon's Diversity Index has been used widely as a surrogate for tree-size diversity (Mcwethy, Hansen & Verschuyl 2009; Hui & Pommerening 2014). However, Simpson's Diversity Index was used as it is less sensitive to sample size (Magurran 2004) and in some transects there were relatively few trees. Canopy height was estimated at the beginning and end of each transect on a five-point scale (1 = 0-5m; 2 = 5-10m; 3 = 10-15; 4 = 15-20m; 5 = >20m). Canopy openness was estimated using a spherical densiometer (Lemmon 1957). Four readings (in the cardinal directions N;E;S;W) were taken at three points along each transect (1m; 7m; 14m) and averaged to give an indication of openness along the transect. Ground vegetation was surveyed at six points along each transect (0m; 3m; 6m; 9m; 12m; 15m) using a 1m x 1m quadrat. Total percentage cover of vegetation within the quadrat was estimated (VC), all species present were identified to give a measure of diversity (VS and VSQ) and vegetation height (VH) was measured at the centre of each quadrat. Data from both transects per site were combined and averaged to give an overall snapshot of structural and species diversity for each recording location (see table 4.1 for vegetation survey codes).

Table 4.1. Environmental data codes and descriptions.

Data Type	Code	Description
Vegetation structure from field-based measures	VH	Average height of ground vegetation along transects
	VC	Amount of ground vegetation cover along transects
	VS	Total number of ground vegetation species
	VSQ	Average number of ground vegetation species per quadrat.
	Rh	Length of Rhodedendron touching the transect
	DBH	DBH of tree which ARUPI was attached to.
	CO	Canopy openness
	CH	Estimate of canopy height
	TT	Total number of tree trunks with DBH greater than 5cm
	BA	Rough indication of total basal area per transect.
	DWf	Fallen Dead basal area - as an indication of fallen deadwod volume
	DWs	Standing Dead basal area
	DW	Total deadwood basal area
	TD	Tree Species Diversity
	SD	Structural Diversity based on different size trees (including saplings - DBH
GIS data and landscape heterogeneity measures	Age	Age of forest stand
	AG	Age group (1-5)
	AvA	Average age of forest stands in a 100m buffer zone aroun d recording unit
	TP	Total length of perimeter/edge within 100m buffer zone
	EDn	Density of forest stand edges/different habitat edges within 100m buffer
	SH	Species-based heterogeneity within 100m buffer zone
	AH	Forest stand-age heterogeneity within 100m buffer zone
	HH	Habitat heterogeneity within 100m buffer zone
	%RC	Percentage of 100m buffer zone attributed to recreational areas
	%BL	Percentage of 100m buffer zone attributed to broadleaf woodland
	%CF	Percentage of 100m buffer zone attributed to coniferous woodland
	%WC	Percentage of 100m buffer zone attributed to worked coppice
	%OA	Percentage of 100m buffer zone attributed to open areas
	%OW	Percentage of 100m buffer zone attributed to open water
	Eds	Distance of recording unit to nearest stand edge.

Table 4.1. continued...

Data Type	Code	Description
GIS data and landscape heterogeneity measures	RR	Distance to Recreational Routes and Forestry Commission roads (no public vehicle access)
	RD	Distance to nearest road (including A and B roads as well as all minor
	A_Rd	Distance to nearest A-road (i.e. major highway)
	B_Rd	Distance to nearest B-road (i.e. main road)
	WD	Distance to nearest source of water (rivers/lakes/streams/ponds)

4.3.5 Landscape Heterogeneity

Using GIS data obtained from the Forestry Commission National Forest Inventory, ArcGIS 10.4.1 (ESRI 2014) was used to measure the different facets of landscape heterogeneity (table 4.2). Buffer zones around each recording location of 100m were intersected with FC polygon data. The area of each new polygon within the buffer zone was calculated. Three measures of heterogeneity were calculated for each buffer zone using Simpson's diversity index (1-D) whereby the areas of different classes of polygon were entered as abundance or count data (Katayama *et al.* 2014). Species-heterogeneity (SH) was based on the diversity of primary species of each forest stand within the buffer zone, where a high diversity score would mean that there were many different primary species within the buffer zone (list of species in Appendix 4.2). Age-heterogeneity (AH) was based on the age of each stand within the buffer zone, where higher scores indicate a greater diversity of different aged forest stands (NB: any polygons that were not classified as forest were entered a separate, unclassified, entity to ensure that heterogeneity was based on the same area for each site). Habitat-heterogeneity was calculated based on the primary habitat-type of polygons within the buffer zone (see table 4.2 for habitat groups). The average age of forest stands (AVA) in the buffer zone was also calculated. The percentage of each buffer zone attributed to each habitat type was also calculated to explore any habitat-based relationships in the data. Some habitat types were combined in order to improve the spread of the data across all sites. The amount of edge-habitat within each buffer zone was calculated by dividing the total perimeter length by total area to give edge density (EDn).

Table 4.2. Habitat types used for calculating habitat heterogeneity.

Habitat Code	Description	Total Area (sq m)
RC	Recreational areas such as picnic spots	15967
Deer_Glade	Deer glade	862
LMD	Lowland mixed deciduous woodland	57620
BM/YW	Broadleaf/Mixed/Yew Woodland	36664
CF	Coniferous woodland	319422
WC	Worked coppice	764942
OA	Open areas	9165
OW	Ponds and lakes	3657
Other	Gardens, residential and parking areas	46687

NB: *LMD and BM/YW were combined to form % broadleaf woodland (BL) for analysis. Deer_Glade was combined with OA and Other was combined with RC.*

Distances from recording units to important landscape features were also calculated. Distance to the nearest forest stand edge (EDs) was calculated by converting the Bedgebury forest polygon shapefile to a line-based file and generating a near table in ArcGIS. Distance to recreational routes and private access Forestry Commission roads (RR) was calculated in the same manner. Distance of recording units to the nearest road (RD) was calculated using the roads shapefile obtained from Open Street Map (McGarva 2009). Since some of the nearest roads were small and quiet, the distance to the nearest A-road (A_Rd) and B-road (B_Rd) was calculated separately as the traffic on these roads is often considerably larger in volume, with higher speed limits so the noise generated from them is considerably louder. The distance to the nearest water source (including ponds/lakes and rivers) was also calculated (WD).

4.3.6 Sound Analysis

All recordings were analysed using the *soundecology* function in R (R Core Team 2015; Villanueva-Rivera & Pijanowski 2015). Six acoustic indices were generated for each one minute recording (ACI; ADI, AEI, BAI, H, NDSI) as in Turner, Fischer & Tzanopoulos (2018). The proportion of sounds above -50dBfs in ten 1KHz frequency bands (from 1KHz –

11KHz) were calculated using *seewave* package in R using the batch-analysis script (Villanueva-Rivera *et al.* 2011). Five distinct periods were identified in the temporal analyses and mean index values for each period per site were used in spatial analyses. All recordings were listened to and explored visually using Audacity® 2.0.5 (Audacity Development Team 2013) and scored "yes" or "no" for rain and predominant wind noise and these noisy recordings were removed from spatial and temporal analysis.

4.3.7 Data Analysis

Since the recording units were only programmed to collect four one minute recording every hour, five different sampling periods were identified. Mean values per site per sampling period were then calculated (i.e. N=40 x 5 periods). This ensured that sites were characterized by a greater number of recordings than if average hourly values were used. Normality of acoustic index data was explored using SPSS Statistics 23 (IBM Corp. 2015); visually using histograms and QQ plots and numerically using Kolmogorov-Smirnov normality tests. Data transformations for several acoustic index values were attempted but failed to achieve normality. Subsequently, these data were analyzed using non-parametric tests where appropriate. Frequency band data were not normally distributed so only non-parametric tests and visual inspection of trends were used in their analysis.

4.3.8 Temporal Analysis

Activity levels in different frequency band values were used to explore temporal patterns in the Bedgebury forest soundscape. Mean hourly values were plotted on line charts for each 1 KHz frequency band. These plots were used to describe the daily pattern of the forest as a whole. Error bar plots were used to explore hourly changes in acoustic index values and give a further indication. These graphical depictions of the soundscape were used to identify five sampling periods. Non-parametric repeated measures ANOVA (Friedman tests) with post-hoc analysis (Wilcoxon signed rank tests) were used to determine whether index values differed significantly between periods.

4.3.9 Spatial Analyses

Spearman rank correlation matrices were used to explore associations between environmental variables and acoustic index values. These correlations were used to guide further analyses. Linear regression models were used to determine relationships between normally distributed index values and environmental predictors; scatter plots and residual plots were used to assess the models for homoscedasticity. If data did not meet the assumption of homoscedasticity, the results were limited to interpreting the Spearman rank correlation matrices to look for potential relationships (i.e. H and ACI). To explore relationships between non-normal acoustic index data and categorical variables, non-parametric ANOVA (Kruskal-Wallis Independent samples test) was used. Non-linear (cubic) regressions were used to explore the relationship between NDSI and distance to the nearest road. Two separate principal components analyses (PCA) were used, both with Varimax rotation to improve the fit of the axes to the input variables. One PCA condensed the vegetation structure variables, which also included stand-age. The other condensed the landscape heterogeneity variables. Distance-based variables (except distance to stand edge – EDs) were not included in the final PCAs as they tended not to be associated with other landscape variables, were generally independent from one another and were deemed to be important predictors in themselves. As such, distance variables were entered into subsequent models as standalone predictors. The PCA factors and distance measures were inputted into General Linear Models to explore the relationships between environmental data and acoustic index values. Multicollinearity of independent variables entered into the GLMs was tested using correlation matrices and was not deemed to be a problem in any of the presented results. The PCA factors were also used in a Canonical Correspondence Analysis (CCA) (Ter Braak 1986) which investigated the nature of the relationship between sound activity in ten 1 KHz frequency bands (1-11 KHz) and the environmental data using PC-Ord v6 (McCune & Mefford 2011). CCA scores were standardized using centering and normalizing, and the scaling method was a compromise between environmental data and frequency band data. Distance to nearest A-road and stand-age were also included as grouping variables to determine whether there were any patterns in the soundscape that related to either of these variables. A Monte Carlo randomization test using 1000 permutations was run to test the null hypothesis that there was no relationship between the frequency band data and the environmental variables.

4.4 Results

4.4.1 Survey Effort and Sound Analysis

Four ARUPI units were deployed at 48 sites and 40 sites were successfully surveyed. Eight sites were unsuccessful either due to teething problems with ARUPI unit 1 (three sites), corrupted data files after sampling (two sites) and handling error (three sites: two battery failures, one failure to connect the phantom power unit to power the microphone). The teething problem with ARUPI unit 1 was due to a bug in the script that switches the unit on and off and did not affect recording quality. Unfortunately, two of these sites were younger stands aged <10years, which significantly reduced the number of stands in that age category (table 4.3). A total of 6930 one minute recordings equaling 115 hours and 30 minutes of soundscape recordings were collected. After removal of noisy (windy/rainy) recordings there were 5870 one minute recordings totaling 97hours 48mins of audio files that were analyzed. The average contribution of usable recordings from each site was 2hours 24minutes, with only 5 sites contributing less than 2 hours, one of which only contributed 54 minutes (this was due to battery failure) and four site contributing more than 3 hours.

Table 4.3. Site selection and survey effort of sweet chestnut coppice stands.

Age-Group	**No. of sites selected**	**No. of sites sampled**
0-10	6	4
10-20	11	7
20-30	11	11
30-40	10	9
40-50	10	9

4.4.2 Temporal Patterns

Splitting the soundscape into ten 1 KHz frequency bands (i.e proportion of sound above -50dBfs per band) shows that sounds in the lower frequencies are more prevalent in the soundscape (figure 4.2). Band 1 (1-2 KHz) displays two distinct peaks during the 24hr period. The first is sharp, starting between 04:00 and 05:00, peaking at 06:00, dropping to a relative low at 09:00 before rising again at 10:00 and fluctuating until around 14:00. The second peak is more gradual from around 14:00 and peaking around 18:00 and gradually dropping until 20:00 when it drops sharply through to 00:00. These peaks largely follow peak traffic times and are potentially mostly indicative of the technophony. This pattern is loosely observed in band 2 (2-3KHz) though the second peak is less prominent. Bands 3-7 (3KHz-8KHz) display a similar morning peak (which may be due to the onset of the dawn chorus) but there is no second peak. Instead, the most noticeable pattern is when sound levels start dropping from around 19:00 until around 00:00. Between 00:00 and 04:00, levels remain constantly low until the cycle begins again. A similar pattern is observed in bands 8-10 (8-11KHz) though the activity levels in these bands are considerably lower than in the other bands.

Acoustic activity tended to be highest between 04:00 and 10:00 and gradually declined throughout the day with the period of lowest activity between 23:00 and 04:00. Due to this pattern the mean acoustic index values for five periods were used in subsequent analyses. [Index]_1 = 04:00 – 10:00; [Index]_2 = 10:00 – 15:00; [Index]_3 = 15:00- 20:00; [Index]_4 = 20:00 – 22:00; [Index]_5 = 22:00 – 04:00. Friedman tests reveal that BAI exhibited the strongest differences between these time-periods (Appendix 4.3) ($\chi^2_{(4)}$= 106.274, p<0.001); followed by ACI ($\chi^2_{(4)}$=100.337, p<0.001); AEI ($\chi^2_{(4)}$=72.989, p<0.001); ADI ($\chi^2_{(4)}$=69.053, p<0.001); and NDSI ($\chi^2_{(4)}$= 44.168, p<0.001). The smallest changes between periods were observed in H indicating that this index was the least sensitive to changes in the acoustic composition of the soundscape ($\chi^2_{(4)}$=27.221, p<0.001). Post-hoc analysis using pairwise-comparisons (Wilcoxon signed rank tests) indicate that there were significant differences in BAI values between all five periods suggesting that these five periods represent distinct periods within the soundscape (table 4.4). When considering other indices, there were four distinct periods in ACI, ADI and AEI, three periods of NDSI and two periods using H. The five distinct period groupings were used in subsequent spatial analyses for all indices as they are indicative of changes in the acoustic activity of the biophony (i.e. 3-8KHz) and retaining the same periods across all indexes allows for better comparisons between index performance.

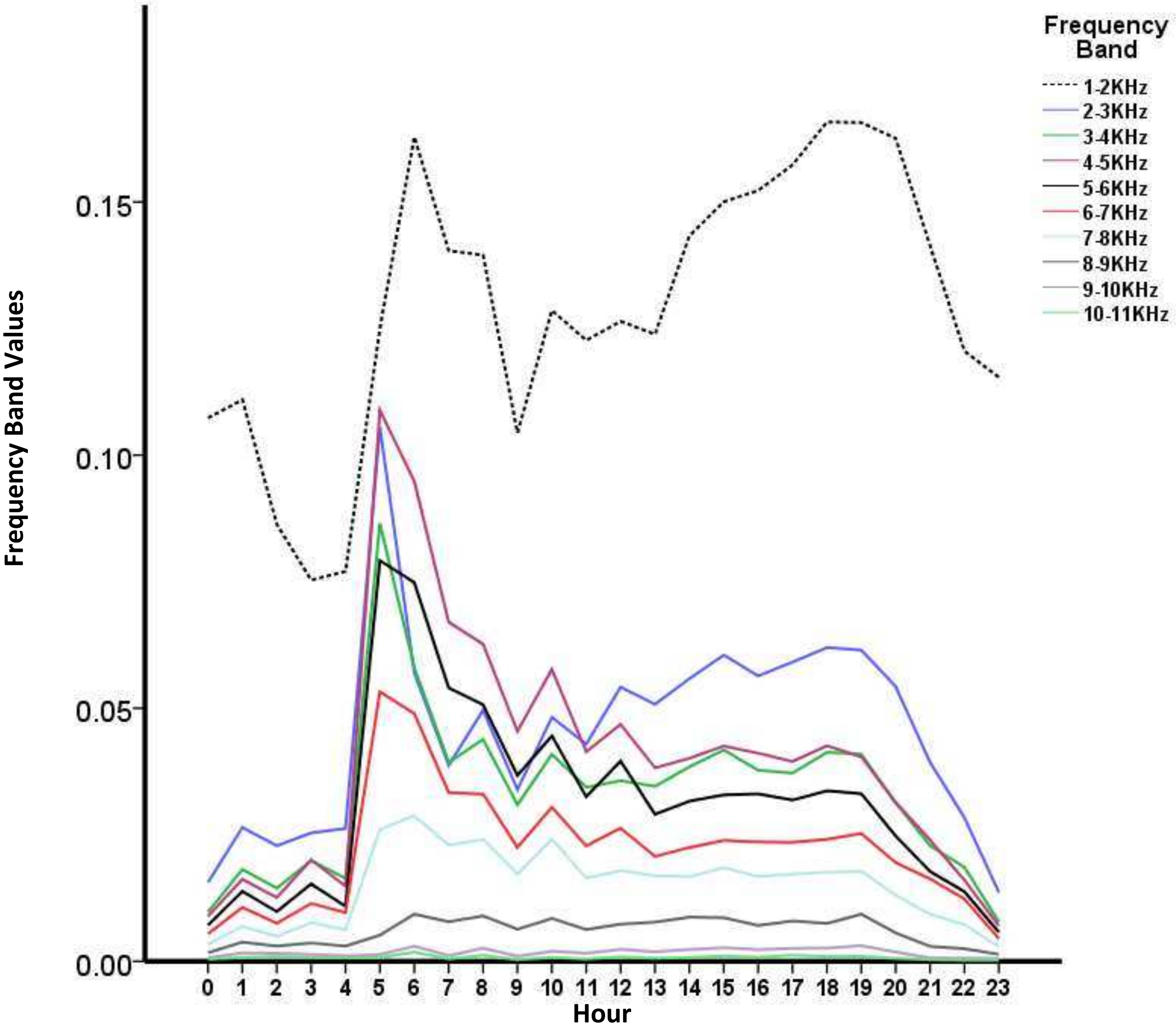


Figure 4.2. Mean frequency band values (i.e. proportion of sounds above -50dBfs in each band) across forty sites in Bedgebury Forest during a typical 24 hour period (between and the 17th June and 18th July 2015). Frequency band 1 (1-2KHz) is the most prevalent sound in the forest and is mostly comprised of road noise (i.e. technophony).

4.4.3 Vegetation Structure

For each index at least one periodic mean was correlated with one or more measures of habitat structure. There were no particularly strong correlations between acoustic index values and habitat structure but there were a number of moderately significant findings. In the following text p1= 04:00–10:00; p2 = 10:00 – 15:00; p3 = 15:00-20:00; p4 = 20:00 – 22:00; p5 = 22:00 – 04:00. Stand age bore only two significant correlations indicating that ACI (p1) was highest in young stands (Kruskal-Wallis $\chi^2_{(4)}$ =11.202, p<0.001) and NDSI (p5) tended to be higher in older stands (table 4.5). ACI, ADI and AEI were the only indices to bear any relationship with ground vegetation. ACI (p1) was positively correlated with VH and VC suggesting that ACI was higher in sites with a greater coverage of ground-based vegetation. This echoes findings in chapters two and three, where it was observed that ACI tended to be higher in more open areas. ADI (p2) was negatively correlated with VSQ whilst AEI (p2) bore the opposite relationship suggesting that greater ground vegetation diversity may result in lower acoustic diversity. This relationship is likely linked to canopy characteristics as ADI (p3) and AEI (p3) are the only indices to bear significant relationships with canopy openness (CO) indicating that sites with a more open canopy had lower acoustic diversity. BAI (p5) was the only index to bear a significant correlation with a taller canopy (CH), though this relationship was not very strong (table 4.5). Interestingly, the mean values of six 1KHz frequency bands (2-8KHz) indicate that older sites with taller canopies on average had more activity in these bands (appendix 4.4), though this relationship was not statistically significant.

TT was the only structural variable that bore a relationship with every acoustic index (though not in every period). BAI(p2,p3) and NDSI (p4) bore negative relationships with total number of trees larger than 5cm DBH (TT) suggesting that denser forest stands had lower activity in the biophony (i.e.3-11KHz). ACI (p5), ADI (p2, p5) and H (p2-5) displayed positive correlations with TT suggesting that denser stands had higher acoustic diversity. ACI (p1-5) tended to be lower in sites that had higher structural diversity of trees. ADI (p1) and H (p2, p5) also decreased in sites with greater structural diversity of trees. Although basal area (BA) and TT were correlated with one another (appendix 4.5), NDSI (p2) was the only index to show a relationship with BA indicating lower NDSI values in sites with a greater total basal area of live trees. ACI (p1, p2), ADI (p1) and BAI (p1, p2) were lower in sites with a larger amount of deadwood. BAI (p2, p3) also tended to be higher when the recording unit was attached to a larger tree (r_s= 0.388; $p<0.05$). Only three indexes were related to structural variables when considering total mean index value per site. ACI was negatively correlated with SD (r_s= -0.462; $p<0.001$) and H was positively correlated with TT (r_s= 0.368; $p<0.05$). BAI was lower in stands that had a greater volume of standing deadwood (r_s= -0.349; $p<0.05$) and total deadwood (r_s= -0.350; $p<0.05$) and also tended to be higher when the recording unit was attached to a larger tree (r_s= 0.388; $p<0.05$).

Table 4.4. Friedman post-hoc analysis (Wilcoxon signed rank tests) showing differences between acoustic index values between different sampling periods (P1;P2;P3;P4;P5). BAI was significantly different between all periods. ADI and AEI were significantly different across all periods except P2 and P3 were not significantly different to one another.

		P2 - P1	P3 - P1	P4 - P1	P5 - P1	P3 - P2	P4 - P2	P5 - P2	P4 - P3	P5 - P3	P5 - P4
ACI	Z	-0.573	**-2.554**	**-4.814**	**-5.442**	**-2.833**	**-5.331**	**-5.442**	**-4.651**	**-5.256**	**-4.167**
	p	.567	**.011**	**.000**	**.000**	**.005**	**.000**	**.000**	**.000**	**.000**	**.000**
ADI	Z	**-3.502**	**-3.377**	**-4.828**	**-5.442**	-0.879	**-2.665**	**-4.507**	**-2.93**	**-4.355**	**-3.468**
	p	**.000**	**.001**	**.000**	**.000**	.379	**.008**	**.000**	**.003**	**.000**	**.001**
AEI	Z	**-3.328**	**-2.889**	**-4.787**	**-5.442**	-1.34	**-3.084**	**-4.005**	**-3.145**	**-3.938**	**-2.608**
	p	**.001**	**.004**	**.000**	**.000**	.180	**.002**	**.000**	**.002**	**.000**	**.009**
BAI	Z	**-4.749**	**-5.024**	**-5.289**	**-5.442**	**-2.484**	**-3.754**	**-5.442**	**-2.997**	**-5.497**	**-5.135**
	p	**.000**	**.000**	**.000**	**.000**	**.013**	**.000**	**.000**	**.003**	**.000**	**.000**
H	Z	-0.007	-0.349	**-4.34**	**-3.6**	-1.284	**-3.852**	**-3.042**	**-4.315**	**-3.038**	-1.438
	p	.994	.727	**.000**	**.000**	.199	**.000**	**.002**	**.000**	**.002**	.150
NDSI	Z	**-3.604**	**-4.284**	**-4.689**	**-3.475**	**-3.921**	**-3.238**	-0.461	-1.21	**-2.083**	**-2.715**
	p	**.000**	**.000**	**.000**	**.001**	**.000**	**.001**	.645	.226	**.037**	**.007**

Table 4.5. Spearman rank correlations between mean acoustic index values and habitat structural metrics. See table 4.1 for vegetation variable codes. Acoustic index values are the mean value for each period for each site. Period 1: 04:00-10:00 (N=39); Period 2: 10:00-15:00 (N=39); Period 3: 15:00- 20:00 (N=40); Period 4 = 20:00 – 22:00 (N=40); Period 5 = 22:00 – 04:00 (N=40). Period T = total mean value per site across all periods (N=40). ** Correlation is significant at the 0.01 level; * Correlation is significant at the 0.05 level.

