Automated acoustic biodiversity assessment in cities

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A thesis submitted in partial fulfilment of the requirements for the degree of:

Engineering Doctorate in Urban Sustainability & Resilience

University College London

2017

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Declaration

I, Alison J. Fairbrass, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Alison J. Fairbrass
27th September 2017

Abstract

In the last 40 years more than half of the world's wildlife populations have disappeared while anthropogenic disturbance continues to push many species to extinction. Cities, which now support over half of the world's human population, also support biodiversity. Yet the green infrastructure (GI) components of cities are not currently supporting high biodiversity, partly due to the resource-intensity of biodiversity assessment in urban environments. Ecoacoustics, which uses biotic sound as a proxy for biodiversity, could provide an improved way of assessing urban biodiversity, although the use of ecoacoustics in cities dominated by anthropogenic noise remains untested. Here, I demonstrate how ecoacoustics can be used to assess biodiversity in complex and highly disturbed urban environments. I set the scene by using a global terrestrial urban studies database to show that GI does not currently mitigate against biodiversity losses in cities. Then, using an annotated urban ecoacoustics dataset, CitySounds2017, generated from audio data I collected within and surrounding Greater London, UK, I show that several commonly used Acoustic Indices are unsuitable for use in cities without the prior removal of non-biotic sounds from audio data. Next, using CitySounds2017 I develop CityNet, a pair of machine learning algorithms for quantifying biotic and anthropogenic sound in urban audio data. Finally, I show that a strong correlation exists between acoustic and environmental measures in urban GI habitats in London. I anticipate the methods developed here to be a starting point for improved assessment of biodiversity that informs management to maximise the wildlife supported by cities. For example, CityNet could be integrated into urban sensing networks to facilitate large-scale biodiversity assessment. As anthropogenic disturbance increases globally, the need for methods of biodiversity assessment that are reliable in disturbed environments will only increase, and I see these methods as having the potential to support biodiversity assessment globally.

Impact Statement

Ecoacoustics provides new methods for assessing biodiversity at scales not possible with traditional biodiversity assessment methods. However, the use of ecoacoustics to assess biodiversity in complex and acoustically disturbed cities is not well understood. This thesis showcases a new tool and knowledge for applying ecoacoustics for biodiversity assessment in the urban environment.

The tool and knowledge developed in this thesis are of interest to a range of disciplines of academic research including biodiversity science, urban studies, acoustic engineering and computer science. The research has been presented to a wide audience from broad ecological conferences to specialised international ecoacoustic conferences. The work in this thesis has also been published in a leading international peer reviewed journal. Once published, the CityNet tool will be made available on open-source platforms so that it can be used by other scientists in other study systems.

There is interest in this research from a range of industries responsible for the design and management of the built environment, including the construction industry, environmental consultancy, architecture and urban design, as well as public bodies including local and regional authorities, DEFRA, the Environment Agency, public health bodies, and the environmental NGO sector. The research has been presented to a wide practitioner audience through presentations at national industry conferences. Project stakeholders representing these industries, sectors and organisations have been consulted throughout the project and the research will be disseminated through this network. Immediate impact is likely to be limited to London and the UK, but when the CityNet tool is made freely available it is hoped that the impact will become international as the tool is tested in international study systems.

Acknowledgements

Firstly, and most importantly, to my dear Charlie. For having confidence in me always.

To my parents, Valerie and Dennis, who have supported me in so many ways to pursue a career that I love, and to my family and friends with whom I definitely could not have done this without.

To my supervisors Kate Jones, Helena Titheridge and Carol Williams who have been such great mentors. Your different skills and characters have complimented each other wonderfully as supervisors. Thank you for your overwhelming intelligence, patience and care throughout. I am very grateful to have had you to guide me through this journey. I would also like to thank Kelly Gunnell and Lisa Hundt for your supervision and roles in developing the research project.

I am very grateful for the support of the Doctoral Training Centre of Urban Sustainability and Resilience (USAR), it has been a very enlightening experience working in such an interdisciplinary research centre. I am also very grateful to have been a part of the Centre for Biodiversity and Environment Research (CBER) which has been a very stimulating place to be a student. Jane Doogan and Chris Langridge have been immensely supportive throughout. To my fellow students in USAR and CBER, especially Patrick Cottam, Henry Ferguson-Gow, Roee Maor, Laura Nunes, and the Kate Jones lab group past and present. Life would have been a lot duller without you.

I feel very fortunate to have been supported by the Bat Conservation Trust. It has been a pleasure to be part of this wonderful organisation that works so hard for the conservation of bats and has so much fun doing it!

Thank you to Michael Firman and Peter Rennert for being so great to work with. It has been a lovely experience learning the ways of the computer scientist.

I would like to thank Brian Cuthbertson immensely for supporting the data collection of the research. I am very grateful for your support throughout the project. I am also very grateful to Andy Lester, David Kirby and Craig Llewellyn for producing such excellent data.