[Index]_period	**VH**	**VC**	**VS**	**VSQ**	**CO**	**CH**	**TT**	**TD**	**SD**	**SDW**	**BA**	**DWf**	**DWs**	**DW**	**DBH**
ACI_1	**.342***	**.335***	.086	.024	.096	-.194	.194	-.048	**-.411***	-.162	-.063	-.110	**-.359***	**-.382***	-.081
ACI_2	.221	.213	.176	.028	.117	-.181	.077	-.139	**-.497****	-.301	-.077	-.283	**-.467****	**-.514****	-.109
ACI_3	.100	.054	.094	-.031	-.054	-.196	.225	-.100	**-.446****	**-.368***	-.030	-.281	-.200	-.272	-.183
ACI_4	.075	.021	.044	.003	-.065	-.149	.185	-.002	**-.335***	**-.329***	-.085	-.092	-.184	-.221	.006
ACI_5	.147	.083	.169	.033	-.079	-.290	**.414****	-.110	**-.455****	-.112	.131	-.034	-.069	-.133	-.207
ACI_T	*.200*	*.153*	*.091*	*-.016*	*.001*	*-.210*	*.245*	*-.076*	***-.462*****	*-.288*	*-.025*	*-.179*	*-.259*	*-.302*	*-.140*
ADI_1	.055	.119	.107	.064	.028	.042	.020	.117	**-.320***	-.187	-.109	-.233	**-.323***	**-.391***	.145
ADI_2	-.260	-.219	-.133	**-.344***	-.308	.117	**.322***	-.022	-.073	-.156	.280	-.082	.109	.001	-.037
ADI_3	-.192	-.116	-.007	-.080	**-.350***	.063	.307	.176	-.083	-.031	.277	.055	.081	.077	-.030
ADI_4	-.087	-.132	.038	-.037	-.214	-.082	.279	-.042	-.200	-.194	.066	.098	-.029	-.077	.039
ADI_5	.013	-.031	.288	.081	-.069	-.060	**.343***	-.052	-.275	-.051	.089	-.019	-.046	-.069	-.100
ADI_T	*-.115*	*-.085*	*.068*	*-.063*	*-.190*	*.055*	*.292*	*.060*	*-.216*	*-.137*	*.141*	*-.034*	*-.095*	*-.152*	*.026*
AEI_1	-.101	-.152	-.131	-.101	-.064	-.028	-.009	-.124	.315	.157	.127	.236	.302	**.352***	-.160
AEI_2	.274	.213	.149	**.347***	.303	-.119	-.288	.004	.046	.147	-.255	.108	-.134	-.034	.050
AEI_3	.195	.100	.006	.082	**.346***	-.085	-.282	-.202	.091	.013	-.212	-.024	-.087	-.092	.043
AEI_4	.103	.123	-.035	.026	.191	.066	-.227	.064	.171	.180	.012	-.078	.048	.107	-.097
AEI_5	-.038	.019	-.299	-.091	.038	.052	**-.357***	.033	.259	.059	-.095	.021	.033	.060	.037
AEI_T	*.080*	*.026*	*-.083*	*.019*	*.159*	*-.061*	*-.236*	*-.107*	*.217*	*.129*	*-.076*	*.082*	*.086*	*.132*	*-.039*

Table 4.5 (contd). Spearman rank correlations between acoustic index values and habitat structural metrics. ** Correlation is significant at the 0.01 level; * Correlation is significant at the 0.05 level.

[Index]_period	**VH**	**VC**	**VS**	**VSQ**	**CO**	**CH**	**TT**	**TD**	**SD**	**SDW**	**BA**	**DWf**	**DWs**	**DW**	**DBH**
BAI_1	.213	.164	.156	.228	.268	-.001	-.294	-.152	-.166	-.217	-.221	-.248	**-.440****	**-.498****	.222
BAI_2	-.009	.046	-.017	.010	.225	.064	**-.347***	-.149	.015	-.069	-.154	-.004	**-.341***	**-.373***	**.422****
BAI_3	.012	.095	.023	.111	.177	.068	**-.406***	-.103	.173	-.023	-.092	.080	-.265	-.243	**.432****
BAI_4	-.006	-.062	-.034	.067	.048	.033	-.165	-.091	.109	-.092	-.062	.040	-.173	-.157	.282
BAI_5	-.129	-.196	.191	.049	-.062	**.358***	.052	.081	.248	.170	.203	.041	.018	.096	.303
BAI_T	*.075*	*.062*	*.102*	*.160*	*.228*	*.077*	*-.299*	*-.164*	*.005*	*-.128*	*-.150*	*-.104*	***-.349****	***-.350****	***.388****
H_1	.012	.097	.092	-.007	-.136	-.047	.283	.133	-.317	-.089	.041	.069	-.215	-.229	-.008
H_2	-.107	-.088	.026	-.171	-.230	-.068	**.415****	.011	**-.333***	-.184	.149	.009	-.036	-.058	-.176
H_3	-.047	-.036	.076	-.043	-.206	-.057	**.390***	.062	-.287	-.044	.170	.113	-.041	-.031	-.173
H_4	-.036	-.017	.091	.005	-.154	-.109	**.329***	-.037	-.283	-.108	.081	.113	-.075	-.072	-.056
H_5	.028	.003	.240	.081	-.091	-.110	**.355***	-.118	**-.330***	-.121	.048	.024	-.077	-.085	-.156
H_T	*-.016*	*.030*	*.082*	*-.017*	*-.170*	*-.070*	***.368****	*.003*	*-.312*	*-.117*	*.134*	*.058*	*-.081*	*-.086*	*-.128*
NDSI_1	.180	.198	.092	.181	.253	.036	-.221	.206	-.145	-.142	-.290	-.309	-.206	-.269	-.013
NDSI_2	.050	.192	-.021	.034	.240	.004	-.315	.075	-.019	.026	**-.386***	-.189	-.165	-.215	.054
NDSI_3	.116	.259	-.021	.067	.193	-.040	-.201	.101	-.034	.014	-.291	-.096	-.115	-.181	.016
NDSI_4	.051	.143	.032	.124	.182	.111	**-.365***	.163	.136	.120	-.306	.054	-.121	-.119	.182
NDSI_5	.122	.256	.067	.166	.292	.196	-.226	.162	.189	.154	-.180	.043	-.046	-.050	.246
NDSI_T	*.093*	*.230*	*.014*	*.119*	*.215*	*.078*	*-.283*	*.137*	*.029*	*.015*	*-.293*	*-.106*	*-.178*	*-.227*	*.125*

4.4.4 Landscape Heterogeneity

There were several significant relationships between acoustic indices and landscape-based heterogeneity measures (table 4.6). AH was positively correlated with ACI (p5), ADI (p1), and NDSI (p1) and negatively associated with AEI (p1) suggesting that acoustic diversity was higher in sites with a greater diversity of different aged forest stands in the surrounding area. Similarly, ACI (p4), ADI (p1), BAI (p4) and NDSI (p1) were higher and AEI (p1) lower in sites with greater species-based heterogeneity (SH) and habitat heterogeneity (HH). NDSI was positively correlated with SH in all time periods, but this may be explained by the positive correlation between SH and distances to busy roads (appendix 4.6). All six indices displayed relationships with HH. ACI; ADI; BAI and H have positive relationships with BL (percentage of broadleaf woodland) whilst AEI displays a negative one. This may be because sites that had a greater proportion of broadleaf woodland in their buffer zone also tended to be more heterogeneous. Indeed BL is positively correlated with the landscape heterogeneity measures AH, SH and HH (appendix 4.6). However, CF is also positively correlated with these measures to a similar degree but the only index to show any strong correlations with CF is NDSI. In fact, ADI and H are negatively correlated with CF and AEI positively, suggesting that sites with a greater proportion of broadleaf woodland displayed greater acoustic diversity than those with mostly coniferous woodland. The relationship between NDSI and CF may be explained by the moderately strong positive correlation between distance to nearest A-road and CF (appendix 4.6).

Table 4.6. Spearman rank correlations between mean acoustic index values and landscape metrics. See table 4.1 for variable codes. Acoustic index values are the mean value for each period for each site. Period 1: 04:00-10:00 (N=39); Period 2: 10:00-15:00 (N=39); Period 3: 15:00- 20:00 (N=40); Period 4 = 20:00 – 22:00 (N=40); Period 5 = 22:00 – 04:00 (N=40). Period T = total mean value per site across all periods (N=40).

[Index]_period	**Age**	**AG**	**AVA**	**EDs**	**RD**	**A_rd**	**B_rd**	**WD**	**RR**	**%RC**
ACI_1	**-.346***	**-.333***	-.022	-.224	**-.414****	**-.365***	-.099	.037	.058	.230
ACI_2	-.219	-.207	-.029	-.175	**-.366***	-.236	-.036	.038	-.011	.267
ACI_3	-.144	-.142	-.031	-.282	-.219	**-.318***	-.136	-.032	.060	.227
ACI_4	-.153	-.130	.043	-.310	-.274	-.115	.062	-.138	-.170	**.344***
ACI_5	-.213	-.233	-.288	-.253	**-.426****	-.263	-.036	-.205	.059	**.475****
ACI_T	-.257	-.258	-.056	-.193	**-.414****	**-.367***	-.138	.018	.041	**.316***
ADI_1	-.025	.030	.019	**-.446****	**-.426****	.097	**.338***	-.089	-.314	**.316***
ADI_2	-.005	-.010	-.281	-.138	**-.509****	-.215	-.060	.040	-.092	.157
ADI_3	.063	.058	-.253	-.063	**-.335***	-.203	-.147	-.076	-.076	**.327***
ADI_4	-.112	-.091	-.129	**-.318***	-.247	-.269	-.123	**-.375***	-.148	**.356***
ADI_5	-.009	-.033	-.228	-.033	**-.415****	**-.441****	-.227	-.158	.025	**.326***
ADI_T	-.013	-.003	-.179	-.245	**-.519****	-.215	-.010	-.164	-.176	**.357***
AEI_1	.030	-.021	.000	**.405***	**.431****	-.126	**-.353***	.023	**.345***	**-.334***
AEI_2	-.001	-.009	.294	.094	**.493****	.161	.032	-.099	.122	-.098
AEI_3	-.071	-.072	.242	.046	.311	.149	.105	.015	.119	-.259
AEI_4	.077	.043	.099	.283	.242	.155	.015	**.321***	.218	**-.349***
AEI_5	-.032	-.005	.219	.094	**.416****	**.339***	.124	.171	.081	**-.357***
AEI_T	-.015	-.035	.165	.235	**.479****	.100	-.079	.068	.246	**-.329***
BAI_1	-.115	-.071	.126	-.301	-.143	.256	.300	-.109	-.124	.116
BAI_2	.068	.103	.126	-.150	-.295	**.362***	**.350***	.081	-.263	.215
BAI_3	.069	.110	.143	-.187	-.103	**.330***	.276	-.041	-.238	.228
BAI_4	-.051	-.013	.107	**-.393***	.056	.252	.164	-.197	**-.319***	.156
BAI_5	.283	.267	-.117	-.014	-.293	-.098	-.134	.085	-.111	-.065
BAI_T	-.006	.029	.140	-.266	-.197	.284	.261	-.064	-.241	.150
H_1	-.028	-.022	-.133	-.265	**-.416****	-.262	-.018	-.126	-.139	**.396***
H_2	-.040	-.071	-.174	-.208	**-.378***	**-.400***	-.176	-.075	.048	.306
H_3	-.029	-.058	-.165	-.072	-.316	-.301	-.159	-.131	.038	**.373***
H_4	-.047	-.070	-.078	-.098	**-.361***	**-.429****	-.214	-.202	.017	**.391***
H_5	-.039	-.072	-.167	-.043	**-.341***	-.447**	-.242	-.159	.091	**.335***
H_T	-.036	-.068	-.116	-.130	**-.354***	-.361*	-.165	-.149	.018	**.372***
NDSI_1	.021	.053	.102	-.256	.110	**.753****	**.672****	.089	**-.455****	.122
NDSI_2	.092	.130	.146	-.032	.213	**.763****	**.643****	.294	**-.405***	-.006
NDSI_3	.065	.076	.073	-.097	.280	**.806****	**.666****	.178	**-.417****	.118
NDSI_4	.191	.222	.191	-.219	.246	**.864****	**.707****	.154	**-.576****	.067
NDSI_5	**.366***	**.361***	.314	-.131	.198	**.776****	**.728****	.112	**-.528****	.114
NDSI_T	.162	.187	.197	-.172	.243	**.855****	**.726****	.143	**-.521****	.106

Table 4.6 (contd). Spearman rank correlations between mean acoustic index values and landscape metrics. See table 4.1 for variable codes.

[Index]_	**AH**	**SH**	**HH**	**TP**	**EDn**	**%BL**	**%CF**	**%WC**	**%OA**	**%OW**
ACI_1	.258	.097	.218	.142	.142	**.328***	-.129	-.121	-.027	-.081
ACI_2	.312	.067	.131	.255	.255	.304	-.110	-.102	-.160	.053
ACI_3	.310	.112	.230	.245	.245	**.325***	-.067	-.132	-.163	.010
ACI_4	.285	**.348***	**.404***	.250	.250	**.447****	-.014	-.296	-.001	.134
ACI_5	**.333***	.026	.241	.160	.160	**.408****	-.344*	-.023	-.056	.117
ACI_T	.231	.123	.237	.120	.120	**.341***	-.156	-.116	-.056	-.035
ADI_1	**.418****	**.421****	**.452****	**.418****	**.418****	**.428****	.137	**-.446****	-.022	.209
ADI_2	.031	.028	.088	.148	.148	.287	-.200	-.032	.036	.040
ADI_3	.037	.046	.159	-.039	-.039	.129	-.249	.010	-.118	.053
ADI_4	.197	.209	**.340***	.199	.199	**.595****	-.179	-.221	-.111	.203
ADI_5	.139	-.043	.124	.070	.070	**.420****	**-.366***	.031	-.091	.256
ADI_T	.205	.194	.313	.198	.198	**.439****	-.150	-.195	-.046	.200
AEI_1	**-.418****	**-.431****	**-.445****	**-.379***	**-.379***	**-.368***	-.154	**.442****	.009	-.218
AEI_2	.015	-.016	-.045	-.129	-.129	-.230	.181	.007	-.068	-.055
AEI_3	-.005	-.049	-.134	.034	.034	-.083	.203	-.009	.091	-.059
AEI_4	-.153	-.247	**-.339***	-.162	-.162	**-.532****	.146	.239	.079	-.204
AEI_5	-.182	-.025	-.183	-.111	-.111	**-.442****	**.313***	.044	.048	-.255
AEI_T	-.187	-.228	-.311	-.185	-.185	**-.370***	.090	.216	.020	-.198
BAI_1	.257	.211	.244	**.332***	**.332***	.212	.139	-.287	.035	.049
BAI_2	.235	.219	.170	.235	.235	.088	.130	-.256	.087	.047
BAI_3	.205	.223	.201	.174	.174	.080	.156	-.253	.011	.133
BAI_4	.271	**.359***	**.373***	**.368***	**.368***	**.355***	.211	**-.432****	.047	.211
BAI_5	-.033	-.136	-.028	.065	.065	.087	-.162	.048	.136	-.029
BAI_T	.248	.254	.259	.314	.314	.229	.139	**-.325***	.091	.108
H_1	.313	.203	**.326***	.217	.217	**.385***	-.143	-.168	-.179	.210
H_2	.192	.090	.209	.120	.120	**.381***	-.221	-.078	-.048	.055
H_3	.128	.055	.197	-.006	-.006	.246	-.254	-.016	-.058	.059
H_4	.140	.083	.213	-.020	-.020	**.408****	-.264	-.037	-.153	.151
H_5	.118	-.032	.129	.014	.014	**.383***	**-.361***	.045	-.140	.175
H_T	.171	.085	.218	.045	.045	**.357***	-.247	-.050	-.146	.115
NDSI_1	**.326***	**.497****	**.372***	**.348***	**.348***	-.116	**.526****	**-.493****	.187	.228
NDSI_2	.200	**.350***	.133	.181	.181	-.304	**.405***	**-.269**	.124	.171
NDSI_3	.198	**.374***	.218	.230	.230	-.279	**.426****	**-.334***	.061	.219
NDSI_4	.288	**.455****	.309	**.357***	**.357***	-.127	**.497****	**-.426****	.087	**.316***
NDSI_5	.246	**.454****	.278	.123	.123	-.195	**.533****	**-.418****	.064	.195
NDSI_T	.255	**.464****	.290	.289	.289	-.192	**.493****	**-.423****	.066	.237

4.4.5 General Linear Models and Principal Components Analysis

Fourteen vegetation structure and diversity measures were entered into a PCA and condensed into 5 factors which explained 82.59% of the variation in the vegetation data (table 4.7). Nine landscape variables (EDs; AH; SH; HH; EDn; %RC; %BL; %CF; %WC) were entered into a separate PCA and reduced into three factors which explain 86.27% of the variation in the landscape data (table 4.8; for descriptions of both sets of PCA factors see table 4.9). GLM reveals that L2, RD and A_Rd were the strongest predictors of ADI_1 and AEI_1 (table 4.10). This finding indicates that acoustic diversity in the morning (between 05:00-11:00am) was higher in sites that were closer to minor roads (RD) and lower in sites closer to busy main roads in areas with a greater proportion of broadleaf woodland and diversity of different aged forest stands. Linear regression indicates a moderate but significant relationship between ADI_1 and L2 (figure 4.3). ADI_2 was most associated with RD, V1 and V5 indicating sites closer to minor roads, with greater tree density and less ground vegetation cover were more acoustically diverse. RD and V1 were the best predictors for AEI_2, indicating that acoustic evenness was greater further away from small roads and in sites with more ground vegetation cover (table 4.10). RD, V1, L2 and L3 were the strongest predictors for ADI_T indicating that acoustic diversity was greater closer to small roads, in sites with greater landscape heterogeneity and less ground-vegetation cover. The inverse was true of the same predictors and AEI_T (table 4.10). BAI_1 was higher in sites that had a high percentage of ground-vegetation, lower volumes of deadwood and further from A-roads (table 4.10). BAI_2 was strongly associated with distance to the nearest A-road (being higher in sites further from the road) and RD (being higher in sites closer to smaller roads) and was higher in sites with a taller more open canopy that had lower volumes of deadwood and a good covering of ground vegetation. BAI_T was associated with RD, A_Rd, V1 and V2 but was also associated with L2 indicating that a greater variety of different aged stands, with a higher proportion of broadleaf woodland was also important in predicting BAI (table 4.10).

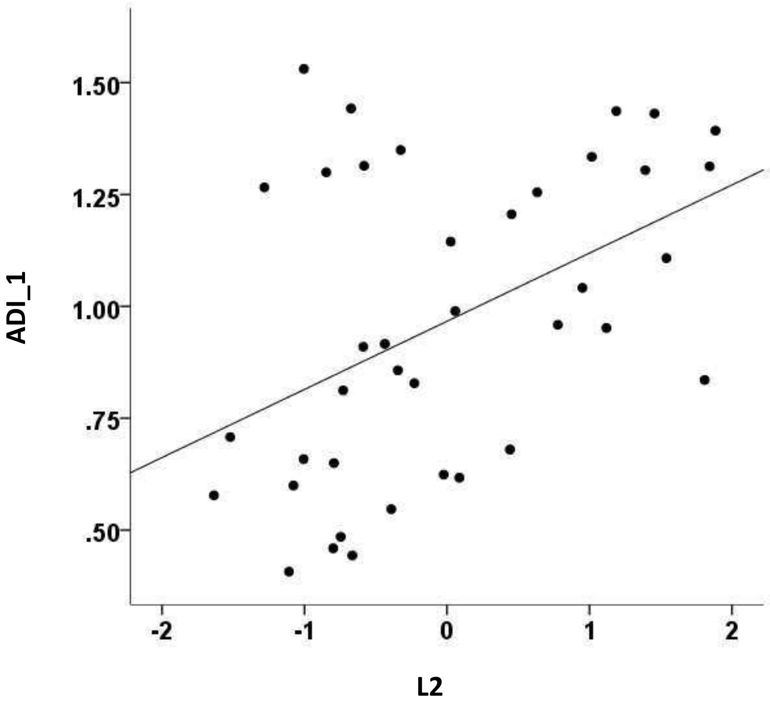


Figure 4.3. Linear regression indicates the predictive power of L2 on ADI_1 values (r^2=0.206, $p<0.001$).

Table 4.7. PCA axis loadings for vegetation structure variables. See table 4.1 for variable codes. Stand age was included as it highlights the association with increased structural complexity and stand age. Cumulative percentage = 82.56%.

Veg. Structure	**Axis**				
	1 (22.29%)	**2 (17.71%)**	**3 (15.44%)**	**4 (15.08%)**	**5 (12.06%)**
Age	***-.552***	**.646**	.322	-.006	-.018
VH	**.880**	-.185	.272	.055	.129
VC	**.891**	-.050	.237	-.051	.058
CO	**.766**	-.206	.037	-.253	-.297
TD	***-.424***	.224	**.432**	.209	.002
CH	-.443	**.771**	.156	-.058	-.009
SD	-.359	**.647**	.004	.397	.255
DBH	.092	**.850**	-.205	.085	-.212
VS	.117	-.039	**.919**	-.134	.004
VSQ	.348	-.008	**.879**	.038	-.146
DWs	-.072	-.015	-.077	**.930**	.165
DW	-.061	.129	.035	**.943**	.007
TT	.049	-.373	.078	-.026	**.844**
BA	-.041	.200	-.206	.238	**.842**

Table 4.8. PCA axis loadings for landscape heterogeneity variables. See table 4.1 for variable codes. Stand age was included as it highlights the association with increased structural complexity and stand age. Cumulative percentage = 82.56%.

Landscape variable	**Axis**		
	1 (33.40%)	**2 (30.41%)**	**3 (22.45%)**
EDs	-.452	***-.684***	-0.36
EDn	.242	**.863**	-0.05
AH	.371	**.573**	0.44
SH	**.795**	.275	0.49
HH	**.622**	.457	**0.58**
%Rec	.015	.108	**0.96**
SUM%BL	.007	**.841**	0.21
%CF	**.968**	.033	-0.21
%WC	***-.806***	-.438	-0.33

Table 4.9. Factors obtained from principle components analysis of field-based vegetation structure measures (V1-V5) and landscape-based heterogeneity metrics (L1-L3).

Factor	**Description**
V1	Younger stands with greater coverage of ground vegetation, a more open canopy and less tree-species diversity
V2	Older stands with a taller canopy and more structural diversity and a larger ARUPI_tree
V3	Great diversity of ground vegetation
V4	Greater volumes of deadwood
V5	Greater density of trees and a higher overall basal area
L1	high levels of species and habitat heterogeneity and high percentage of coniferous woodland
L2	high proportion of edge habitat, high percentage of broadleaf woodland and greater stand-age heterogeneity
L3	greater proportion of recreational land and private gardens, with high levels of habitat heterogeneity

Table 4.10. General Linear Models showing the combined effects of different environmental variables on acoustic index values. P-values: *** ≤0.005; ** ≤0.01; * ≤0.05. n.b.1 = 0.059; n.b.2=0.071; n.b.3=0.066; n.b.4=0.057; n.b.5=0.072. Although the n.b. p-values were above the usual cut-off for significance, the decision to retain those variables in the model was based on their influence on the overall model and the fact that these variables were significant predictors in other analysis.

	Corrected Model			RD	A Rd	V1	V2	V4	V5	L2	L3
Index	d.f.	F	r2	F	F	F	F	F	F	F	F
ADI_1	3, 35	11.092***	0.487	17.504***	5.074**	n/a	n/a	n/a	n/a	14.491***	n/a
ADI_2	3, 35	9.444***	0.447	16.615***	n/a	9.091***	n/a	n/a	4.674**	n/a	n/a
ADI_T	4, 35	8.662***	0.497	20.112***	n/a	3.819 $^{\text{n.b.1}}$	n/a	n/a	n/a	7.998**	5.265*
AEI_1	3, 35	8.962***	0.434	15.116***	5.908**	n/a	n/a	n/a	n/a	9.698***	n/a
AEI_2	2, 36	9.532***	0.346	14.740***	n/a	7.705**	n/a	n/a	n/a	n/a	n/a
AEI_T	4, 35	6.493***	0.426	15.794***	n/a	3.471 $^{\text{n.b.2}}$	n/a	n/a	n/a	4.789*	4.086*
BAI_1	3, 35	6.137***	0.345	n/a	3.612 $^{\text{n.b.3}}$	7.904**	n/a	7.160*	n/a	n/a	n/a
BAI_2	5, 33	7.599***	0.535	9.357***	13.381***	4.398*	4.275*	5.453*	n/a	n/a	n/a
BAI_T	5, 34	4.676***	0.407	3.891 $^{\text{n.b.4}}$	8.159**	3.459 $^{\text{n.b.5}}$	4.621*	n/a	n/a	5.515*	n/a

4.4.6 Influence of Road Noise on the Soundscape

The strongest observed relationships in the study were between NDSI (all periods) and distance to the nearest A-road. NDSI values increased with increasing distance from the nearest busy road following a non-linear relationship (figure 4.4). There was also a strong positive relationship between NDSI and distance to the nearest B-road, though the relationship was linear: NDSI_1 ($r^2=0.404$, $p<0.001$); NDSI_2 ($r^2=0.340$, $p<0.001$); NDSI_3 ($r^2=0342$, $p<0.001$); NDSI_4 ($r^2=0.487$, $p<0.001$); NDSI_5 ($r^2=0.501$, $p<0.001$); and NDSI_T ($r^2=0.487$, $p<0.001$). BAI (p2, p3) and AEI (p5) increased with distance from the nearest A-road but these correlations were fairly weak (table 4.6). ACI (p1, p3, t), ADI (p5) and H (p2, p4) all decreased with distance from the nearest A-road suggesting that acoustic diversity was higher closer to these busy highways, but again these correlations were relatively weak (table 4.6). ACI, ADI and H were negatively associated with RD (distance to nearest road) indicating that acoustic diversity was higher closer to these roads. RD represents all roads so includes all minor routes that run close to and through Bedgebury forest in some places so increased acoustic diversity may, in some cases, be attributed to the acoustic activity of road users, including pedestrians, equestrians and cyclists.

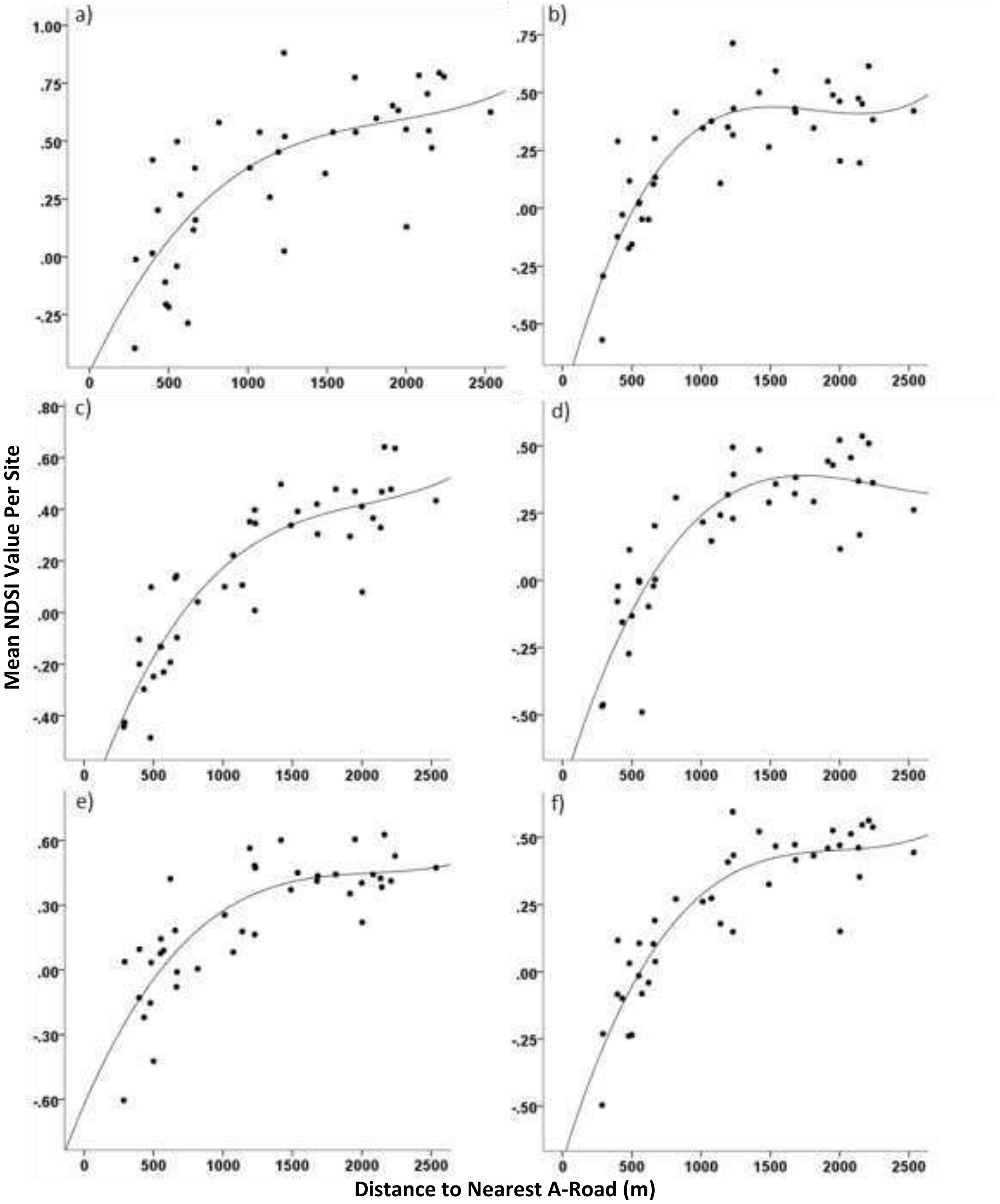


Figure 4.4. Non-linear regression models indicate that NDSI values increase with increasing distance from the nearest A-road (metres) in all 5 time periods. a) NDSI_1 (cubic r^2=0.566, p<0.001, N=39); b) NDSI_2 (cubic r^2=0.718, p<0.001, N=39); c) NDSI_3 (cubic r^2=0.76, p<0.001, N=40); d) NDSI_4 (cubic r^2=0.811, p<0.001, N=40); e) NDSI_5 (cubic r^2=0.676, p<0.001, N=40); f) NDSI_T (cubic r^2=0.815, p<0.001, N=40).

4.4.7 Canonical Correspondence Analysis (CCA)

A CCA using 13 environmental variables was built entering the proportion of sound in each of ten 1 KHz frequency bands as individual species. Three axes cumulatively explained 56.9% of the variance in the frequency band data (table 4.11). The Monte-Carlo randomisation test indicated that the null hypothesis can be rejected and that there is a significant relationship between frequency band data and the environmental data (p=0.002). Axis 1 is strongly positively correlated with the technophony (1-2KHz) and negatively correlated with sounds between 2KHz and 9KHz. It is also negatively associated with distance to nearest A-road, B-road and water source as well as species and habitat heterogeneity (L1) and ground vegetation diversity (V3) and positively correlated with distance to recreational routes, tree density and age-based heterogeneity (table 4.12). Sites that are positively associated with axis 1 can therefore be described as being closer to roads and water and further away from forest recreation routes, with greater tree density and lower ground vegetation diversity. These sites tended to have lower acoustic activity in frequencies above 2KHz. Sites that are negatively associated with axis 1 had greater activity in the biophony (2-9KHz), and were further away from busy roads. Sites that are positively associated with axis 2 might be described as having greater volumes of deadwood and being closer to water and B-Roads. These sites were also more associated with frequencies above 6KHz. Positive associations with axis 3 would be indicative of sites with greater ground vegetation coverage, potentially with a taller more open canopy that were generally further away from water but with a higher proportion of recreational areas nearby. This axis was particularly strongly associated with sounds above 8KHz. By far the strongest predictor of the variation between frequency bands was distance to the nearest A-road and when sites are grouped according to their distance from the nearest A-road this becomes evident (figure 4.5). Sites situated over 1500m from the nearest A-road have significantly different soundscapes with regard to the composition of ten 1 KHz frequency bands. This is not so surprising since road noise (i.e. the technophony; 1-2KHz) will logically dissipate and diminish with increasing distance from the nearest road. However, there is some evidence that the higher "biophony" frequencies (3-8KHz) do have a negative relationship with the technophony. This may suggest that there is more biophonic activity at sites that are over 1500m from the nearest road regardless of habitat structure and stand-age. Indeed, plotting the same CCA but using stand-age as the grouping variable indicates that stand-age does not have a great influence of the composition of the soundscape (figure 4.5). Furthermore, the relationships between ADI and BAI with distance to the nearest A-Road is further evidence that the biophony is lower with proximity to busy roads (table 4.10).

Table 4.11. Canonical correspondence analysis axis summary.

	Axis		
	1	2	3
Eigenvalue	0.081	0.007	0.004
Variance in FB data explained (%)	49.9	4.4	2.6
Cumulative variance (%)	49.9	54.3	56.9
Kendall Rank Correlation FB-ENV (tau)	0.582	0.215	0.315

Table 4.12. Axis associations with ten 1 KHz frequency bands (1-11KHz) and environmental variables included in the final CCA.

	Axis		
	1	2	3
FB1	**0.63**	-0.02	-0.05
FB2	***-0.26***	-0.18	***0.55***
FB3	***-0.5***	***-0.37***	-0.07
FB4	***-0.58***	***-0.2***	***-0.26***
FB5	***-0.49***	0.1	***-0.23***
FB6	***-0.47***	***0.36***	-0.09
FB7	***-0.42***	***0.79***	-0.04
FB8	***-0.2***	**1.04**	***0.37***
FB9	-0.08	***0.57***	***0.72***
FB10	-0.14	***0.46***	***0.67***
RD	-0.02	-0.02	0.07
AR	***-0.90***	-0.04	0.13
BR	***-0.75***	**0.26**	0.05
WD	***-0.40***	***0.29***	***-0.35***
RR	**0.46**	-0.12	**0.23**
V1	-0.04	*0.00*	***-0.61***
V2	-0.12	-0.10	***-0.32***
V3	***-0.29***	0.11	0.05
V4	0.07	**0.42**	0.17
V5	***0.45***	*0.10*	0.11
L1	***-0.438***	**0.265**	-0.058
L2	**0.272**	-0.069	0.118
L3	-0.089	0.157	**0.574**

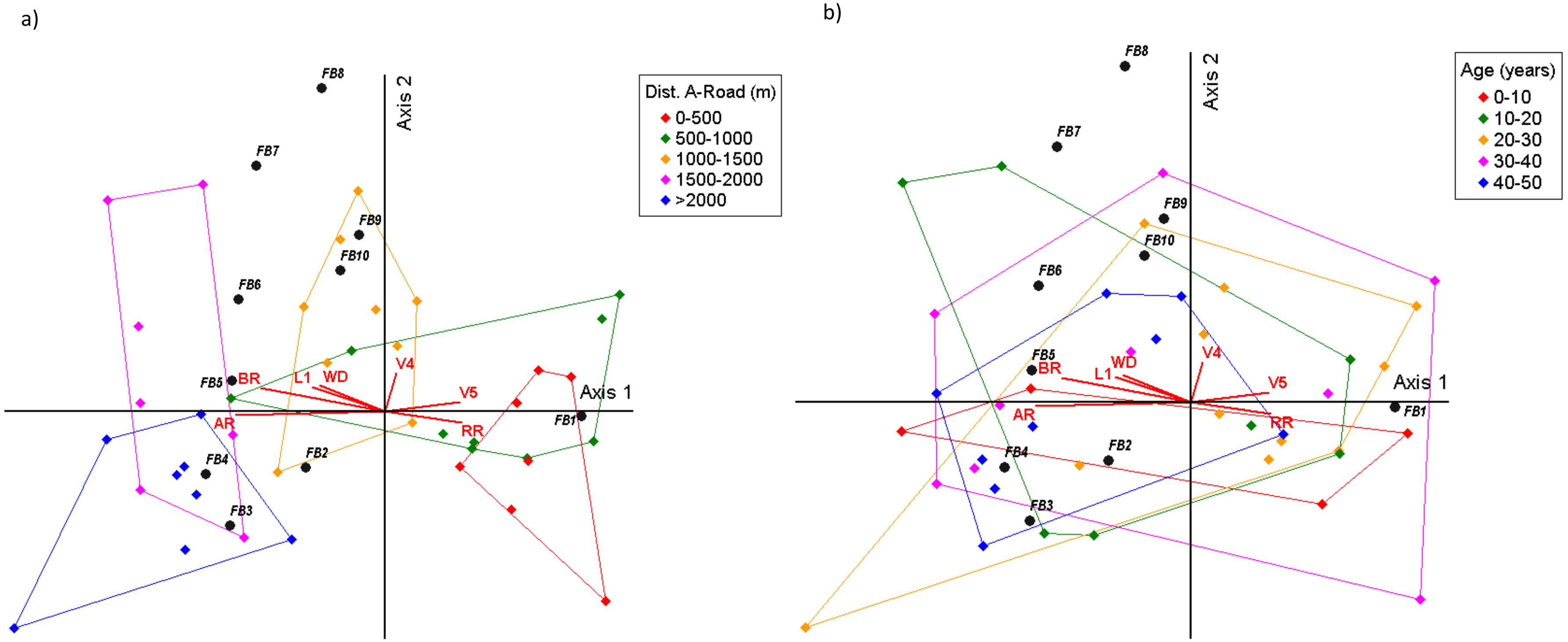


Figure 4.5. CCA ordination using mean frequency band values (FB1 = 1-2KHz; FB2 = 2-3KHz; FB3 = 3-4KHz; FB4 = 4-5KHz; FB5 = 5-6KHz; FB6= 6-7KHz; FB7 = 7-8KHz; FB8 = 8-9KHz; FB9 = 9-10KHz; FB10 = 10-11KHz) from 40 coppiced woodland sites (r^2 cutoff for environmental variables = 0.1;   N=40; see table 4.1 for variable codes; and tables 4.10 and 4.11 for CCA outputs). a) Sites grouped in accordance with their distance to the nearest highway (A-Road), indicating that sites over 1500m from the nearest busy road displayed distinct soundscape composition from those nearer to the road. b) Sites grouped according to their stand-age, indicating that road distance has a stronger influence on soundscape composition.

4.5 Discussion

4.5.1 Temporal Patterns

Understanding temporal patterns in the soundscape is an important step for determining suitable sampling schedules in different environments. As with any data-collection procedure, the general rule is that the more audio data you collect the better the representation of the soundscape. One problem facing soundscape ecologists is finding the balance between the explanatory power of their data and having the resources to analyze and store it efficiently (Sueur *et al.* 2012; Farina *et al.* 2015). Another issue is having the battery power to collect it in the first place. Indeed, the sampling protocol used in this study was a compromise between these logistical issues. However, the daily pattern observed indicates that enough information was collected to determine several distinct periods within the soundscape depending upon which acoustic index is employed. The changes in acoustic activity levels between these periods can likely be attributed to changes in bird activity (the biophony – 3-8KHz), and road-traffic noise (the technophony – 1-2KHz). This is particularly evident in the high-levels of activity monitored during the morning (period 1) and the low levels during the night time (period 5). These temporal differences in the soundscape have been observed in other studies and were expected in this study. The differences serve as a proxy for validating the ability of the Bio-Acoustic Index (BAI) at detecting biophonic activity within the soundscape. An important finding within the NDSI was that periods two and five were not significantly different from one another. However, period 5 was the lowest in terms of biophonic activity (BAI) and acoustic diversity (ACI, ADI, AEI). This is significant because a number of studies have investigated the suitability of using NDSI as a proxy-measure of species-richness (Fuller *et al.* 2015; Fairbrass *et al.* 2017; Machado, Aguiar & Jones 2017) but this study shows that two periods of the day with significantly different levels of biophonic activity (i.e. different levels of bird activity) yield similar NDSI values. This unsurprising since NDSI is a ratio between technophonic and biophonic noise. Based on this study it is reasonable to state that NDSI could not be used as a standalone proxy for species-richness – its relationship with other indices would have to be explored to understand its relationship with species-richness.

4.5.2 Vegetation Structure

The trend in acoustic index values across sites of different ages and therefore structural composition does share similarities with bird-richness trends found in previous coppice studies. The general consensus is that coppice management is beneficial to bird diversity due to the mosaic of different aged-habitats its creates (Fuller & Moreton 1987; Fuller & Henderson 1992; Buckley & Howell 2004; Schulz, Brauner & Gruß 2009; Maccoll, du Feu & Wain 2014). Young coppice (<8years) is particularly good for nesting migrant species who depend on open/cleared areas and ground vegetation cover (Fuller & Warren 1993). As the canopy closes, the resident/migrant ratio changes in favour of more UK resident, forest-species (Fuller & Moreton 1987). The UK resident species tend to be present in all age-classes of coppice stand (up to 20years at least) and become more abundant when the stand reaches an age unsuitable for migrant-nesting birds. As such, the overall species-richness of coppice stands declines as they become older. Although this study did not have a great number of sites <8years (N=4 due to corrupted data files) there was an observable trend in that the youngest sites had relatively high levels of acoustic diversity, which dropped off in stands aged 20-30years and then started to rise again in stands >30years (appendix 4.4). Although these findings were not statistically significant, the trend appears to follow what one might expect. Other studies have shown that older abandoned coppice stands are also good for bird diversity (Laiolo, Rolando & Valsania 2004) indicating that restoration of unmanaged coppice into semi-natural woodland may yield significant biodiversity benefits.

The negative relationships between BAI and deadwood volumes are initially counter-intuitive, since deadwood is an important facet of a healthy bio-diverse forest ecosystem (Ferris & Humphrey 1999; Smith *et al.* 2008). An old growth forest will have an assortment of deadwood at different stages of decay providing a variety of niches for different facets of biodiversity (Ferris & Humphrey 1999). It is important to note that the sampling of deadwood in this study was relatively crude in that it did not distinguish different states of decay and so does not provide information on the diversity of deadwood. However, from an observational point of view, the majority of deadwood in this study was in the early stages of decay. This assumption can be corroborated by the fact that deadwood is not commonplace within coppiced woodland due to the management focus being on removing stems (Kirby, Buckley & Mills 2017). Furthermore, the deadwood observed was largely comprised of dead stems of coppiced sweet chestnut aged between 10 and 30 years (appendix 4.7), indicating that the trees may have been self-thinning. This could be due to a change in coppice management at Bedgebury Forest, which is currently undergoing restoration to semi-natural woodland. A typical coppice cycle for sweet chestnut is around 12-16 years but for some products that cycle may be as long as 45 years (Buckley & Howell 2004; Forestry Commission 2015). The majority of UK studies investigating bird species-richness in coppiced woodlands focus their survey effort on actively managed stands up to 20years old (Fuller & Moreton 1987; Fuller & Green 1998; Maccoll, du Feu & Wain 2014), which typically do not contain significant volumes of deadwood. However, (Laiolo, Rolando & Valsania 2004) found that bird species richness and abundance does increase with stand age when considering older-aged forests, and they suggest that this increase in richness is partly due to higher volumes and diversity of deadwood. Deadwood is important for some European bat species (Tillon *et al.* 2016), and deadwood diversity, over volume, is a powerful indicator of saproxylic beetle species-richness (Brin, Brustel & Jactel 2009; Redolfi De Zan, Battisti & Carpaneto 2014). Over half of the stands in this study were older than 20 years but all were younger than 50 years old, so the volume of deadwood observed may not have represented a great diversity of decaying states to provide biodiversity enhancements at the time of the study.

The relationship between vegetation structure and the different acoustic indices changed depending on the time of day. ACI was the only index that maintained a consistent relationship with a single vegetation structure metric. ACI was higher where the structural diversity (SD) of the stand was lower. This is an unexpected result as previous studies have found ACI to be higher where there is more vegetation-structural diversity (Farina & Pieretti 2014). The measure of structural diversity in this study was strongly positively correlated with canopy height (appendix 4.5), which indicates that ACI was higher in less complex stands with a shorter canopy. These sites also tended to have greater cover of ground vegetation and higher tree density (due to the small size of trees). Acoustic entropy (H) also displayed negative correlations with structural diversity and positive correlations with tree density. A potential explanation could lie in the findings of Fuller & Moreton (1987) which indicate that younger coppice stands have richer avian communities. Younger coppice stands are typically associated with high densities of stems and a good covering of ground vegetation providing habitat for both migrant nesting birds and UK resident species (Ferris & Humphrey 1999; Buckley & Howell 2004). As stands age and the canopy closes, the nesting habitat for migrant species disappears and the resident species abundances increase. Interestingly, BAI shares the opposite relationship with tree density to H and ACI – in that it was higher in less densely packed stands. This disparity between index relationships with vegetation metrics may be explained by there being a greater richness of bird species in the younger stands but a greater total abundance in the older stands. ACI and H essentially provide measures of acoustic diversity based on temporal and spatial attributes of sounds but BAI does not measure diversity - it is a measure of total abundance.

There are alternative explanations to the findings discussed above. The presence of the geophony (particularly the wind) is a concern that faces all soundscape-studies that collect data using automated recordings units. An overriding concern when interpreting ACI values in relationship to habitat structure is that ACI is known to be significantly affected by wind (Towsey *et al.* 2014; Duarte *et al.* 2015). It seems that the sites most correlated with higher ACI values were also most likely to be susceptible to even small amounts of wind (i.e. younger more open stands). Care was taken to remove particularly windy recordings but it was not considered appropriate to remove all wind events such as sudden gusts and the occasional light breeze. Similar findings between ACI and open areas were observed in chapters two and three, where recordings were not made in windy conditions and light breezes were noted for each recording. There were significant correlations between ACI and breezy recordings, which is a serious problem for anyone using the ACI with automated recording units. Data from nearby Metoffice weather stations was obtained to aid interpretation of recordings in this study, but it was not detailed enough to capture micro-events that may be having a significantly strong effect on acoustic index values and was therefore excluded from the analysis in favour of listening to and removing recording with significant geophonic noise in them. It would be useful to set up small weather stations alongside any recording units in order to get a more detailed picture of meteorological events before, during and after recordings.

The effect of vegetation structure on sound attenuation may also exert an influence on acoustic index values. Bird-song detection rates are significantly affected by the habitat in which they take place - there are major differences in bird detection ability of automated recording units between interior forest surveys and those conducted on forest roads (Yip *et al.* 2017). The effect that forest structure has on sound attenuation is an important consideration when trying to interpret acoustic index values. For example, it may be that more open forest stands yielded higher BAI values (as mentioned in the previous paragraph) due to better sound propagation through less cluttered environments (Embleton 1963; Tarrero *et al.* 2008). Vegetation structure is known to be an important predictor of species-diversity (MacArthur & MacArthur 1961; Hewson *et al.* 2011) but since it also has a significant effect on sound attenuation and propagation (Cosens & Falls 1984; Kuczynski *et al.* 2010), it is important that future studies aim to understand the effect that vegetation structure has on the sound detection and attenuation of acoustic communities.

4.5.3 Landscape Heterogeneity

The relationship between ADI/AEI and L2 was particularly interesting. It indicates that acoustic diversity is greater in areas with higher proportions of broadleaf woodland and age-structures of forest. These findings echo numerous studies into the relationship between bird-diversity and landscape heterogeneity. Bird diversity is higher in more heterogeneous landscapes (Cleary *et al.* 2005; Cerezo, Conde & Poggio 2011; Katayama *et al.* 2014). The same is true for more heterogeneous forests, particularly with reference mosaics of different aged forest stands. Increased canopy and stand heterogeneity leads to higher bird species richness and abundance (Calladine *et al.* 2017). These findings are economically important as increased heterogeneity can lead to increases in natural insect pest control (Bereczki *et al.* 2014; Barbaro *et al.* 2017). Hewson *et al.* (2011) suggest that conservation planning should take into consideration species-specific responses to habitat variation. They suggest that landscapes should be managed for increased habitat heterogeneity embracing both structural and floristic diversity. This study shows that patterns in landscape heterogeneity were evident in the soundscape. It indicates that the use of soundscape methods could be a useful tool in landscape-scale management, whilst offering the opportunity to determine the species-richness of acoustic communities.

4.5.4 Influence of Road Noise on the Soundscape

There is a surprising scarcity of studies investigating the impact that roads have on acoustic index values in terrestrial soundscapes. This is surprising considering the wealth of studies highlighting the negative impact of human-induced noise pollution on the behaviour and abundance of birds (Slabbekoorn & Ripmeester 2008; Francis, Ortega & Cruz 2009) and on marine wildlife (Codarin *et al.* 2009; Slabbekoorn *et al.* 2010b).This study provides some evidence that the biophony was more active at distances further from busy roads but these relationships are not particularly strong. However, the CCA clearly shows that the composition of the soundscape at sites over 1500m from the nearest road was different to site closer than 1500m. Part of this finding will be due to the fact that sites situated closer to the busy roads will have greater noise activity in the 1-2 KHz frequency band. However, there was some evidence that BAI increased with greater distance from busy roads, especially when taking into consideration vegetation structure and landscape heterogeneity (table 4.10), suggesting that there may be an element of road-avoidance within the biophony. Further studies explicitly designed to investigate the relationship between roads of different traffic-flow patterns and the soundscape in different habitats may provide a means of carrying out environmental impact assessments and modeling the impact of roads on natural soundscapes.

The finding that acoustic diversity tended to be higher in sites closer to roads, including small roads is perhaps somewhat counter-intuitive. Birds and other wildlife have been shown to avoid roads (McClure *et al.* 2013; Schepers & Proppe 2017). This finding could be indicative of there being more human-pedestrian activity in the form of dog walkers, cyclists and equestrians closer to these roads. Fairbrass *et al.* (2017) highlight that BAI and ACI are affected by anthropogenic noise such as human voices and suggest that the use of automated identification of such sounds could be used to remove them from final acoustic index-based analysis. However, the presence of human voices within the recordings in this study was not considered to be problematic due to their relative scarcity. Furthermore, one might expect stronger relationships with distances to recreational routes as these were the most likely source of human voices within the forest. Another possible explanation to this finding could be due to road avoidance behaviour in local deer populations. Deer populations in the UK are currently unsustainably high and they are having adverse ecological effects (Fuller & Gill 2001), notably on nesting migratory bird populations due to their browsing habits (Fuller 2001). Several recent studies have shed light on the effect that roads have on the behaviour of ungulates. Roads induce a predation-risk behavioural response in elk in the US, and as such, elk were shown to select areas farther from roads at all times of the day (Prokopenko, Boyce & Avgar 2017). In Europe similar patterns of road avoidance have been observed in red deer, regardless of road surface and traffic volume (though busier roads do invoke a stronger response) (D'Amico *et al.* 2016). If deer in the UK avoid roads in a similar manner, it is possible that their forage-impact on habitats closer to roads may be lower than in sites further away from roads. However, there are studies that suggest that traffic noise is not the driver of reductions in bird abundance in proximity with roads, although they do observe that bird richness and abundance declines with proximity to road (Summers, Cunnington & Fahrig 2011). Conversely, there are studies that explicitly show that birds avoid road noise (McClure *et al.* 2013) and that road noise reduces the health and breeding success of birds (McClure *et al.* 2017). Although not possible to determine in this study, the impact of small roads on deer behaviour and how that relates to songbird nesting success may be an interesting line of research. Proximity to quieter roads may potentially provide a form of deer protection and more suitable habitat for songbirds that would normally be badly affected by excessive browse-related damage. However, other findings in this study and previous research highlight that proximity to busy roads can have a negative impact on biophony-related sounds (i.e. bird activity).

4.6 Conclusions

This study presents the first soundscape study that uses the ARUPI - a DIY automated recording unit developed using the Raspberry Pi computer for the purposes of conducting this study. The cost of four of these units with battery power and data storage was less than the cost of one unit of the leading market alternative. The use of automated recording units allows for greater volumes of data to be collected per unit of effort. The survey effort in this study was adequate to detect some meaningful temporal and spatial relationships, though greater effort or a different approach to sampling design may have yielded more clarity or depth to these relationships. The sampling design was aimed at comparing the soundscapes of different aged-coppice stands. There was a lack of stands aged <10 years but this was primarily due to data becoming corrupted or due to recorder error. As such the power of the analyses was somewhat affected but the data still yields some interesting findings. The study may be improved by sampling more sites but this study sampled in almost half of all the worked coppice stands in Bedgebury Forest. Perhaps broadening the focus would have enabled greater investigation into the relationship between landscape, habitat and the soundscape. Extending the frequency range to include ultrasonic vocalisations may also improve the explanatory power of the data, since many insects and small mammals (including bats) produce sounds above 11KHz (up to 115KHz in the case of the lesser horseshoe bat, *Rhinolophus hipposideros*, present across South West England).

The relationship between habitat heterogeneity and acoustic diversity echoes the findings in previous studies that link the landscape to the soundscape (Tucker *et al.* 2014; Fuller *et al.* 2015). Future studies using a systematic grid-sampling approach at different resolutions/scales could be used to identify areas of high and low acoustic diversity and spatial analyses could identify patterns between the physical landscape and the soundscape. In this study acoustic diversity was higher in areas that had greater levels of landscape heterogeneity. This kind of approach could be a useful tool for monitoring managed woodland and ensuring complexity in the landscape is contributing to acoustic diversity. In conclusion, this study provides evidence that soundscape-based monitoring techniques could provide useful tools in forest management and best practice guidelines, with particular reference to road-disturbance and landscape heterogeneity.

Chapter 5 - Developing an Automated Recording Unit - the ARUPI (Automated Recording Unit PI)

5.1 Introduction

The field of soundscape ecology has mushroomed since Sueur *et al.* (2008) presented the acoustic entropy index (H) and Pijanowski *et al.* (2011) presented an introduction to the field from a landscape ecology point of view. The availability of open-source acoustic analysis software has greatly aided this expansion, such as the Seewave (Sueur *et al.* 2014a) and soundecology (Villanueva-Rivera & Pijanowski 2015) packages within R (R Core Team 2015) and SoundscapeMeter (Farina *et al.* 2012) plugin extensions for WaveSurfer (Sjölander & Beskow 2000). But perhaps the most important development has been the increased availability of affordable digital recording devices (particularly Automated Recording Units, ARUs) and relatively inexpensive high-volume data storage in the form of SD cards and micro USB sticks. The range of available recording devices currently offers the soundscape ecologist a great many options. Selecting suitable equipment largely depends upon the type of study. Handheld recording devices, coupled with directional microphones, are often used in bioacoustics studies where capturing species-calls is the priority (eg. Slabbekoorn & Smith 2002; Touchton, Seddon & Tobias 2014). Similar setups have been used in soundscape studies using omnidirectional microphones. Some makes and models of handheld devices occur frequently in the literature such as the Zoom H4 (Farina & Pieretti 2014; Farina *et al.* 2015); Marantz PMD range (Bormpoudakis, Sueur & Pantis 2013; Touchton, Seddon & Tobias 2014; Holt & Johnston 2015); Sony PCM (Krause, Gage & Joo 2011) and the Roland/Edirol range (Vermeij *et al.* 2010). Aside from peer-reviewed journals, there is an abundance of information available on the internet through amateur nature recording websites/forums and forums for general recording enthusiasts, which often provide sample recordings. These sites are especially useful to soundscape ecologists on a limited budget and often have advice on building your own recording equipment, especially microphones.

Automated recording systems (ARUs) have revolutionised the fields of bioacoustics and essentially paved the way for the field of ecoacoustics to take off. These systems have been around for almost 30 years but it is only in the past 10 years or so that they have been developed on a commercial scale and seen great improvements in functionality. In the literature they may be referred to as Passive Acoustic Monitoring systems (PAMs); Automated Recording System (ARS); Automated Digital Recording Systems (ADRS); Autonomous Recording Units/Automated Recording Units (ARUs); or some other combination of those key words. Essentially they have enabled researchers who are interested in acoustic signaling in biology, ecology and conservation to survey much greater temporal and spatial scales than previously possible. Most commercially available ARUs can be deployed in the field for months at a time and programmed to record to any desired schedule. The first notable automated recording systems were developed for studying amphibians and reptiles, so-called frogloggers (Peterson & Dorcas 1992). Indeed the Froglogger® (www.frogloggers.com) has been in production since 1994. With the digital age, a number of newer systems have been developed, again with herpetologists leading the way: the Amphibulator (Cambron & Bowker 2006), which no longer seems to be in production and the ADRS (Acevedo & Villanueva-rivera 2006), which is not available commercially. All of these systems essentially integrate a handheld recording device, a microcontroller (typically made by Texas Instruments or Atmel) and real time clock (RTC) to switch the unit on and off, a waterproof casing and waterproof microphone. Only the Froglogger® is commercially available and the cost of these units, therefore vary depending on which handheld recording device is used, but one might expect to pay at least £500 per unit.

Perhaps the most functional commercially available ARUs are manufactured by Wildlife Acoustics®. The SongMeter2 (SM2), which was released in 2007, paved the way for the field of soundscape ecology (now ecoacoustics) to flourish. The opportunity to collect data remotely and passively presented the means with which to explore temporal and spatial variation in the soundscape as never before. The basic units were somewhat customisable, as they were geared towards terrestrial sounds within the human hearing range (i.e. 20Hz-20000Hz) but had the option of ultrasonic frequency sampling available for an extra cost. As such, these units have been used to sample species of interest such as birds (Borker *et al.* 2014), bats (Newson, Evans & Gillings 2015), primates (Heinicke *et al.*

2015) and soundscapes as a whole (Tucker *et al.* 2014; Pieretti *et al.* 2015; Mullet *et al.* 2016). At the start of this PhD, the basic SM2 unit was priced at around £600, not including batteries or SD cards for data storage. The cost is a prohibitive factor in the use of ARUs in the Non-Governmental Organisation (NGO) sector and citizen science initiatives (pers. communication with the BTO and Norfolk Bat Group). The SM2 is no longer available as Wildlife Acoustics ® are now producing their third model the SM4, retailing in 2018 at £636.66 (not including shipping, batteries or memory cards). They also produce the SM3BAT, which records birds and bats (range of 1KHz – 384KHz), which costs £1200. These units are incredibly power efficient and produce high-quality audio recording and as such are perhaps the most widely used units in the scientific literature. However, their cost is not realistic for a large-scale citizen science project and puts severe limitations on the NGO sector.

The use of ARUs carries significant risks. There is a risk of damage due to severe weather events or to the movements of wildlife, but perhaps more importantly there is a great risk of vandalism or theft from humans. Indeed, this problem has plagued studies making use of camera-traps, which led to the development of several armoured boxes to protect digital cameras (Grassman Jr., Tewes & Silvy 2005; Fiehler *et al.* 2007). Similar boxes are available to protect the SM2 and SM4 but these come with extra cost (ca. £60) and are not produced by Wildlife Acoustics®. An alternative way around this fear of losing expensive equipment is to build your own using low-cost parts. This was the approach settled upon in this PhD due to a lack of funding and seeing the opportunity to provide a low-cost solution for citizen scientists, NGOs and budget-limited researchers. The aim of this chapter was to develop an Automated Recording Unit which fulfilled the following criteria.

1. The unit should be waterproof and robust enough to be left out in the field for extended periods in all kinds of weather.
2. The unit should be programmable and able to record schedules to lengthen the battery life and enable the capture of temporal patterns in the soundscape.
3. The unit should be easily replicated by amateur enthusiasts and a set of online instructions should be made readily available once the unit is up and running.

4. The unit should be cheap enough to warrant using them. To build an ARU that costs as much as a commercially available unit would not solve any problems.
5. The unit should be enabled to monitor abiotic factors, such as temperature and humidity, alongside the acoustic data (NB. This objective was not achieved within the remit of this PhD but it is entirely possible and probable).

5.2 Design Process and Equipment Summary

Many of the DIY systems mentioned in the scientific literature are either composed of relatively expensive parts or seem to require a level of expertise that limits their accessibility to the general population. Some studies use handheld recording devices on recording grids and simply press record and leave them out in the field until the batteries die-down (Farina & Pieretti 2014). However, handheld units typically cost at least £100 for a moderate but basic unit (eg. Tascam DR-05), are not robust or weather proof and are immediately recognisable and potentially desirable to the casual thief. However, it is possible to integrate a microcontroller to the hand held recorder enabling the recording of schedules and improve to the longevity of the ARU. This would give the researcher a unit similar to the Froglogger®. These types of microcontrollers used are also widely used in robotics (notably often deployed on the open hardware Arduino® platform). When researching this kind of equipment it is not long before one stumbles across multipurpose self-contained single board computers (SBCs) such as the Raspberry Pi.

5.2.1 Raspberry Pi (RPi) – The Core of the ARUPI (Automated Recording Unit Pi)

The Raspberry Pi Model B single-board computer was released in 2012 at a price of £20, followed shortly after by the Model A. The initial Raspberry Pi was comparable in speed and memory to a typical high end PC in the year 2000, in a package that measured 85.60 mm × 56.5 mm. In 2014 the Models B+ and A+ were released. Since then several more versions have been released. This series of Linux-based SBCs were developed by the Raspberry Pi Foundation, a UK based charity promoting the teaching of basic computing in schools in developing countries. The first units were incredibly popular and were quickly utilised by amateur enthusiasts in the Maker community. The maker community has been borne out of a culture that sought to extend the DIY culture to incorporate modern technologies such as SBCs and microcontrollers (Lindtner 2014; McGrath 2016). With the introduction of low-cost SBCs and microcontrollers the Maker community flourished and soon a whole suite of complimentary boards were being built by makers and manufactured using crowd-funding business models (Riedl 2013). Popular projects included the use of the Raspberry Pi as the platform for remote weather stations, some of which are now featured within the scientific literature (Jiménez-Carvajal *et al.* 2017). There are also projects utilising the Raspberry Pi as a camera trap (Nazir *et al.* 2017) and more recently there are other projects utilising the Raspberry Pi as acoustic sensors (Segura-Garcia *et al.* 2015; Whytock & Christie 2017). It was due to the evident versatility of the Raspberry Pi and the wealth of enthusiasm throughout the Maker community that in 2014 the concept of the ARUPI was borne.

5.2.2 The Sleepy Pi

Like any computer, the Rasbperry Pi needs to be actively switched on and off. Therefore to create an ARU that will switch itself on and off it is necessary to use extra hardware. One option is to use a microcontroller and a real time clock (RTC) (as in Acevedo & Villanueva-rivera 2006). This adds an extra level of complication to anyone wanting to build the ARUPI. The Sleepy Pi is a ready-made unit built for the RPi manufactured by The Spell Foundry, a small family run company based in Bedfordshire, UK. The Sleepy Pi is an add-on board enabling smart power management to the Raspberry Pi. Essentially this unit controls when the Raspberry Pi receives power. The power source is plugged into the Sleepy Pi, which is plugged into the RPi. A schedule can be set on the Sleepy Pi to wake the RPi up as needed.

5.2.3 Soundcard

Selecting a suitable soundcard is an important consideration. Initially, the Wolfson Microelectronics SoundCard (which became the Cirrus Logic Soundcard – used in Whytock & Christie (2017) was investigated. It was not used in the final design for two reasons: it was not possible to connect both the Sleepy Pi and the soundcard to the RPi as they use the same General Purpose Input Output (GPIO) pins (i.e. you can use either the soundcard or the Sleepy Pi, not both); and the software needed to run the Wolfson audio card is quite complex and needs a specialist operating system to run. An alternative was to use a USB soundcard. There are a great many USB soundcards available on the market but the Creative Soundblaster Play! was selected due to its capacity to make high-quality recordings (16bit; 48KHz sampling rate) at an affordabile price (ca. £20). It is also a well-known make from a large company and as such is readily available across many countries. Making the components of the ARUPI accessible for the NGO or citizen science community was a consideration throughout development to offer the potential to compare and contrast landscapes and their soundscapes on an international scale. Finally the Creative Soundblaster Play! is immediately compatible with Linux operating systems so there is no need to install drivers – i.e. it is plug and play.

5.2.4 Microphone

Selecting the right microphone is particularly important in bioacoustics studies where individual songs and acoustic signals are of particular interest. These are important in the field of soundscape ecology but are not the most critical piece of equipment. In a seminal piece of research, that is often overlooked in the literature, Farina *et al.* (2014) demonstrated that extremely low cost recording units (ca. US$10) detect the same general patterns in the soundscape as more expensive equipment. However, the resolution in the data is greatly reduced due to a poor microphone and low sampling rate (16000Hz i.e. it captures sounds up to 8 KHz only), so these units are not suitable for more descriptive studies. But their potential use in large-scale monitoring initiatives is particularly exciting and they have been used in further studies with a certain degree of success (Bobryk *et al.* 2016). For the ARUPIs used in chapter four, single-channel (mono) microphones were built using Primo EM172 electret condenser microphones with an acoustically transparent waterproof film (sold by www.frogloggers.com as the BT172). These are commonly used in many amateur nature recording projects as they have a flat frequency response between 100Hz-10000Hz, low self-noise, high sensitivity and a good signal to noise ratio (SNR = 80dB). The microphones require a 5v power supply and so were powered by a simple-circuit phantom power unit converting a 9v battery supply down to 5v. In the final set of instructions published online the build of the microphone was not included. Any microphone with a 3.5mm stereo jack can be used with the selected soundcard and some other options are given. Although the microphone is important, the prospect of building one might be off-putting, so the decision to reduce that aspect of detail was made. It also allows the maker to think creatively and determine what their needs are.

5.2.5 Data Storage, Power and Waterproof Housing

As with the microphone, these options can be customised to suit the needs of the maker. However, the ARUPI OS provided in the instructions is configured to use the exact USB data storage outlined in the online instructions. Therefore, if selecting a different device, the maker will need to follow the instructions given (at the end of step 6). In terms of power, the use of 8xAA batteries was opted for since battery boxes for these are inexpensive and ubiquitous in electronic shops and online. They are also relatively lightweight and provide a considerable amount of power, recording more than 576 minutes, or 9.6 hours, per 8 batteries. The use of 8xD cell batteries would enable the ARUPI to record for up to 10 times longer (based on a D-cell battery of 15000mAh capacity). This translates as around 5684 minutes of recordings, or 94.7 hours. However, these would make the units considerably heavier and may need a larger waterproof housing. The waterproof housing selected was an IP67 rated (dustproof and waterproof) tough plastic box, typically used for transporting expensive electronic or fragile equipment. A hole was drilled into the box and a 25mm IP68 rated cable gland was used to ensure the microphone connection to the ARUPI unit was watertight. This step is dependent upon microphone selection. The boxes are available from a UK-based company but are likely available in other countries with similar, but not exact, dimensions. There are also other options open to the maker depending on their design preferences and budget. At around £20 these boxes are cheap but there are cheaper options available, such as the one used in the SOLO (Whytock & Christie 2017).

5.3 Programming the ARUPI

The most challenging aspect of developing the ARUPI was the programming. Dr Daniel Knox from the Makerspace at the University of Kent (The Shed) provided the technical assistance and advice on the programming of both the RPi and the Sleepy Pi that enabled the ARUPI to come to fruition. The Arch Linux operating system (OS) was used as it essentially provides a bare-bones starting point and it has three key features: It is free and largely open-source; it enables the user to install packages and software as necessary; it also has no graphical user interface (GUI). These three attributes of the Arch Linux OS provide two important benefits to the ARUPI:

1. The software is free and so the customised version specific to the ARUPI is readily distributable.
2. The bare-bones starting point ensures better power-efficiency. GUIs require lots of processing power and many ready-made OS systems (such as Raspbian) come with pre-installed packages that are not necessary for the ARUPI, including a GUI.

The Advanced Linux Sound Architecture (ALSA) software was installed onto the OS and a simple recording program was written, which is easily customisable and explained in the instructions. A simple program was also written which told the RPi to read the time from the Sleepy Pi (which has an on-board RTC). These two programs are set to run when the RPi powers on using the job-scheduling software crontab (a standard utility in Linux). Crontab is a utility that enables you to run certain programs upon start-up (or any time following startup) and so the sequence used in the ARUPI is essentially: Set time > Record sound > Shutdown.

The jobs that the Sleepy Pi performs are to wake the RPi up when needed and to keep the current time using an RTC powered by a separate battery to the power source used to power the RPi. The code required to do this requires a degree of skill and understanding of the C programming language. In this version of the ARUPI, when the power is switched on, the Sleepy Pi starts a 15minute countdown clock. When it reaches ‘0’ it sends power to the RPi, which does the jobs outlined above. Whilst the RPi is recording, the Sleepy Pi keeps checking whether the RPi has shut down or not. If the RPi is still awake, the Sleepy Pi keeps giving it power. Once the RPi finishes its cycle and shuts down, the Sleepy Pi finds out the

RPi has shut down and kills the power completely, sets a 15minute countdown timer for the cycle to begin again and reduces its own power consumption to a minimal level. On the latest Sleepy Pi2, the on-board RTC has more functionality and the unit can be more easily programmed to wake the RPi at set times (i.e. 8pm, 9pm, 10pm etc). This new functionality will open up the development of the ARUPI to be used as a dedicated automated bat detector unit.

5.4 Discussion and Conclusions

The instructions on how to build an ARUPI were published on one of the largest maker websites (www.instructables.com) on September 16th 2015. A Google search for "Automated Recording Unit" will bring it up as one of the top hits. It is the first ARU to be developed using the Raspberry Pi computer platform and off-the-shelf components. The instructions are easily and openly accessible and all the programs developed by The Shed (i.e. Daniel Knox) are available through a GoogleDrive linked in the instructions. The units themselves perform incredibly well and if built using the same equipment in the published guidelines (appendix 5.1 and 5.2) they are waterproof and robust. They performed exceptionally well in the field and were not subject to theft, vandalism or wildlife/weather related damage (though the foam microphone windshields were nibbled by something, most likely inquisitive squirrels). The units were deployed with stickers indicating their use to explain what they were being used for (figures 5.1 +5.2), though it should be noted that no one contacted me regarding the units, so either nobody saw them, or nobody was interested by what they saw. Either case is a positive in terms of data collection and unit-security. The recording quality is good (figure 5.3) and the power consumption is good.

Property of Anthony Turner, The Durrell Institute of Conservation and Ecology, University of Kent.

This box is part of a PhD research project investigating the soundscapes of different types of habitat. This box isn't worth a lot of money – it is a DIY audio recording unit so has little value unless you are conducting similar research. Thank you for not attempting to open or vandalise this box – if you are curious or would like more information about this project, please feel free to call me on - 07907 379 890. Many thanks ☺

ARUPI_01

Figure 5.1. The ARUPI used in the study of worked coppice stands in Bedgebury Forest. Using a polite sticker explaining what the unit is was deemed a sufficient counter-theft/vandalism measure (NB: the phone number is no longer active).

Figure 5.2. Deploying the ARUPI. The use of a telescopic ladder enables one to comfortably attach ARUs (in general) out of sight and out of reach. Being lightweight and easily transported, although not terribly long, they offer a means of minimising both human and wildlife risks to recording units.

The ARUPI does not have the same capabilities as many commercially available ARUs. The commercially available units from Wildlife Acoustics® are superior to the ARUPI in many ways. But the ARUPI can be bought for a fraction of the price, are easily customised and are essentially modular in that they are made using several low-cost, easily replaceable and interchangeable components. The ARUPIs used in chapter four cost around £135 each (including data storage). Therefore, researchers on a budget could buy five ARUPIs for the price of one SM4 unit (assuming one buys a 64gb high-speed SD card to store audio recordings made by the SM4). As of November 2017, makers from various countries (including the United States, UK, Denmark and Sweden) and professions, including biologists, ecologists and artists have contacted me to discuss the ARUPI and have started to build them.

Numerous studies state the influence the geophony has on interpreting the soundscape using acoustic indices (Towsey *et al.* 2014; Mullet *et al.* 2016). The ARUPI achieved four of the five key objectives of this project, and although it is not currently set up to record abiotic data (objective 5), it remains a possibility. Incorporating a fully functioning weather station to the ARUPI could conceivably be done for less than £100 extra (+extra power requirements). Although bumping up the cost considerably, this would provide a powerful tool for improving data-processing speeds enabling removal of unwanted sounds. It would provide time-matched abiotic data which may shed light on the effects of meteorological events on animal behaviour (Hovi 1995; Schäfer *et al.* 2017) and acoustic propagation. A further addition that could provide the ultimate automated, passive wildlife monitoring system would be the addition of a camera module that would enable the ARUPI to act as a camera-trap. Camera-traps have been widely used over the past 20 years but they too are expensive and face the risk of theft and vandalism. Attaching a dedicated Raspberry Pi camera module, infrared detector and flash would add ca. £40 to the total cost (+extra power requirements). These extensions are achievable with current technology if the researcher has access to support staff with some hardware and software expertise. Furthermore, the development of wireless sensor networks (WSNs) to monitor environmental change (Dong, Meyland & Karaomeroglu 2017) could enable the development of ARUPI networks to generate forest-wide sound-maps. Such networks have been developed to monitor traffic noise in urban environments (Segura-Garcia *et al.* 2015; Noriega-Linares & Navarro Ruiz 2016) so it is conceivable that similar low-cost networks could be developed to monitor certification schemes and other green-initiatives. Perhaps due to the ethos of the Maker community, keeping costs low is a core consideration in the development of WSNs. Such values are in-line with that of biodiversity conservation so making connections between these two fields of expertise should be beneficial to both.

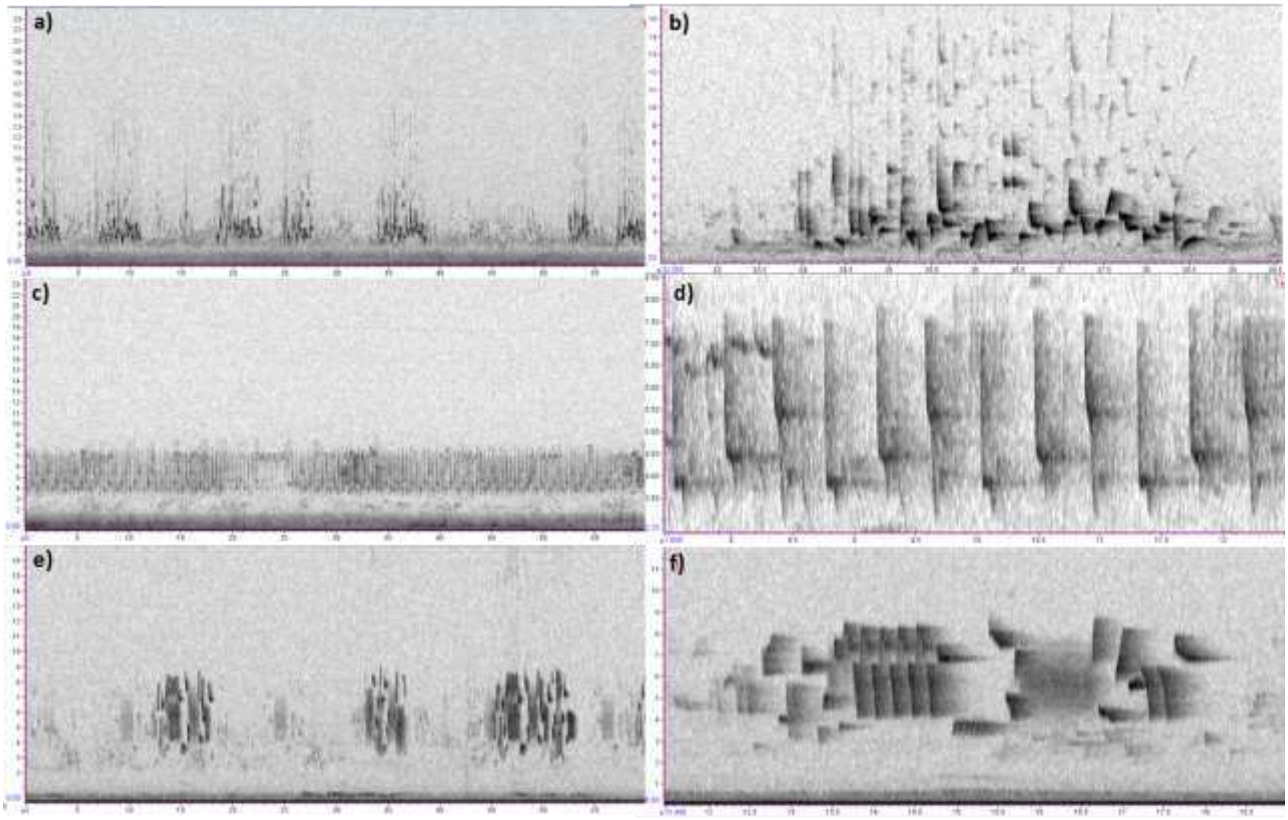


Figure 5.3. Spectrograms from one minute recordings made using the ARUPI in coppiced woodland in the UK (a, c, e). b) Blackcap call identified in image a. d) Chiff Chaff call from image c. f) Wren song identified in image e.

Chapter 6 - Synthesis and Discussion

6.1 Summary of key findings:

This study explored spatial and temporal patterns in the soundscape of two types of plantation forest using a suite of acoustic indices. In chapter two there were significant relationships between forest stand age (and associated vegetation structural metrics including canopy height and ground vegetation cover) with acoustic diversity, particularly with the acoustic diversity index (ADI). This relationship was observed in consecutive years indicating the repeatability of these methods. In chapter three significant differences in acoustic diversity between two coniferous plantations (Thetford forest and Bedgebury forest) were observed. These relationships are likely due to the different management histories of the two landscapes, with Bedgebury forest being a planted on ancient woodland site (PAWS), situated in a landscape abundant with fragments of ancient woodland and Thetford forest being a 100 year old man-made plantation. Indeed, in Chapters three and four there were significant relationships between measures of landscape heterogeneity and acoustic indices. These relationships echo previous studies investigating the relationship between biodiversity and landscape heterogeneity. Temporal influences on the soundscape were observed in Thetford forest at two different times of the year (early summer vs late summer) indicating that acoustic diversity is higher the closer it is to spring (bird breeding season). And in Chapter four, temporal patterns in the 24 hours daily period were observed, giving insights on the use of different acoustic indexes particularly the Normalized Difference Soundscape Index (NDSI). In all three data chapters (2-4) the influence of proximity to roads was of particular interest. There was some evidence that the relationship between road proximity and NDSI was different in the different landscapes (i.e. Thetford forest vs Bedgebury forest). It highlights that the use of NDSI to map road noise could prove a useful tool for noise mitigation and landscape planning. Finally this thesis offers insights into low-cost monitoring solutions that may be implemented in conservation initiatives and the non-governmental organisation (NGO) sector. It offers instructions on how to build a low cost automated recording unit (the ARUPI) for a quarter of the cost of one of the leading market alternative. And it highlights the potential for using low-cost handheld recording devices to map forest soundscapes. As such, this thesis offers a significant contribution to the field of soundscape ecology (and ecoacoustics) and offers several considerations for future research in this field.

6.2 Use of Acoustic Indices

This study used several acoustic indices to characterize the soundscape in the context of vegetation and landscape structure. These indices have been extensively reviewed for their suitability as proxies for species-richness. Previous studies indicate that ACI (Pieretti, Farina & Morri 2011), ADI (Machado, Aguiar & Jones 2017), AEI (Fuller *et al.* 2015), H (Sueur *et al.* 2008; Depraetere *et al.* 2012), and BAI (Boelman *et al.* 2007) can act as suitable indicators of avian activity and diversity. However, Towsey *et al.* (2014) suggest that using multiple indices can achieve better estimates of avian species richness. Xie *et al.* (2017) use several analytical steps to produce species-richness estimates of frog calls. They essentially pass their recordings through a filter and then classify each recording using several acoustic features, two of which are ACI and ADI. In this study, there were no significant correlations between ACI and ADI in coniferous woodland (chapter two and chapter three). However, in the coppiced woodland (chapter four), these two indices were strongly correlated with one another, and most strongly related during the "quietist" periods of the day, between 8pm and 4am (table 6.1). With this in mind, studies using multiple (or single) indices to determine species richness, should take into account the habitat type, time of day and other factors affecting sound production and propagation. This thesis shows how the relationship between different indices changes depending upon the time of year, time of day and habitat structure. This indicates potential considerations when using several acoustic indices to characterize a soundscape and highlights the need for more studies that incorporate vegetation structure and landscape metrics whilst investigating the relationship between different acoustic indices.

One potential explanation for changing relationships between indices could be differences in sound propagation between the two forest types (Embleton 1963; Martens *et al.* 1985; Price, Attenborough & Heap 1988; Padgham 2004). Bird detection using acoustic methods is affected by sound attenuation in different habitat types (Schiek 2017; Yip *et al.* 2017) and at different heights in the same habitat (Waide & Narins 1988). Typically, higher frequencies attenuate faster than lower frequencies and sound attenuates faster in broadleaf woodland. However, over short distances reverberation of narrow-frequency band calls can be beneficial to some birds (Slabbekoorn, Ellers & Smithi 2002). And some birds can alter their singing behaviour (by selecting singing perches at optimal heights) to minimize attenuation (Blumenrath & Dabelsteen 2004). Therefore the position of the microphone amongst sound-altering objects (i.e. vegetation) is likely to be an important factor in how sounds are collected and the resulting data interpreted. Furthermore, the sound propagation characteristics of different habitats are believed to be drivers of evolutionary traits in birds (Tobias *et al.* 2010), bats (Schnitzler & Kalko 2001) and some marine life is known to select sites based on their sound signatures (Stanley, Radford & Jeffs 2009; Radford *et al.* 2010, 2011). In the field of soundscape ecology and the development of acoustic indices, sound propagation characteristics often seem over-looked though there are a wealth of studies highlighting its importance to species-evolution and behaviour. Only a handful of studies to date have measured vegetation structural characteristics and none have measured sound propagation characteristics at their study sites (this one included). Understanding the sound propagation properties of a habitat may provide important caveats that could be included in acoustic analysis and potentially improve species-estimates.

Table 6.1. Spearman correlation matrix of acoustic complexity and acoustic diversity indices in worked coppice sites in Bedgbury forest, at different times of the day. 1= 4am-10am (N=39); 2=10am-3pm(N=39); 3=3pm-8pm(N=40); 4-8pm-10pm(N=40); 5=10pm-4am(N=40). Total is the mean value per site (N=40). **. Correlation is significant at the 0.01 level; *. Correlation is significant at the 0.05 level

	ACI_1	ACI_2	ACI_3	ACI_4	ACI_5	ACITotal
ADI_1	**.573****	.583**	.454**	.544**	.509**	.580**
ADI_2	.331*	**.382***	.350*	.466**	.553**	.483**
ADI_3	.263	.263	**.353***	.412**	.547**	.450**
ADI_4	.399*	.481**	.515**	**.743****	.661**	.589**
ADI_5	.536**	.543**	.589**	.561**	**.785****	.705**
ADITotal	.510**	.564**	.516**	.652**	.728**	**.666****

6.3 Temporal Patterns

This study provides insights into three levels of temporal variation: annual variation, seasonal variation and daily/hourly variation. Chapter two indicated that ADI and AEI values remained similar in two consecutive years on the same grid. This is the first study (to my knowledge) that has repeated a study of the soundscape on one grid in consecutive years. The purpose for doing this was to assess the suitability of such methods in long-term soundscape monitoring and the results were encouraging. The patterns of ADI/AEI remained fairly similar between years and small variations could probably be explained by changes in meteorological conditions (i.e. wind). However, dramatic changes in ADI/AEI between 2014 and 2015 were observed in a stand that was clear-felled and there was visual evidence of acoustic diversity dispersal. Interpolation maps indicate that areas surrounding the clear-felled stand displayed higher acoustic diversity after the disturbance event. Although the data are fairly limited, the pattern follows what one might expect. Biodiversity typically responds to logging events by dispersing from the logged area and gradually moving back over time as vegetation structure recovers and niches are re-established. Indeed, the idea behind retention forestry and continuous cover forestry is to minimize this initial impact on biodiversity and ensure a variety of habitats are retained post-logging (Mason *et al.* 1999; Gustafsson *et al.* 2012). The apparent dispersal of acoustic diversity observed at the clear-fell site in this study, although a relatively small coincidental finding, offers an insight into a potential means of monitoring biodiversity responses to different management practises in the forestry sector. This may be particularly useful since many indicators used in the forestry sector focus on vegetation structure and species-diversity (Marchetti 2004) and in many certification schemes and restoration schemes the biodiversity assessment is often dependent upon the means and skill-level of the land owner/manager (Thompson *et al.* 2003; Forest Stewardship Council 2015). Incorporating a standardized acoustic monitoring protocol to capture a snapshot of the audible faunal community may provide a means of detecting broad scale patterns in biodiversity and deepen our understanding of the relationship between the soundscape and structural diversity.

Determining optimal temporal sampling patterns is considered a priority in soundscape ecology (Rodriguez *et al.* 2014; Pieretti *et al.* 2015) though it is not necessarily essential for a long-term monitoring initiative. The daily (24h) patterns of acoustic activity evident in chapter four are broadly in-line with what one might expect to observe if conducting a bird survey – i.e. 4am to 10am display the highest levels of activity/diversity, with the highest activity being between 4-6am (during the so-called dawn chorus). Indeed, the British Trust for Ornithology (BTO) stipulates that volunteers on the Breeding Bird Survey (BBS) start their 90 minute surveys no earlier than 6am to avoid peak bird activity during the dawn chorus and no later than 9am. Soundscape studies could be developed using a more traditional approach to collecting data. Where monitoring is concerned, rather than searching for temporal patterns, controlling for them might be more appropriate. In chapters two and three, significant relationships between habitat structure and landscape composition with the soundscape were uncovered by conducting surveys at the same time of day and time of year. The key issue using this type of approach is generating enough data (i.e. recording length and/or repetition) per sampling point. However, Bormpoudakis, Sueur & Pantis (2013) demonstrated that it is possible to detect distinct habitats from two minute recordings of ambient soundscapes and in chapters two and three in this thesis, six minutes was adequate. Although there is a proliferation of studies using ARUs to investigate the soundscape to uncover spatial and temporal patterns, it is important to note that handheld units can be utilized effectively when combined with more traditional ecological methods that aim to control for external factors which may influence the data acquired. Further research into the use of handheld recording devices to uncover spatial (and temporal) patterns in the soundscape could pave the way for, or be incorporated into, a citizen-science initiative (see section 6.6).

6.4 Structural and Spatial Patterns

The relationship between forest age and canopy height with ADI in Thetford Forest was particularly encouraging and followed a similar pattern as that observed by Pekin *et al.* (2012). Similar relationships to vegetation structure were observed in the coppiced woodland (chapter four). Sites with a taller but more open canopy tended to display higher BAI values, which is indicative of higher levels of bird activity. Due to the lack of bird-species data from these sites it is not possible to determine the extent that this pattern is being caused by bird species-richness but it is almost certain that a significant degree is caused by bird activity levels. The relationship between acoustic indices with bird species richness and vocal activity is well documented (Boelman *et al.* 2007; Pieretti, Farina & Morri 2011;

Depraetere *et al.* 2012; Machado, Aguiar & Jones 2017). When acoustic indices do not perform well as proxies for species-richness, it is usually when they are compared with bird point-count data (Mammides *et al.* 2017), which is itself victim to observer-error and bias (Farmer, Leonard & Horn 2012; Schiek 2017). The geophony can also have a significant effect on the performance of acoustic indices as proxies for species-richness (Sueur *et al.* 2012; Towsey *et al.* 2014). Since the geophony was largely controlled for in this study (i.e. wind and rain either avoided or removed post-recording) it may be safe to assume that high acoustic diversity values were due to higher biological activity and to some extent diversity. Furthermore, bird diversity is higher with greater structural complexity (MacArthur & MacArthur 1961; James & Wamer 1982; Goetz *et al.* 2007) so the pattern observed in all three chapters broadly follow what would be expected and has been observed in other recent studies. For example, Hilje, Stack & Sánchez-Azofeifa (2017) recently found that liana abundance is positively associated with the acoustic complexity index which they attribute to bird species-richness. Likewise, landscape heterogeneity is a known driver of biodiversity (Fahrig *et al.* 2011; Grant & Samways 2016; Neumann *et al.* 2016) so the relationship between acoustic diversity and heterogeneity was not wholly unsurprising. Finally, when entering all sites from this study using age-category as a grouping variable, there are fairly clear differences between different aged stands (figure 6.1).

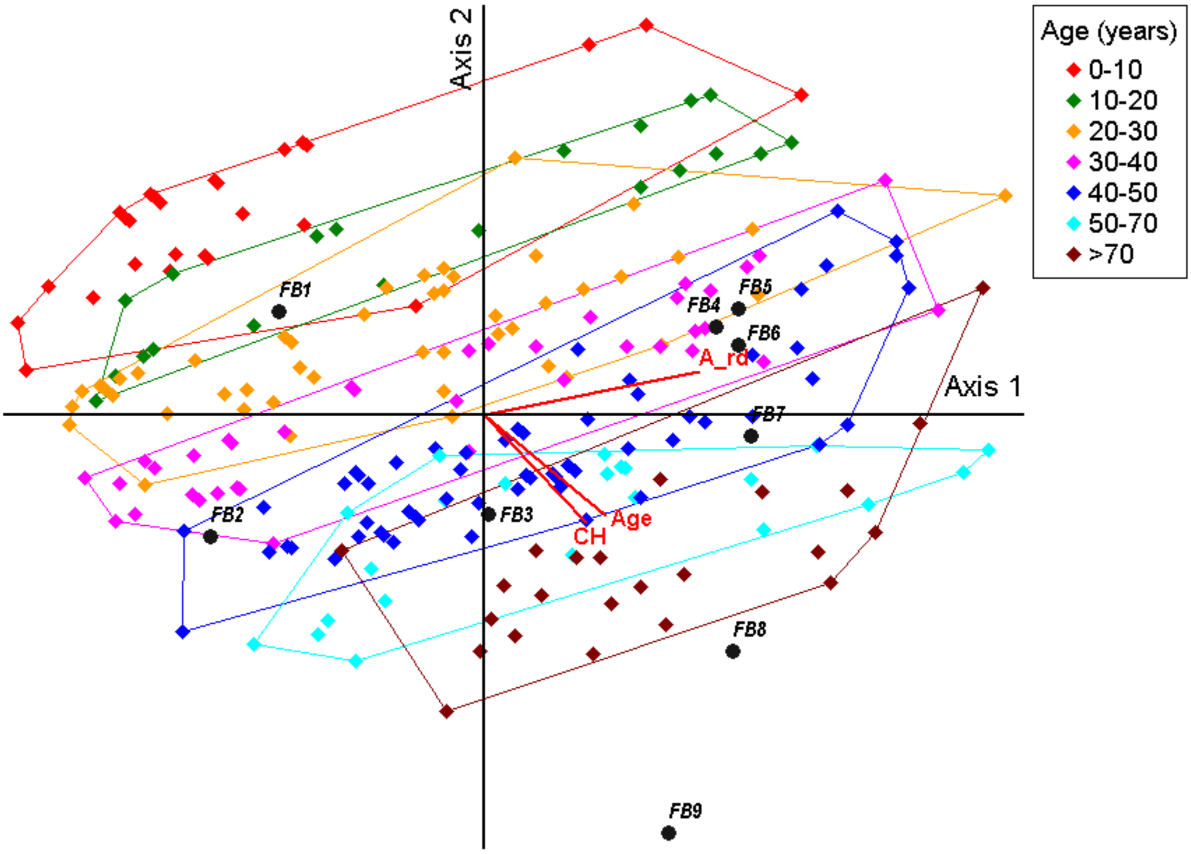


Figure 6.1 Canonical correspondence analysis using nine frequency bands (FB1-FB9) from all sites from this thesis (N=247). Three environmental variables are in red – Age = Stand Age; CH = Canopy Height; A_rd = distance to nearest A-road. There seems to be a clear pattern in differences in acoustic diversity in relation to forest stand age and canopy height. The overall CCA accounted for 27.2% of variation in the data (Axis 1 = 24.6%; Axis 2=2.5%; Axis 3 = 0.1%). This graph essentially sums up the two key findings of this study quite nicely. Firstly that stand age (and therefore structure) is an important driver of acoustic diversity – with frequencies greater than 3 KHz (i.e. FB4 and higher) being more associated with older habitats (>30 years old). Secondly that distance to the nearest road has a significant influence on soundscape composition, with the heart of the biophony (FB4-FB7) being more represented at a greater distance from busy roads. These data are just presented as a graphical indication of the broad patterns observed in this study. It is important to note data from worked coppice stands and coniferous woodland were not collected using the same recording equipment or sampling schedule.

6.5 Perspectives on the Influence of Roads

Several studies that investigate the efficacy of acoustic indices as proxies for species-richness include NDSI in their analyses (Tucker *et al.* 2014; Fuller *et al.* 2015; Machado, Aguiar & Jones 2017) or use NDSI to describe biophonic activity (Ritts *et al.* 2016). The daily temporal pattern observed in chapter four highlights a key issue regarding this type of use of NDSI. Though there are no studies that explicitly state that NDSI provides a good measure species-richness, it is probably not wise to use it in any species-estimation context. It does however show great promise for noise modelling but only one study to date investigates the relationship between NDSI and distance to the nearest road. Machado, Aguiar & Jones (2017) present a linear relationship between NDSI and distance to nearest road. This thesis presents both linear and non-linear relationships between NDSI and road proximity. This may be due to differences in habitat structure and landscape configuration at different sites. In this thesis, figure 2.4 (chapter two – coniferous plantation, Thetford forest) displays a clear linear relationship between NDSI and proximity, whilst figure 4.4 (chapter four – coppice plantation, Bedgebury forest) shows a non-linear relationship. One key difference between these two sites is that Bedgebury forest has much higher landscape heterogeneity and a higher proportion of broadleaf woodland, whilst Thetford forest is predominantly comprised of uniformly planted coniferous woodland. Broadleaf woodland has better sound attenuation properties than coniferous plantations due to the higher vegetation surface area, which absorbs and deflects sound (Aylor 1972; Tarrero *et al.* 2008). As such it is likely that different habitats will present different relationships between NDSI and road proximity. Furthermore, it is possible that the linear model used to describe the relationship presented in figure 6 in Machado, Aguiar & Jones (2017) could actually be improved by fitting a non-linear model.

Alternatively, differences in the avian community at both sites may be affecting the relationship between NDSI and road proximity. All recording sites on the Santon Downham grid were within 1500m of a busy main road in a landscape with low sound attenuation properties. This proximity to such an intrusive source of anthropogenic noise may influence bird community composition through species-avoidance of roads (Brotons & Herrando 2001; McClure *et al.* 2013) or reduced the health and breeding success of individuals (McClure *et al.* 2017). Further studies into the effect that roads have on the biophony are necessary to determine the potential for using NDSI in noise mitigation strategies. There is a moderately good understanding of the impact that technophonic noise has on animal signalling behaviour (Slabbekoorn & Ripmeester 2008). But there are far fewer studies that show the detrimental effects that noise might be having on animal health. It is well known that technophonic noise is a cause of ill health in humans leading to afflictions including sleep-disturbance, cognitive impairment, increased stress and annoyance and cardiovascular disease (Marquis-Favre, Premat & Aubree 2005; Goines & Hagler 2007). Recent studies are beginning to shed light on how noise might cause harm to wildlife. Frogs exposed to high traffic noise levels produced elevated levels of stress hormones which resulted in an immunosuppressive response (Troïanowski *et al.* 2017). Their vocal sac colouration was also affected indicating that road noise can have serious health and long-term fitness implications in tree frogs. Similarly McClure *et al.* (2017) demonstrated reduced fitness and reproductive success in birds exposed to road traffic noise in the field.

Road noise, and its mitigation, is often considered in terms of sound pressure levels (SPL) (DEFRA 2014). This approach is adopted in many studies investigating the impact of road noise on wildlife (Berthinussen & Altringham 2012; Troïanowski *et al.* 2017). More in depth studies into the relationship between roads and the soundscape may provide tools for a more holistic approach to noise mitigation. That is to say that considering the balance between the biophony and technophony and how they interact in different landscapes could feed into models for so-called tranquillity mapping (Watts & Pheasant 2015) and provide more nuanced insights into the effects of road-traffic noise on wildlife. There is evidence to suggest that greenspace areas with low NDSI values (i.e. high levels of technophony) had higher levels of anti-social behaviour and litter in areas of Sheffield (Peet 2014). As the insidious negative impact that noise pollution has on human health becomes more clear (Brown & van Kamp 2017) and the health benefits of natural surroundings are championed in social welfare (Li 2010; Lanki *et al.* 2017; Triguero-Mas *et al.* 2017), there may be opportunities to tie in species-conservation with human-welfare. The use of soundscape-based monitoring may have far reaching applications and NDSI might offer a bridge between human-health and social welfare with the conservation and ecology sectors. It may also provide a tool to monitor biophony/technophony balance before and after any management decisions, such as planting strips of mixed-species non-uniform deciduous woodland along roadsides to mitigate noise levels.

6.6 Perspectives for Monitoring and Citizen Science

The potential for producing low-cost objective measures of biodiversity with insights into habitat and landscape structure offers a real opportunity for long-term monitoring in certification schemes and other environmental initiatives. As mentioned in the introduction, one of the greatest pitfalls of agri-environment schemes and forest certification initiatives has been the lack of suitable monitoring (Kleijn & Sutherland 2003; Angelstam *et al.* 2013). This may largely be due to the guidelines often given to landowners and managers, which essentially boil down to "do what you can". This is absolutely understandable given the complexities with selecting suitable biodiversity indicators (Noss 1990), coupled with the vast differences in the monetary and temporal means of scheme participants. This thesis offers two important insights with regard to soundscape recording as a long-term monitoring solution:

1. Collecting short soundscape recordings using a relatively low-cost handheld recording unit can yield important information about forest and landscape structure that is objective and related to biodiversity.
2. The soundscape patterns on a grid within an FSC certified forest remained fairly constant between years, though large changes were observed around a clear-felled stand.

These findings support the notion that a soundscape-based monitoring approach could make a useful rapid assessment tool (Sueur *et al.* 2008), particularly for forest certification and restoration schemes, where monitoring can play an important role in adaptive-management. Current monitoring guidelines for such initiatives are often open to interpretation and are dependent upon the skill-level and the monetary and temporal means of those taking part. One suggestion in woodland restoration is to take periodic photographs to assess change objectively over a number of years (Thompson *et al.* 2003). The simple addition of taking periodic audio recordings may yield a surprising amount of information for very little extra effort. With the ubiquity of handheld recording devices in the form of smart phones, the addition of such a tool would cause minimal disruption and cost to current monitoring efforts. Conducting pilot studies in several woodland sites across the UK would enable a better evaluation of the suitability of such methods.

Dumyahn & Pijanowski (2011) suggest that soundscapes should be managed as an ecosystem service. They can have a significant impact on human health and wildlife health.

They can be used to identify species-richness and they are easily captured using digital recording media. With these things in mind, the field of soundscape ecology could benefit from a large-scale monitoring project to further our understanding of the interaction between these different subjects. One such initiative now exists in Record the Earth (www.recordtheearth.org), a mobile phone app for making soundscape recordings. However, there is no real structure to the data collection except that it only allows recordings to be uploaded on Earth Day (April 22) each year. As such, its scientific rigour does not fulfil criteria considered essential for a citizen science initiative that will provide statistically sound data (Magurran *et al.* 2010). Citizen science initiatives such as the National Bat Monitoring Programme (NBMP) (Barlow *et al.* 2015) and the Breeding Bird Survey have given great insights into population trends of various UK species. One concern with citizen science data is that it can be prone to observer bias and error (Farmer, Leonard & Horn 2012) but good experimental design and statistical analysis can overcome such issues (Magurran *et al.* 2010; Schiek 2017). The use of acoustic recording units can be used to further reduce these errors. Newson, Evans & Gillings (2015) demonstrate that setting up an automated bat detector lending service can produce an unbiased, large-scale data set whilst also introducing new scientific methods to members of the public who are interested in taking part. This kind of approach could form the basis of a citizen-science soundscape initiative in the UK. The use of ARUs is not necessary as most people possess mobile phones, which are relatively high-quality recording units when compared to the ones used in Farina *et al.* (2014) and Bobryk *et al.* (2016).

Instead of focussing on a taxonomic group or species community, a soundscape initiative might be more appropriate when focussed on a particular habitat type. The development of a citizen-science based woodland monitoring initiative, for instance, could provide invaluable information to land managers such as the Forestry Commission. In the UK between 2015 and 2016 there were an estimated 604 million visits to woodland and around 61% of the UK population have visited woodland in the last five years (Forestry Commission 2017b). Even if just 0.01% of those visits each produced a one minute soundscape recording that would be equivalent of 60,400 minutes (or over 1000 hours) of data. During the course of this study there were a number of familiar faces who visited the same parts of the forest almost every morning, often walking their dogs and often interested in learning more about this study. This positive reception indicates that there may be an opportunity to nurture this interest and develop a citizen-based data collection protocol that capitalizes on the ubiquity of smart phone ownership (i.e. handheld recording devices) and the British public's enjoyment of recreational woodland. Dog-walkers in particular would be ideal targets for such an initiative since they often visit the same woodland on a regular basis. The UK public have demonstrated their willingness to participate in citizen-science initiatives by contributing to the BBS and the NBMP to produce informative datasets that have increased our understanding of bird and bat population trends. The importance of natural soundscapes for human health and well-being (Smith & Pijanowski 2014) combined with the information they contain pertaining to biodiversity (particularly birds); landscape configuration; and anthropogenic noise disturbance suggests that they may draw interest from a wide cross-section of society. With this in mind, the development of a citizen-science initiative within the UK seems like a logical next step for both soundscape ecology as a field of research and institutions such as the Forestry Commission, for whom monitoring of their land could prove invaluable.

6.7 The ARUPI

The ARUPI presents a building block that will open up the availability of ARUs to NGOs, budget-limited researchers and potentially citizen science projects similar to that presented by Newson, Evans & Gillings (2015). There are other DIY ARU options available but currently, it seems that only the ARUPI is easily and freely available. A unit called the AudioMoth is perhaps the best low-cost acoustic monitor as it claims to have the ability to sample at up to 384,000Hz and so is equipped to detect ultrasonic frequencies. It also uses just three AA batteries and appears to have a long battery life. Its downfall is its availability – it is not commercially available and in order to purchase it one must pay for the circuit boards (PCBs) to be printed by an external company. They are currently unavailable due to some parts not being available. The ARUPI is essentially modular and can be made using off-the-shelf parts and it is possible to customize it to also record meteorological data and even take photographic images. Indeed, the geophony remains a problem when analysing and interpreting soundscape data. Wimmer *et al.* (2013) suggest incorporating data from nearby weather stations to aid interpretation of acoustic index data. Other studies have developed algorithms for detecting rain within recordings (Bedoya *et al.* 2017). The ARUPI may provide a simple means with which to remove the geophony from recordings. Furthermore, weather events, such as high temperatures, can alter bird behaviours that are related to mating and signalling (Hovi 1995; Luther & Danner 2016). Time and space-matched acoustic-meteorological data may be an important step in understanding community-level behaviour in response to abiotic stimuli. Development of the ARUPI to detect bats is underway using a USB powered ultrasonic microphone and when successful they may be incorporated into the Norfolk Bat Monitoring Project outlined in Newson, Evans & Gillings (2015). There are also plans to build some ARUPIs with volunteers from a small Sheffield based charity, Heeley City Farm, in order to map the acoustic diversity across the farm site and introduce people to the Raspberry Pi, soundscape ecology and the outdoors.

6.8 Conclusions and Future Directions in Soundscape Ecology

The incorporation of sound propagation models into acoustic analysis may improve our understanding of soundscape composition. Since it is clear that sound propagation is an important driver of evolutionary divergence and convergence (Kuczynski *et al.* 2010; Tobias *et al.* 2010) it will no doubt be an important factor when exploring evidence for the acoustic niche hypothesis (Krause 1987). For example, in chapter four, BAI was higher when ARUPI units were attached to larger trees. This finding is likely due to a larger tree being indicative of an older, more structurally complex stand, but it may also be due to reverberations of sound waves on the tree trunk. Investigating the nature of sound propagation in the context of soundscape composition may provide important insights into how acoustic indices can be interpreted. The acoustic indices used in this study are conceptually straightforward in their computation. There are other developments using unsupervised machine learning algorithms to categorize different habitats based on their soundscape signature (Bormpoudakis, Sueur & Pantis 2013) or as an alternative means of estimating species-richness (Eldridge *et al.* 2016). No doubt more complex computational methods can and will be developed. For example, it may be possible to combine the use of multiple acoustic indices (as suggested by Towsey *et al.* (2014); and Xie *et al.* (2017)) with techniques used in other bioacoustics fields, such as using microphone arrays to detect distance and direction of sound sources (Blumstein *et al.* 2011; Mennill *et al.* 2012). Or using generalized Random

Encounter Models (Lucas *et al.* 2015) to estimate abundance of call-types, perhaps incorporated with an unsupervised automated call-recognition algorithm (Stowell & Plumbley 2014). These developments are conceptually possible and will no doubt add an extra dimension to current acoustic index calculation methods. However, in the meantime it is also important to collect field-recordings alongside detailed vegetation structural measures. There is a strong focus towards species-estimation which should not become the sole-focus of the field. Determining the relationship between the soundscape and the structural habitat and wider landscape should also be a priority due to the nature of sound propagation and attenuation through different structural landscapes. The findings in this study suggest that further research using NDSI as a tool for modelling road-noise in different habitats and investigating its effects on wildlife might be particularly useful. With further developments on these suggested research topics, soundscapes may become important tools that will inform both conservation initiatives and landscape planning.

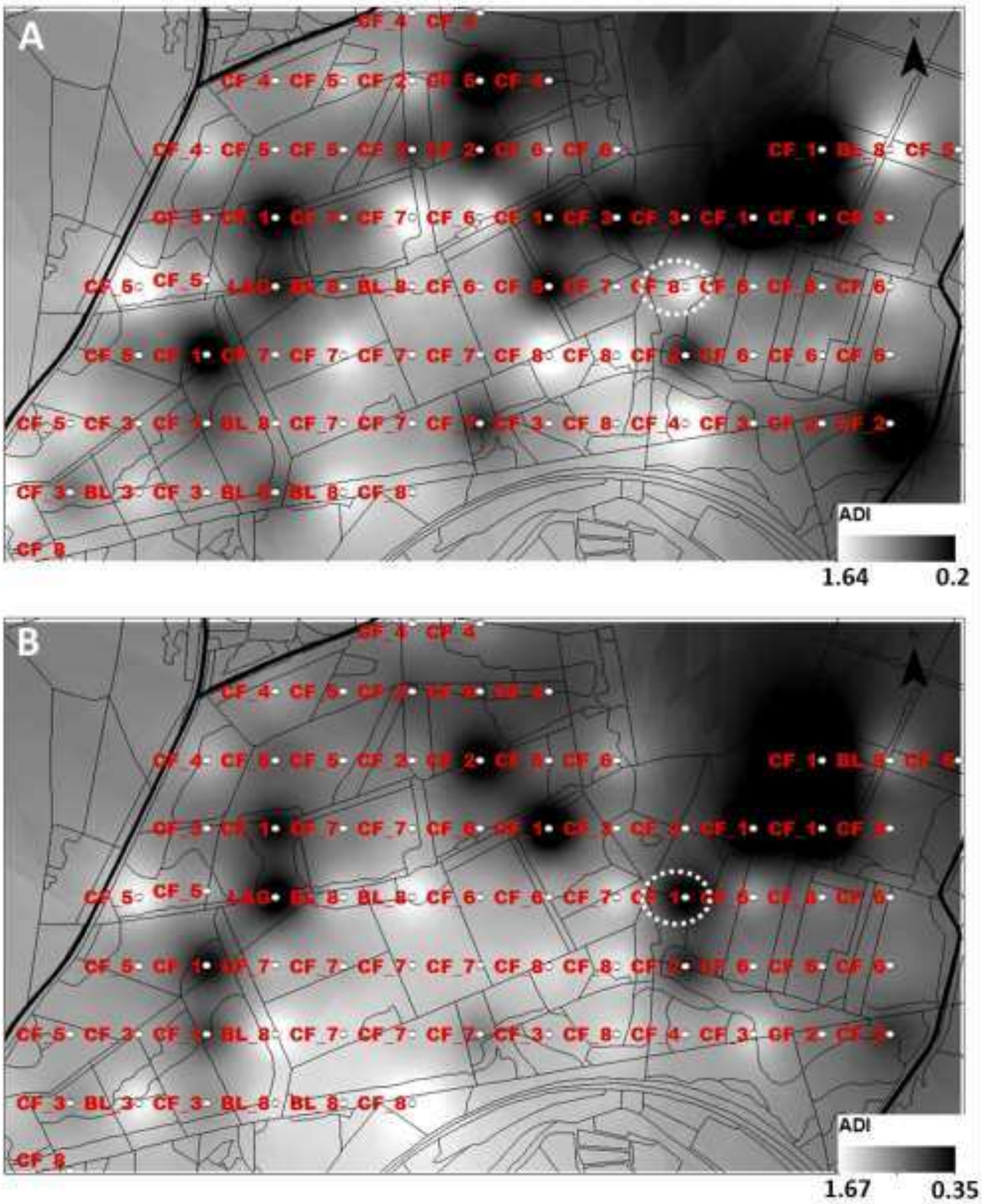
Appendices

Appendix – Chapter 2

Appendix 2.1. Correlation matrix showing intra-set correlations between environmental variable and three ordination axes of the CCA. **Bold** values show positive relationships.

Variable	Axes 2014			Axes 2015		
	1	2	3	1	2	3
TRDN	-0.303	**0.177**	**0.544**	-0.028	**0.016**	**0.916**
TRSp	**0.805**	**0.364**	**0.375**	-0.932	-0.184	-0.122
CNHT	**0.749**	**0.099**	**0.001**	-0.486	-0.386	**0.36**
CCVR	**0.2**	**0.541**	**0.469**	-0.37	-0.275	**0.594**
GCHT	**0.489**	-0.087	-0.681	-0.284	**0.631**	-0.404
GCDV	**0.407**	-0.207	-0.846	**0.462**	-0.329	-0.647
0-1KHz	-0.325	**0.133**	-0.146	**0.511**	-0.076	-0.165
1-2KHz	-0.309	-0.190	**0.185**	**0.260**	**0.125**	**0.277**
2-3KHz	**0.820**	-0.448	-0.100	-0.322	**0.266**	**0.419**
3-4KHz	**0.199**	-0.555	**0.310**	-0.734	**0.239**	-0.142
4-5KHz	**0.690**	-0.165	-0.209	-0.687	**0.219**	-0.276
5-6KHz	**0.649**	-0.008	-0.292	-0.638	**0.241**	-0.250
6-7KHz	**0.636**	**0.101**	-0.144	-0.633	**0.121**	-0.195
7-8KHz	**0.552**	**0.736**	**0.218**	-0.607	-0.622	**0.196**
8-9KHz	**0.528**	**0.986**	**0.597**	-0.699	-1.111	**0.275**
9-10KHz	**0.593**	**0.809**	**0.527**	-0.681	-0.596	-0.498

Appendix 2.2 Interpolation maps of ADI values across the study grid.



A) 2014 data. B) 2015 data. Darker areas indicate lower acoustic diversity. Site labels are those used in CCA analysis and a key can be found in table 2.1 in main body of text. These maps highlight how the acoustic diversity of the area displayed a similar pattern in both years. The dotted circular line (in both maps) shows site 63, which was felled between sampling years and so displayed major changes in the soundscape. These maps highlight the potential for using such sound-mapping techniques for monitoring change between years. Further research into selecting appropriate resolutions in different habitats is key to optimising performance of such tools.

Appendix – Chapter 4

Appendix 4.1 Table showing land-use and habitat types in Bedgebury Forest.

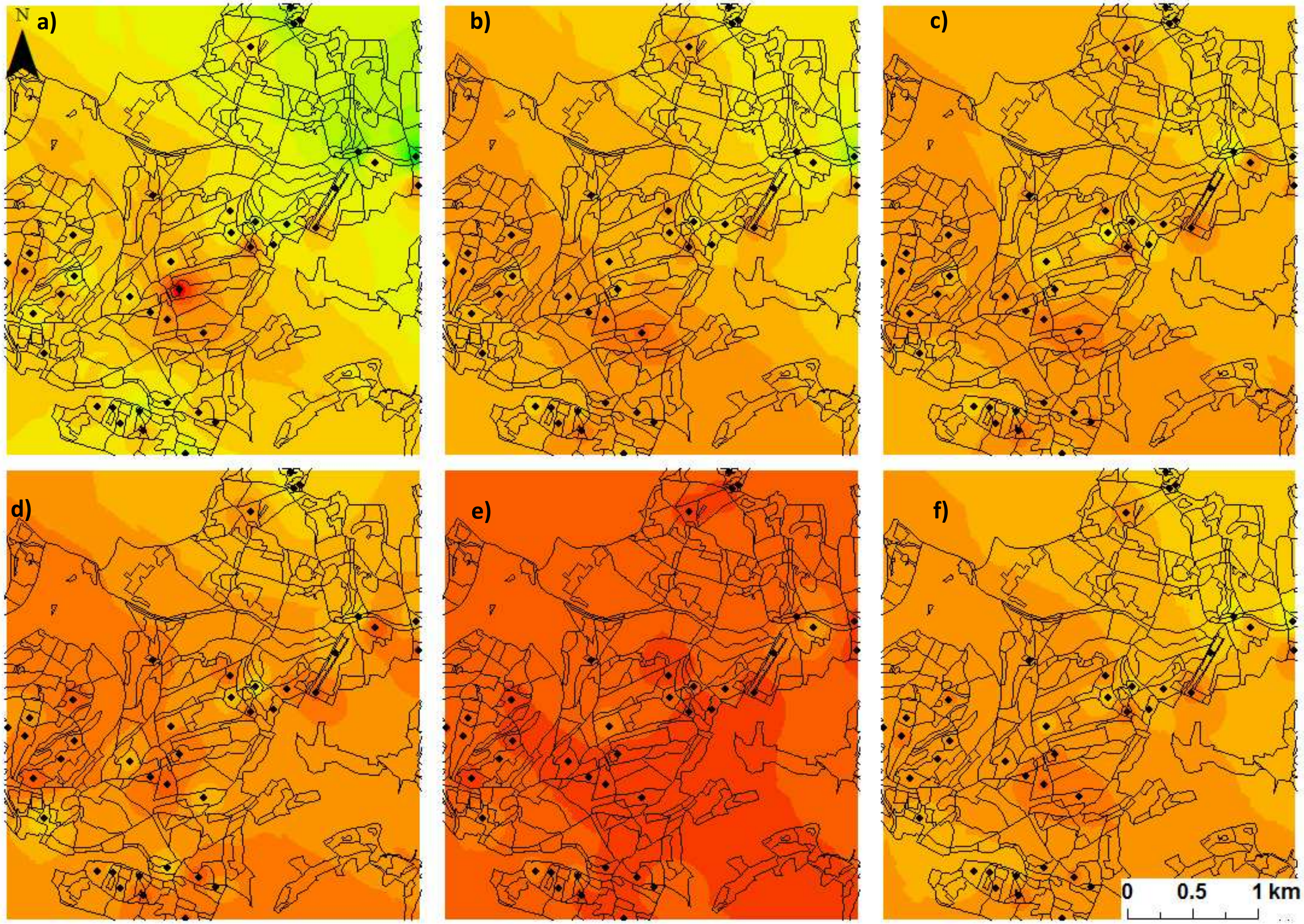
Land Use/*Habitat Type*	**Total Area (m^2)**	**% Cover**
Arboreta	**565969**	**6.35**
BROADLEAVED; MIXED/YEW WOODLANDS	*565969*	*6.35*
Car Parks/Picnic Areas	**54948**	**0.62**
BUILT UP AREAS & GARDENS	*46555*	*0.52*
UNKNOWN	*8393*	*0.09*
Christmas Trees	**78542**	**0.88**
CONIFEROUS WOODLANDS	*78542*	*0.88*
Deer glades	**2719**	**0.03**
BRACKEN	*1140*	*0.01*
UNKNOWN	*1579*	*0.02*
High Forest	**6534606**	**73.29**
Lowland Mixed Deciduous Woodland	*1065966*	*11.96*
BROADLEAVED; MIXED/YEW WOODLANDS	*702374*	*7.88*
CONIFEROUS WOODLANDS	*4766266*	*53.45*
Open	**38805**	**0.44**
Lowland Mixed Deciduous Woodland	*16931*	*0.19*
BOUNDARY & LINEAR FEATURES	*6840*	*0.08*
BROADLEAVED; MIXED/YEW WOODLANDS	*7862*	*0.09*
CONIFEROUS WOODLANDS	*7172*	*0.08*
Open Water	**29785**	**0.33**
STANDING OPEN WATER/CANALS	*29785*	*0.33*
Other Built Facility	**13174**	**0.15**
BUILT UP AREAS & GARDENS	*13174*	*0.15*
Other Recreation	**13620**	**0.15**
UNKNOWN	*13620*	*0.15*
Residential	**2966**	**0.03**
BUILT UP AREAS & GARDENS	*2966*	*0.03*

Appendix 4.1. continued.

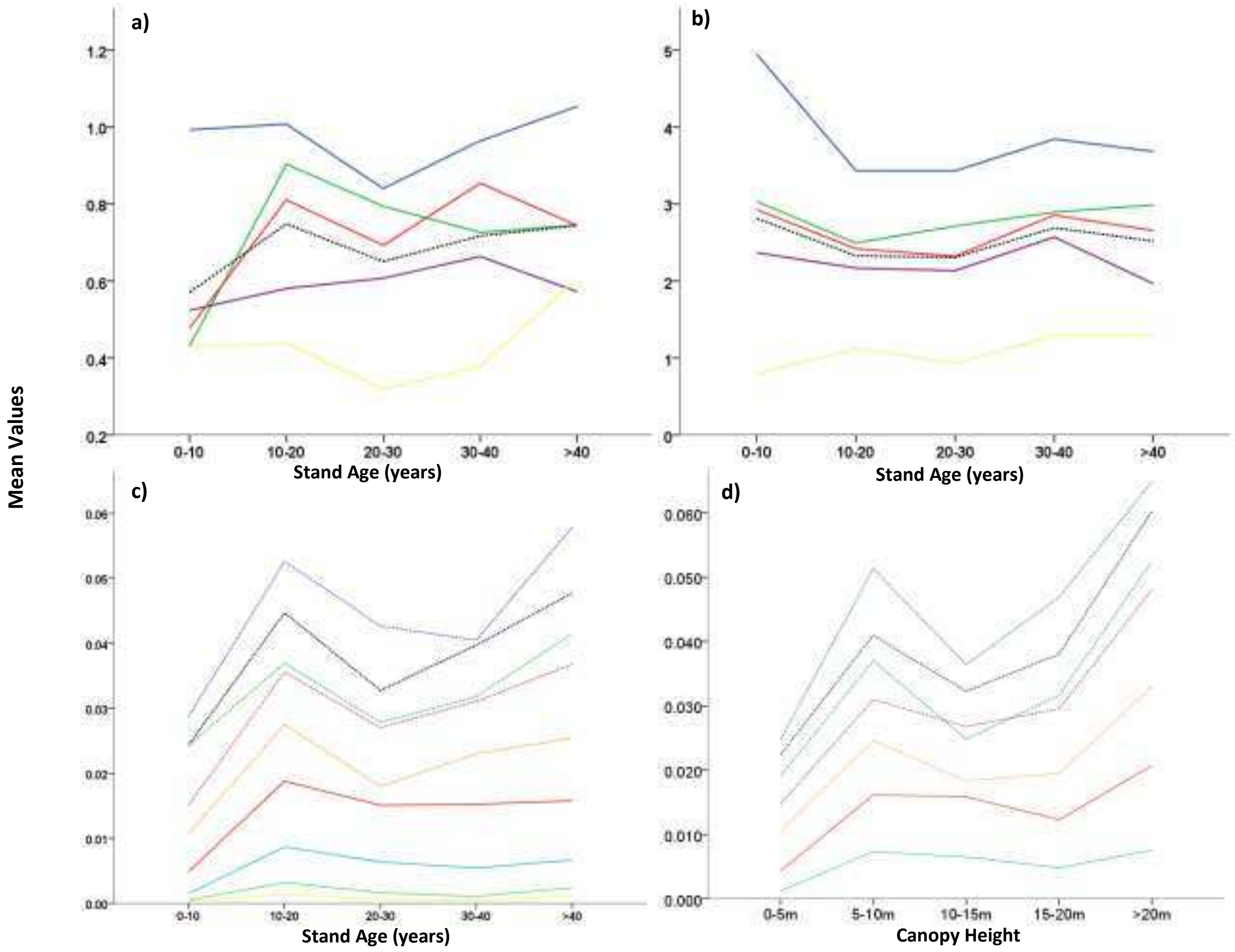
Land Use/Habitat Type	Total Area (m2)	% Cover
Unplantable or bare	**11374**	**0.13**
CONIFEROUS WOODLANDS	*11374*	*0.13*
Worked Coppice	**1569961**	**17.61**
Lowland Mixed Deciduous Woodland	*11656*	*0.13*
BROADLEAVED; MIXED/YEW WOODLANDS	*1558305*	*17.48*
Total Area (m^2)	**8916469**	

Appendix 4.2. List of primary tree species found in 100m buffer zones around all sampling points (N=40)

Tree Type	**Total Area (m^2)**
Not Planted	29651
Ash	720
Beech	4437
Birch (downy/silver)	10433
Corsican pine	178475
Douglas fir	14151
European larch	2569
Hybrid larch	5403
Hybrid poplar	136
Japanese cedar	10586
Japanese larch	3766
Mixed broadleaves	25332
Norway spruce	3069
Oak (robur/petraea)	43738
Scots pine	99488
Sweet chestnut	771665
Sycamore	196
Western hemlock	4484



Appendix 4.3. Interpolation maps indicating mean BAI values in Bedgebury forest at different times of the day. a)Period 1 04:00 – 10:00; b) Period 2 10:00 – 15:00; c) Period 3 15:00-20:00; d) Period 4 20:00 – 22:00; e) = Period 5 22:00 – 04:00; f) mean values across all periods. The brightest green areas indicate BAI values of between 8 – 8.5; Dark red values indicate BAI values of 0 - 0.5.



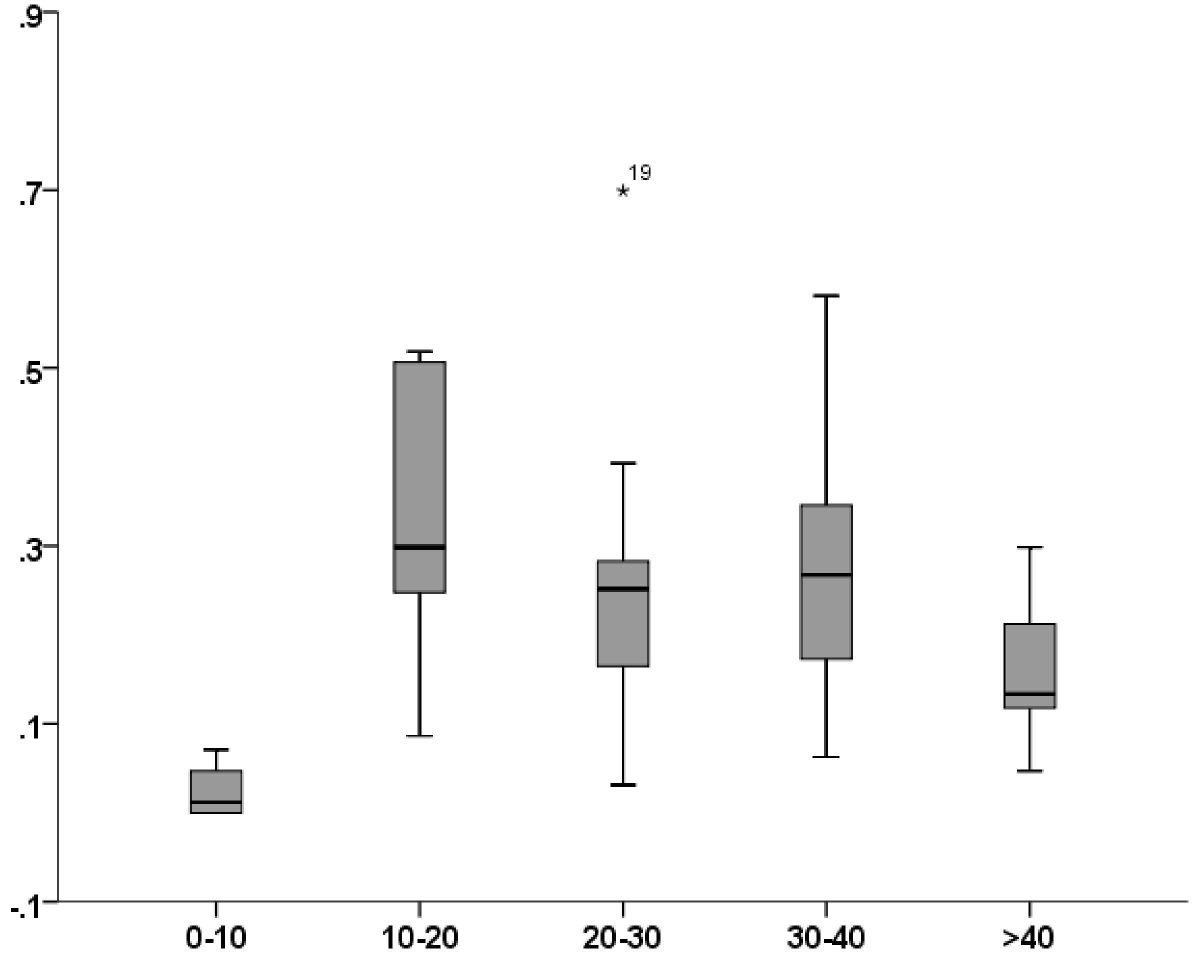
Appendix 4.4. Means plots indicating trends in ADI (a) and BAI (b) across different aged forest stands (in years) at different times during the day. Blue line = 04:00-10:00; Green line = 10:00-15:00; Red line = 15:00-20:00; Purple line = 20:00-22:00; Yellow line = 22:00-04:00; Black dotted line indicates mean values across all periods. c) Means plot indicated mean proportion of sound energy in nine 1 KHz frequency bands. Dotted lines key: Dark Blue = 2-3 KHz; Green = 3-4 KHz; Black 4-5 KHz; Purple = 5-6 KHz; Orange = 6-7 KHz. Solid lines key: Red = 7-8 KHz; Light Blue = 8-9 KHz; Light Green = 9-10 KHz; Yellow = 10-11 KHz. The dotted bands represent the majority of avian vocalisations in UK woodland. NB: 1-2 KHz frequency band not included as it alters the scale and affects visual interpretation of these bands. Interestingly frequency band 1-2 KHz follows a similar pattern to the other bands up until stands aged 20-30 years, but beyond 30years it continues to decline potentially indicating that the effects of road noise and technophony becomes somewhat moderated. d) Mean frequency band values across different canopy heights. Although not statistically significant, mean values look to be increasing with canopy height. Frequency band colours are as with figure c, but the top two bands (9-11KHz) are not included.

Appendix 4.5. Spearman correlations between vegetation structural variables, including stand age. * p-value < 0.05 **p-value <0.01. See table 4.1 for codes.

	VH	VC	VS	VSQ	CO	CH	TT	TD	SD	SDW	BA	DWf	DWs	DW	DBH
Age	-.470**	-.258	.279	.189	-.205	**.728****	-.195	.301	**.392***	.254	.020	.070	.001	.059	.365*
VH	1.000	**.832****	.311	**.496****	**.629****	**-.423****	.227	-.156	**-.375***	-.102	.013	-.163	-.070	-.055	-.139
VC	**.832****	1.000	.308	**.523****	**.657****	-.298	.062	-.126	-.232	-.043	.009	-.058	-.182	-.141	-.043
VS	.311	.308	1.000	**.819****	**.394***	.050	-.026	.188	**-.374***	-.031	-.266	-.247	-.249	-.218	-.094
VSQ	**.496****	**.523****	**.819****	1.000	**.504****	-.008	-.161	.180	-.268	-.011	**-.327***	-.196	-.185	-.107	.050
CO	**.629****	**.657****	**.394***	**.504****	1.000	-.278	-.160	-.127	-.172	.049	**-.354***	.049	-.162	-.059	.174
CH	**-.423****	-.298	.050	-.008	-.278	1.000	-.311	**.414****	**.617****	.444**	.129	.108	.007	.087	**.441****
TT	.227	.062	-.026	-.161	-.160	-.311	1.000	-.138	**-.335***	-.218	**.514****	-.089	.311	.171	**-.435****
TD	-.156	-.126	.188	.180	-.127	**.414****	-.138	1.000	.096	.280	-.075	.116	-.102	.031	.008
SD	**-.375***	-.232	**-.374***	-.268	-.172	**.617****	**-.335***	.096	1.000	**.563****	**.324***	**.422****	**.413****	**.470****	**.558****
SDW	-.102	-.043	-.031	-.011	.049	**.444****	-.218	.280	**.563****	1.000	.195	**.562****	.310	**.472****	.308
BA	.013	.009	-.266	**-.327***	**-.354***	.129	**.514****	-.075	**.324***	.195	1.000	.102	**.457****	**.340***	-.119
DWf	-.163	-.058	-.247	-.196	.049	.108	-.089	.116	**.422****	**.562****	.102	1.000	.065	.273	.298
DWs	-.070	-.182	-.249	-.185	-.162	.007	.311	-.102	**.413****	.310	**.457****	.065	1.000	**.915****	.010
DW	-.055	-.141	-.218	-.107	-.059	.087	.171	.031	**.470****	**.472****	**.340***	.273	**.915****	1.000	.146
Rh	.006	.010	-.018	.068	-.096	.030	.087	**.342***	-.112	-.059	-.004	**-.360***	-.064	-.110	-.252
DBH	-.139	-.043	-.094	.050	.174	**.441****	**-.435****	.008	**.558****	.308	-.119	.298	.010	.146	1.000

Appendix 4.6. Spearman correlations between landscape metrics.* p-value < 0.05 **p-value <0.01. See table 4.1 for codes.

	Age	AG	AVA	EDS	RD	A_rd	B_rd	WD	RR	AH	SH	HH	EDN	%Rec	%BL	%CF	%WC	%OA	%OW
Age	1.000	**.976****	.253	-.043	.225	.223	.197	-.076	-.165	-.049	.124	.080	-.155	.056	-.174	.145	-.107	-.187	.144
AG	**.976****	1.000	.226	-.055	.175	.224	.218	-.039	-.209	-.040	.136	.071	-.153	.008	-.157	.142	-.109	-.123	.156
AVA	.253	.226	1.000	-.243	.231	.193	.202	-.019	**-.357***	.125	.511**	.340*	.016	-.062	.171	**.560****	**-.481****	-.094	-.185
EDS	-.043	-.055	-.243	1.000	-.004	-.208	**-.395***	**.387***	.223	**-.721****	**-.659****	**-.794****	**-.649****	**-.317***	**-.569****	**-.413****	**.756****	-.083	-.038
RD	.225	.175	.231	-.004	1.000	**.358***	.056	-.289	.146	.045	.086	.080	.054	.040	-.085	.071	-.062	-.196	.065
A_rd	.223	.224	.193	-.208	**.358***	1.000	**.814****	-.074	**-.454****	**.351***	**.506****	**.385***	.262	.256	-.203	**.477****	**-.445****	.195	.310
B_rd	.197	.218	.202	**-.395***	.056	**.814****	1.000	-.129	**-.390***	**.468****	**.610****	**.518****	.217	**.385***	.022	**.437****	**-.538****	.297	.307
WD	-.076	-.039	-.019	**.387***	-.289	-.074	-.129	1.000	-.119	-.307	-.242	**-.451****	-.214	**-.527****	**-.576****	.157	.239	.082	**-.383***
RR	-.165	-.209	**-.357***	.223	.146	**-.454****	**-.390***	-.119	1.000	-.303	**-.587****	**-.407***	-.303	-.050	-.056	**-.564****	**.508****	-.198	-.273
AH	-.049	-.040	.125	**-.721****	.045	**.351***	**.468****	-.307	-.303	1.000	**.658****	**.728****	**.674****	**.507****	**.426****	**.343***	**-.661****	.157	.298
SH	.124	.136	**.511****	**-.659****	.086	**.506****	**.610****	-.242	**-.587****	**.658****	1.000	**.909****	**.400***	**.491****	**.342***	**.698****	**-.935****	.255	.297
HH	.080	.071	**.340***	**-.794****	.080	**.385***	**.518****	**-.451****	**-.407***	**.728****	**.909****	1.000	**.535****	**.598****	**.540****	**.513****	**-.895****	.229	**.326***
EDN	-.155	-.153	.016	**-.649****	.054	.262	.217	-.214	-.303	**.674****	**.400***	**.535****	1.000	.119	**.502****	.311	**-.534****	.016	**.323***
%Rec	.056	.008	-.062	**-.317***	.040	.256	**.385***	**-.527****	-.050	**.507****	**.491****	**.598****	.119	1.000	**.336***	-.101	**-.398***	-.070	**.364***
%BL	-.174	-.157	**.171**	**-.569****	-.085	-.203	.022	**-.576****	-.056	**.426****	**.342***	**.540****	**.502****	**.336***	1.000	-.070	**-.426****	.015	.197
%CF	.145	.142	**.560****	**-.413****	.071	**.477****	**.437****	.157	**-.564****	**.343***	**.698****	**.513****	.311	-.101	-.070	1.000	**-.747****	.180	.147
%WC	-.107	-.109	**-.481****	**.756****	-.062	**-.445****	**-.538****	.239	**.508****	**-.661****	**-.935****	**-.895****	**-.534****	**-.398***	**-.426****	**-.747****	1.000	-.218	-.238
%OA	-.187	-.123	-.094	-.083	-.196	.195	.297	.082	-.198	.157	.255	.229	.016	-.070	.015	.180	-.218	1.000	-.107
%OW	.144	.156	-.185	-.038	.065	.310	.307	**-.383***	-.273	.298	.297	**.326***	**.323***	**.364***	.197	.147	-.238	-.107	1.000



Appendix 4.7. Boxplot indicating significant differences in standing deadwood volumes in different aged-stands (Kruskal-Wallis $\chi^2_{(4)}$=14.465, p=0.006). These differences are likely explained by a change in coppice management either due to Bedgebury forest restoration initiative or a reduction in market demand for chestnut coppice fence palings, or a combination of those two factors.

Appendix – Chapter 5

Appendix 5.1 - ARUPI Instructable

The following instructions were published on www.instructables.com on September 16th 2015 and are accessible through the following URL:

https://www.instructables.com/id/ARUPi-A-Low-Cost-Automated-Recording-Unit-for-Soun/

Introduction

This instructable was written by Anthony Turner. The project was developed with lots of help from the Shed in the School of Computing, University of Kent (Mr Daniel Knox in particular was a great help!).

It will show you how to build an Automated Audio Recording Unit for less than £150. You can use this unit to conduct research in the field of Soundscape Ecology (which is why I built this). You could use it to monitor the birds in your garden or just to make nice recordings of the dawn chorus, without having to get up really early.

The ARUPi (Automated Recording Unit Pi) uses the Raspberry Pi computer and an Arduino-based power-control board called the Sleepy Pi. It is fully customisable and you will be able to add different environmental sensors to the units if you wish (not explained here). This instructable will give you a bare-bones unit. I will provide you with an Arch Linux operating system (OS) that is stripped down and has the recording program pre-installed on it.

You may need to do some (very simple) soldering so be prepared for this, but it is possible to build this unit without soldering if you do not own or cannot afford a soldering iron (ca. £10). I will split this instructable into several steps. The first ## steps will deal with getting the software onto your ARUPi and getting the computer side of things up and running (uploading software to Raspberry Pi and Sleepy Pi). Once you have done this, you will be able to go your own way and decide which microphones and casing you want to use. If you want to make what I have made, then continue with the instructable and it will show you how to build some cheap (but good) microphones and assemble some field-tested, fully waterproof, pretty robust ARUPi's (pictured).

Step 1 - Items Needed

a) Raspberry Pi A+ (case optional) - get it from PiMoroni/Ebay/Amazon (figure 1).

b) Sleepy Pi - http://spellfoundry.com/products/sleepy-pi/ (figure 1)

c) Sleepy Pi programmer - http://spellfoundry.com/products/sleepy-pi-program...

   i. This programmer saves a lot of hassle. However, you can build your own for less money if you buy an FTDI 3.3V USB to TTL Arduino Programmer cable/board (http://spellfoundry.com/sleepy-pi/programming-sleepy-pi-standalone-board/). If you are new to programming I recommend buying the Sleepy Pi Programmer.

d) 16GB Kingston Data Traveler Micro (figure 1). You need to format the USB drive to NTFS before plugging it into your Raspberry Pi (format USB using Windows Explorer – figure 2). If you decide to use a different make/model USB storage device, you may need to change some information in the /etc/fstab system files on the ARUPi OS I supply you with. The OS I provide you with mounts the **16GB Kingston Micro DT** to sda1.

e) USB soundcard. I chose the **Creative Soundblaster Play!** (figure 1) because it records 16bit Stereo; 48KHz sampling rate. It is also compatible with the Raspberry Pi and doesn't need any extra drivers - plug and play. However, there are cheaper USB soundcards available so it might be worth investigating.

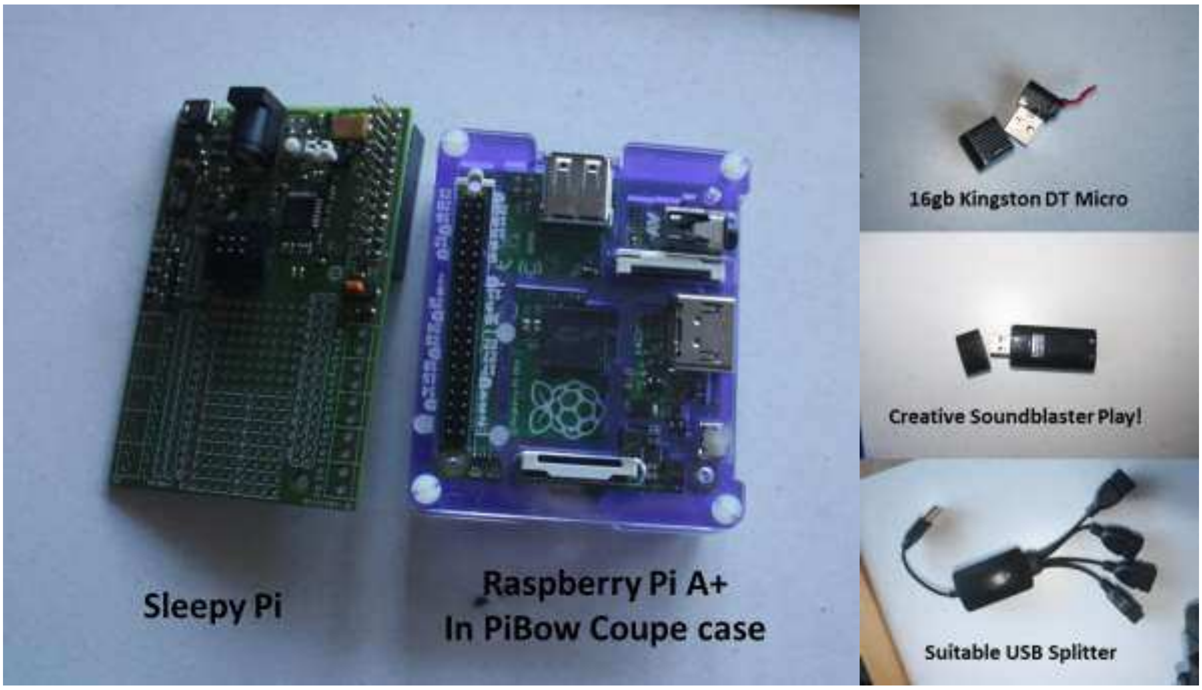
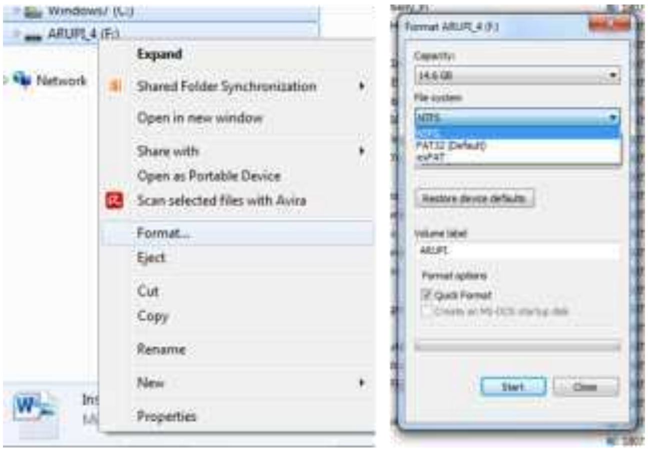


Figure 1. Core hardware items needed to build the ARUPI. The soundcard and USB splitter can be interchanged with other makes/models. The Kingston DT Micro can be interchanged as well but you will need to see Step 5 for enlightenment on how to enable your ARUPI to read a different make/model.



Capacity: 14.6 GB

File system: NTFS

Volume label: ARUPI

☑ Quick Format

☐ Create an MS-DOS startup disk

Figure 2. Format USB drive to NTFS file format – right click on the USB drive in Windows explorer; select <Format>; File System = <NTFS>; <Start>. This step is important.

Step 2 – Software Needed

a) Download and install Win32 Disk Imager® software from http://sourceforge.net/projects/win32diskimager/

b) Install Arduino IDE software onto your computer: https://www.arduino.cc/en/Main/Software

c) Collect the operating system (OS) and other relevant files from my GoogleDrive Account by following this link:

https://drive.google.com/folderview?id=0BxoTy4JIKn...

d) The link should take you to a googledrive shared folder I created. It contains:

   i. the Operating System you need (ARUPi_240415). This file is 7.32GB so may take a while to download. GoogleDrive will also state that it cannot scan the file to check it is safe as it is too large. Don't worry about that - the file is virus free (it is an image of an Arch-Linux Operating System).

   ii. The Folder labelled "Sleepy_Pi" contains "_15min_Pi" (a program that tells the Sleepy Pi to wake the Raspberry Pi every 15 minutes) and a folder called Libraries. You need to save these files into the "Arduino" folder that should be found in the My Documents folder on your computer (assuming you have installed Arduino IDE.

   iii. A more detailed Parts List (ARUPI_PARTS_INFO.xls) with some links to where you can buy some of the parts.

iv. A PDF document that covers step 5. I suggest following the PDFs as it is colour-coded and easier to follow.

Step 3 – Set up the Operating System

a) Write the OS disk image to your micro SD card using Win32 Disk Imager.

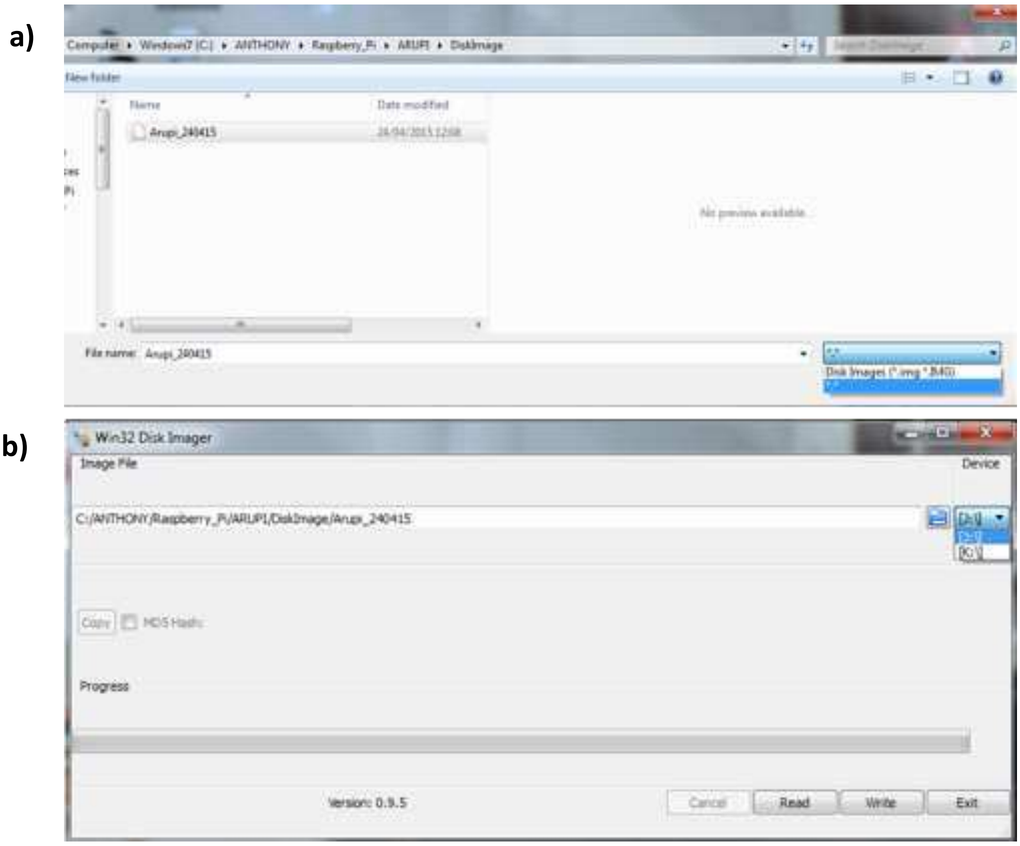
b) When selecting Arupi_240415, you need to change file type to *.* to make it visible (figure 3a).

c) Select the disk drive that corresponds to your micro SD card (figure 3b)

   i. I always make sure I only have my SD card plugged in to avoid accidentally formatting an external HDD or other USB device.

d) Now click the “Write” button

   i. This will write the disk image to the device.



File name: Arupi_240415

Image File: C:/ANTHONY/Raspberry_Pi/ARUPI/DiskImage/Arupi_240415

Figure 3. a) Change file type to make Arupi_240415 visible. b) Select file path that corresponds to your micro sd card.

Step 4 – Program the Sleepy Pi

The Sleepy Pi is one of the most important pieces of kit for this unit. It turns the Raspberry Pi on and off to a schedule that you choose. Therefore, you need to tell the Sleepy Pi what you want it to tell the Raspberry Pi to do.

a) The Sleepy Pi has an onboard Arduino microcontroller, on which instructions can be installed. To do this you need to have installed the Arduino IDE software.

b) Download the entire Sleepy_Pi folder from the GoogleDrive link on the previous step. Place the "_15min_Pi" file and "libraries" folder in the "Arduino" folder created in your "My Documents" folder (i.e. C:\Users\Ant\Documents\Arduino).

    i. Open the script "_15min_Pi.ino" in the Arduino IDE. This script is what you need to upload to the Sleepy Pi. It tells the Sleepy Pi to turn on your Raspberry Pi every 900 seconds (i.e. 15 minutes). You can change this schedule by modifying the following line (i.e. 1800 seconds would equal 30 minutes).

        i. int SYSTEM_SLEEP_TIME_IN_SECONDS = 900;

c) To verify that the script works click on the tick symbol just below the 'file' tab (figure 4a). If the script doesn't run properly, check that you have put all the libraries from my GoogleDrive into your Arduino folder (see above – step b).

d) Connect your Sleepy Pi to your computer and upload the _15min_Pi.ino script to the Sleepy Pi unit. If you have bought the programming unit from the Spell Foundry then follow the instructions given (install correct drivers etc etc). If you have your own FTDI programmer then use this webpage for guidance http://spellfoundry.com/sleepy-pi/programming-sle...

Step 4 In a nutshell:

- Connect the programmer to the GPIO pins of your Sleepy Pi and connect USB to your computer NB: Make sure you connect pins correctly (see webpage given above)!

- Plug in the power supply to your Sleepy Pi (micro USB OR via barrel jack)

- Open "_15Min_Pi" (or your modified script) in Arduino IDE.

- Select Arduino Fio as your board (figure 4b)

- Upload your script to the Sleepy Pi by pressing the "upload" arrow next to the tick.

- If it doesn't work then check the COM Port is correct (figure 4c). You might have to reinstall the drivers for your FTDI serial programmer.

To verify that this script works and you have all the necessary libraries click on the

Select Arduino Fio board as shown.

Select correct COM port. It should detect this automatically, but if it doesn't you might need to reinstall the correct drivers for your device!

Figure 4. a) Checking the script works. b) Selecting the Arduino FIO board. c) Troubleshooting serial port.

Step 5 - Sleepy Pi/Raspberry Pi Connections

IMPORTANT

- **FORMAT USB DRIVE TO NTFS FILE SYSTEM – THE ARUPI OS IS PROGRAMMED TO AUTOMATICALLY INSTALL THE NTFS USB DRIVE. IT WILL NOT WORK IF THE DRIVE IS USING ANOTHER FILE SYSTEM**
- **UPLOAD PROGRAM ONTO SLEEPY PI BEFORE FOLLOWING THESE INSTRUCTIONS**

To install the time on the Sleepy Pi and get it to talk with your Raspberry Pi you must follow these instructions for **each** unit you build.

a) Insert a CR1632 battery into the Real Time Clock (RTC) slot on the Sleepy Pi (figure 5)

b) Plug Sleepy Pi into GPIO pins on the Raspberry Pi as shown in image (figure 5).

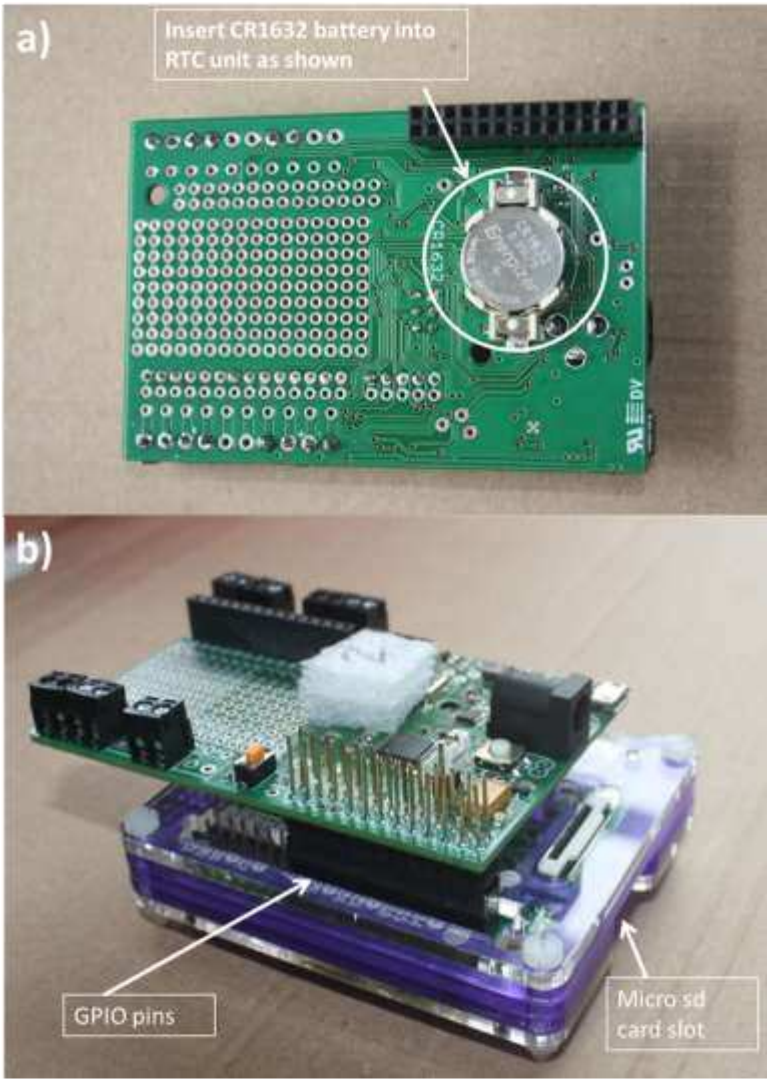


Figure 5. a) Install RTC battery on Sleepy Pi. b) Connect Sleepy Pi to Raspberry Pi.

c) Plug in your usb port splitter and plug in the soundcard, your USB storage device and a keyboard (figure 6 –step 1).

d) If you have a network cable (ethernet), plug it into the Raspberry Pi ethernet port now. Don’t worry if you don’t have one, the instructions will explain all.

e) Plug in a HDMI cable into the Raspberry Pi HDMI socket to connect to your monitor/TV .

f) Ensure the power bypass switch is set to override the Sleepy Pi program (figure 7)

g) Plug the power supply into the micro USB power socket on the **Sleepy Pi** (figure 6 **– step 2**).

h) The Raspberry Pi should boot up (if it doesn’t boot up see note at end of this section).

i. Type in the username: **root** and the password: **root**.

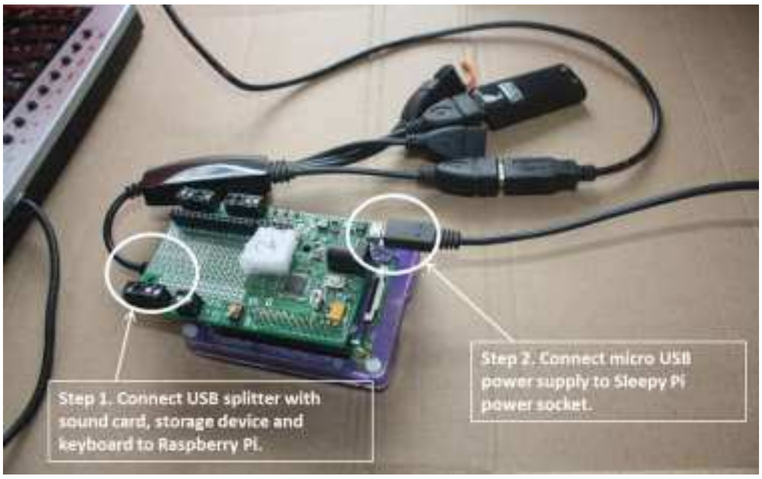


Figure 6. Step 1 indicates where to plug the USB splitter in. Step 2 indicates where to plug power in to power the Raspberry Pi through the Sleepy Pi unit.

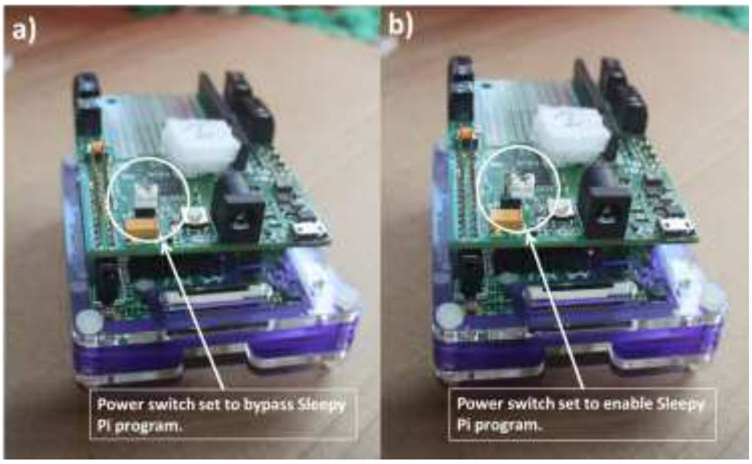


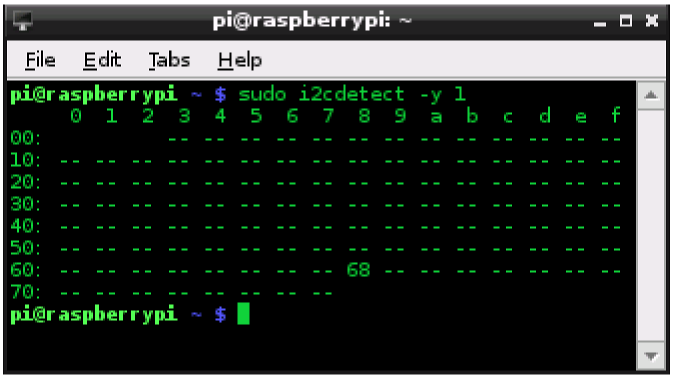
Figure 7. a) How to bypass Sleepy Pi programming to ensure immediate power to Raspberry Pi. b) How the bypass switch should look when placing your finished unit out in the field.

Step 6 - Accessing the sleepy pi clock:

a) Type:

```
i2cdetect -y 1 <enter>
```

The following screen should come up after you press enter



```
pi@raspberrypi ~ $ sudo i2cdetect -y 1
     0  1  2  3  4  5  6  7  8  9  a  b  c  d  e  f
00:          -- -- -- -- -- -- -- -- -- -- -- -- --
10: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
20: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
30: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
40: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
50: -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --
60: -- -- -- -- -- -- -- -- 68 -- -- -- -- -- -- --
70: -- -- -- -- -- -- -- --
pi@raspberrypi ~ $
```

If that doesn’t work try:

i2cdetect -y 0 <enter>

(If that doesn’t work then shutdown Raspberry Pi (type: shutdown) and check you have properly installed the Sleepy Pi onto the Raspberry Pi unit)

If the RTC is detected but the entry at 0x68 is “UU” not “68” then you need to unload the drivers from that address. To do this type:

rmmod rtc-ds1374 <enter>

Now try the i2cdetect command again and you should get the same output as the image above.

The RTC will be detected with the address 0x68.

Note: Remember which **i2cdetect** command worked (i.e. **–y 0** or **–y 1**) as you need to enter **/i2c-0/** or **/i2c-1/** depending on which one worked, in the line after next (highlighted in blue).

b) Now type the following:

modprobe rtc-ds1374 <enter>

/bin/bash -c "echo ds1374 0x68 > /sys/class/i2c-adapter/i2c-1/new_device" <enter>

If you get error messages check very carefully that you have entered exactly what is above.

c) Now check the time on the RTC by typing:

hwclock –r <enter>

It won’t be the correct date.

d) Upload the correct time to the Sleepy Pi RTC. If you have a network cable connected to your Raspberry Pi simply type:

```
hwclock –w <enter>
```

If you don’t have a network cable you have to set the time on your Raspberry Pi. To do this type the following:

```
date –s “dd MTH yyyy hh:mm:ss” <enter>
```

eg. `date –s “15 MAR 2015 18:33:46”` **<enter>**

Now type: `hwclock –w` **<enter>**

e) Now check the time on the RTC by typing

```
hwclock –r <enter>
```

If the time is incorrect, try repeating the necessary steps carefully – it is easy to miss things.

Step 6 NOTE: If the Raspberry Pi Didn’t boot up properly

If you are using a different USB storage device to the one I have recommended it might affect the way the Raspberry Pi boots up. If it does, you will be taken to a command that says type password or D to continue as administrator. This is because this OS is set up to automatically mount the Kingston DT micro 16GB USB stick.

- Type `blkid` <enter>
- Something similar to this should appear

```
/dev/sda1: LABEL=”System Reserved” UUID=”36423FA6423F6A2F” TYPE=”ntfs”
/dev/sda2: UUID=”B6DA024DDA0209F7” TYPE=”ntfs”
/dev/sda3: UUID=”08D44A70D44A5FD4” TYPE=”ntfs”
/dev/sda4: UUID=”f2025d4a-ab25-41de-a530-285f5b979cd0” TYPE=”ext4”
/dev/sdb: UUID=”6ABB-232A” TYPE=”vfat”
```

- Identify your USB drive from the list and make a note of the mount point “`/dev/sda?`” that corresponds to it.
- Now type `nano /etc/fstab` <enter>

- Modify the line that contains /mnt/arupi so that the /dev/sda1 corresponds to the ID/mount point of your USB drive.

Step 7 - Modifying the recording script and Activating the ARUPi

a) Now set your desired recording lengths by typing the following:

```
nano  /root/recordTest.sh <enter>
```

The first few lines that are preceded with"#" are some instructions/information about what is in this file – the # prevents the computer from running the information following it (much like in R, if you are familiar with that language). Basically, the last two digits on the script (the line that isn't preceded with a #) indicate recording length in seconds. The default setting is to record for 60 seconds. So if you want to make two minute recordings delete **60** and change it for **120** (for three minute recordings **180** etc).

b) Finally set the Raspberry Pi to start recording automatically when the Sleepy Pi wakes it up. Type the following:

```
export EDITOR=nano <enter>
crontab –e <enter>
```

The following lines will appear in the **nano** editor:

```
# @reboot /root/setClock.sh &
# @reboot python /root/recordPi.py &
```

These lines are essentially your recording program. At the moment, these lines are not active when the Raspberry Pi boots up. You need to delete the **#** in order to activate them.

@reboot /root/setClock.sh & sets the Raspberry Pi's clock to be the same as the RTC on the Sleepy Pi.

@reboot python /root/recordPi.py & runs a program using python software that makes the Raspberry Pi record for 60seconds when it is booted up and then shuts the Raspberry Pi down.

NOTE: Do not delete the **#** from the first 6 lines on this page – these are just re-iterating the instructions you should follow. Once you have deleted the two # symbols required, your ARUPi is ready to go.

Now press **<ctl> x** to exit nano. It will ask you if you would like to save the changes you made press:

y and **<enter>** for yes

n and **<enter>** if you want to start afresh (in case you accidentally deleted everything or made a mistake but can't remember what it was).

NOTE: when your Raspberry Pi boots up from now on it will automatically run these two files. If you wish to alter anything (i.e. recording length), you will need to reverse what you have just done by placing # at the beginning of the two lines in crontab manager, save the crontab file and then type **reboot** at the command line. You need to do all of this before the pi shuts itself down again (i.e. you have to type fast if your set recording length is one minute or less). If you cannot type fast enough to do that, you can boot up your Pi without the USB stick plugged in. This will log you in as an administrator and you can modify the pi as you like, without having to rush! Also remember to re-activate the Pi (i.e. delete the #s) when you intend to use it in the field.

c) Shutdown the Raspberry Pi by typing:

shutdown <enter>

There will be a delay of around one minute whilst the Raspberry Pi initiates the shutdown so just relax. Now you are ready to go and do some automated audio recording! Alternatively, you can type poweroff <enter> to shut it down more quickly.

d) Once the Raspberry Pi has shutdown, remove the power supply from the Sleepy Pi.

e) Readjust the power bypass switch to enable the Sleepy Pi to control the power to the Raspberry Pi (image **e**).

NOTE:

If you are making multiple units and you have changed anything in this step (i.e. altered the recording length or activated the ARUPi – i.e. deleted the 2 #s in crontab) then you might want to make a disk image of your current micro SD card. To do this, use Win32 Disk Imager to **read** the data from the card into a new image file (eg. MYARUPi_170915). You can then **write** the new image to your subsequent SD cards and they should all perform identically. NB: You will still need to set the time on all of your Sleepy Pi units using a Raspberry Pi.

Some Notes

a) **Progress Update** Now, when you plug a power supply into the Sleepy Pi, the timer on the Sleepy Pi will start counting down from 900seconds (or whatever length of time you stated in step 4).

b) After 900seconds, the Sleepy Pi will turn on the Raspberry Pi and the Raspberry Pi will record audio (WAV) for 60seconds (or whatever you stated). NOTE. If you don't have a microphone plugged into the Soundcard, the audio file will be 60seconds of no sound!

c) The file will be saved on your USB stick and will be labelled "ddmmyyhhmmss.wav" eg. 050715190559.WAV.

d) It is always worth running the unit from your chosen battery supply for a few hours to check the recordings are working OK. Sometimes if the power supply is too low, there can be interferences (beeps and clicks) in the recordings. This is also worth remembering when deploying your units for long periods – find out when the power from your chosen supply method drops to a level where it affects the audio. NOTE. The beeps and clicks mentioned don't seem to appear on any spectrograms so they are not a major problem, but they are an indication that your power supply has dropped or is too low!

e) Now you can mount your recording unit in a waterproof casing.

Step 7 – Final Push

a) You now have an automated recording unit. However, you still need a microphone and power supply. From here on you can use your creativity/research to put your stamp on the unit. But you do need the following three things!

b) Power Supply: - The Raspberry Pi requires at least 5V to function, but this unit requires more since it has several bits of kit attached to it. The Sleepy Pi can regulate a 5.5V to 17V power supply via the power jack to the Raspberry Pi. I used 8xAA (non-rechargeable-ca.2400mAh each) batteries (ca.12V total) to power my ARUPis. They could record one minute of audio, every 15 minutes for ca 7days. The barrel jack shown in the picture comes with the Sleepy Pi unit. - You will need: Battery holder (i.e. 8xAA) pp3 9v battery clip and lead In-line switch (optional - but makes life simpler in the field and reduces stress on plugs and sockets!)

c) Microphone - If you wish to build your own microphone, I recommend the Primo EM172 (or Primo BT EM-172). Please see the Microphone building PDF in my GoogleDrive to learn more about building your own Primo EM172 microphone. It really is quite simple.

d) Waterproof Enclosure - I recommend the one pictured, sold by Solent Plastics amongst other vendors on Ebay and Amazon. It is very robust and comes with modifiable foam inside and I can vouch for their performance in terms of ruggedness and waterproof-ness. However, you can use whatever enclosure you wish. A Lock and Lock tupperware style container would probably be OK. But it is worth getting together your entire ARUPi before buying a container as you need to know how much space you need.

Appendix 5.2. Equipment list for the ARUPI used in Chapter 4.

Item	Make	Model	Seller	UK £	Purpose/Notes
Raspberry Pi A+ with PiBow Coupe Case	Raspberry Pi	A+	PiMoroni/Amazon/ Ebay	25	The raspberry Pi A+ has the lowest power consumption of all the raspbery pis. The case is not essential but it just adds that extra bit of protection for the Pi and you can often buy them together. A Raspberry Pi A+ on its own can cost as little as £17.
8 gb micro sd card	any	class10		5	This is for the Operating System (OS) that will run the Raspberry Pi.
SleepyPi			www.spellfoundry.com	39	This unit controls the power to the Raspberry Pi and can be programmed to switch it on and off as required.
Coin-Cell Battery	Any	CR1632	Ebay/Amazon	1.5	This is for the Real Time Clock on the Sleepy Pi - without this battery, the Sleepy Pi cannot function to a schedule unless it is plugged into the mains.
USB stick	kingston	DT micro 16gb	Ebay/Amazon	5.2	NB: if you get a different make/model/size USB stick, you may need to change a few system files in the Rasbperry Pi. This is not difficult but you should be aware this will need to be done otherwise the unit will not work. Also, I recommend getting two USB sticks per unit. That way you can swap the sticks in the field and keep you unit out recording for longer (you just bring the full USB stick back to retrieve the data).
USB splitter				1.50	the Rpi A+ only has one USB port, so you need this to plug in the USB stick.
Soundcard	Creative	Soundblaster Play!	Ebay/Amazon	20	I am not sure whether these are much better than a cheaper £10 soundcard. You can even get some cards for as little as £3. I went for this one because it can record up to 16BIT/48KHz (i.e.24KHz per channel). This unit is also compatible with the Raspberry Pi and no drivers are needed. So it is hassle free.
Waterproof IP67 Case	??	MAX235H105	Ebay/Amazon OR www.solentplastics.co.uk	20	NB: you can use any case you like - I got these because they are very rugged, waterproof and dustproof and come with internal foam (IP67).

Appendix 5.2 (contd). Equipment list for the ARUPI used in Chapter 4.

Item	Make	Model	Seller	UK £	Purpose/Notes
Microphone and phantom power unit	Primo	BT/EM172	For inspiration search in google for how-to guides and information on nature recording.	11.46	NB: See microphone building pdf if you want to build this. Alternatively you can search for a ready made alternative. It needs to have a 3.5mm stereo jack plug (to fit into the Creative Soundblaster Play!). Alternatively you could investigate buying a USB microphone, but you will need to figure out if extra drivers are needed and how you install them.
battery case/holder	AA	8XAA	Anywhere (but buy good ones).	1.5	NB: you can use different power options - this is just what I used. The Sleepy Pi can regulate a power supply between 5.5V and 17V via the power jack. 8xAA batteries (each being 1.5V) = 12V. I tried using 4xD cell batteries but the voltage was not high enough. I also tried using a USB power bank (often used for charging phones and tablets on the go), but this failed to keep the Sleepy Pi awake. I didn't get round to experimenting with Li-ion rechargeable battery packs.
25mm IP68 cable gland			Screwfix	1.2	The microphone I built used 15mm aluminium tubing. The 25mm cable glands are perfect for mounting the microphone and maintaining a waterproof seal around the fixing point.
glue/sealant	I used Sugru	https://sugru.com/	Ebay/Amazon (ca. £13 for 8 sachets)	1.6	You can use other, cheaper adhesives if you like. I chose Sugru as it is easily mouldable and remains slightly flexible but is strong, yet easy to remove if needs be.
			TOTAL(ish)	**133**	This total will vary depending on market prices and on what equipment you go for. It is worth noting that the only essential items are first four in this list. The other items can be swapped/changed for cheaper or more expensive items - but this might require some tweaking of the OS I provide you with!
Price doesn't include:					
AA batteries	I bought 100 Duracell Procell for around £25. The unit uses 8 batteries, which last for 7/8days (recording one minute every 15 minutes).				
9v battery	*Only necessary if you decide to build the microphone!*				

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