I would like to thank Martin Ballard and Peter Johnson for financially supporting the project. It has been very confidence-boosting to have your support. Also I would like to thank the wide range of industry experts who have intellectually supported the project.

I would like to thank a number of interns who were a wonderful assistance in the data collection and audio analysis of the project including Charles Hearst, Verity Miles, Patrick Bell and Imogen Mansfield.

Finding places to conduct biodiversity surveys in London with suspicious black boxes of audio recorders was a big challenge. I am very grateful to everyone that helped me access study sites including Brian Cuthbertson, Lee Evans, Austin Brown, Simon Bateman, Tony Chadwick, Jean Frame, Stuart Connop, Emma Allen, Brian Roberts, Nick Ketchell, Rosie Sotillo, Lizzie Goodwin, Sarah-Jane Durman, David Perkins, Susan Reid, Anna Konarska, Michael Smythe, Leyla Laksari, Tim Lund, Kate Allardyce, Sylvia Myers, Amanda Durham and Anna Rogers.

Attribution

I received valuable advice on my research direction from my supervisors Dr Helena Titheridge, Prof Kate Jones, and Dr Carol Williams, and earlier industry supervisors Kelly Gunnell and Lisa Hundt. Dr Tim Newbold assisted me with the statistical analysis and Dr Thomas Matthews assisted with the database development of Chapter 2. The work presented in Chapter 3 was conducted in collaboration with Peter Rennert and is now published in Ecological Indicators (Fairbrass et al. 2017, Appendix B). The text presented in Chapter 3 is almost completely reproduced from Fairbrass et al. (2017). I collected, annotated and analysed the data. Peter Rennert wrote the code that underlies the AudioTagger software which created the acoustic data for Chapters 3, 4 and 5. I led the writing of the manuscript with contributions from the co-authors. With Dr Michael Firman I co-developed the CityNet algorithms for Chapter 4 which were used to create the acoustic activity data for Chapter 5. In Chapter 4 Dr Michael Firman wrote the code that underlies the CityNet algorithms and conducted the precision-recall analysis. I conducted all other data generation, analysis and modelling.

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CHAPTER 1

Introduction

1.1 BACKGROUND

In the last 40 years the world's wildlife populations have halved in size (WWF 2016) while climate change continues to push many species to the brink of extinction (Tittensor et al. 2014). There are increasing efforts to slow these trends, in the form of expanding global protected area coverage (Watson et al. 2014; UNEP-WCMC & IUCN 2016) and the development of international agreements on halting and reversing biodiversity loss (Convention on Biological Diversity 2015). However, current trends suggest that losses in biodiversity remain several orders of magnitude greater than background rates of extinction (Pimm et al. 2014). A greater understanding of how biodiversity responds to anthropogenic pressures, and how the negative effects of anthropogenic activities can be mitigated, is required if we are to slow the catastrophic losses to biodiversity that we have seen in recent years.

1.1.1 Biodiversity in Cities

Cities now support over half of the world's human population (UN-DESA 2016) with global urban land cover projected to double by 2030 (Seto, Güneralp & Hutyra 2012). Cities also support high biodiversity (Aronson et al. 2014) providing habitat for native and threatened species. With increasing global agricultural intensification and land cover change (Newbold 2015), cities have become refuges for biodiversity no longer able to persist in highly disturbed nearby rural landscapes (Hall et al. 2016). Cities are novel ecosystems composed of fragmented heterogeneous landscapes of mixed disturbance regimes (Perring et al. 2013). Their role in supporting the conservation of biodiversity may be crucial if the predicted future losses are to be avoided.

Despite the contribution that cities make to biodiversity conservation, our understanding of how to design and manage cities to maximise their capacity to support biodiversity and ecosystems remains limited (McDonnell & Hahs 2013). Urban green infrastructure (GI), the natural and semi-natural features and green spaces in cities (European Commission 2012), provides habitat for biodiversity in urban environments (Sadler et al. 2011; Murphy, Gunnell & Williams 2013). GI features and spaces vary widely and include, but are not limited to, parks, gardens, green roofs and walls, street trees, and sustainable urban drainage systems (Cvejić et al. 2015). Some cities have turned to increasing GI as a method of improving urban environmental quality that is cheaper than traditional engineered solutions to urban environmental problems (Bloomberg & Holloway 2010; Roberts et al. 2012; Greater London Authority 2017). However, the suitability of this wide variety of urban GI to support biodiversity and ecosystems is often not well quantified (Pataki et al. 2011; European Commission 2012).

Urban GI is heterogeneous in terms of the habitats it supports, including forest, grassland, and agricultural land (Cvejić et al. 2015). However, research into how urban GI should be designed to maximise the biodiversity supported is limited by investigating only certain types of urban GI, such as remnant vegetation (Aronson et al. 2014), amenity land (Sushinsky et al. 2013), and forested habitat (Caryl et al. 2016). To date, there is little comparative evidence of what biodiversity is supported by different types of urban GI globally. Urban environments vary considerably within and across cities in terms of GI cover (Fuller & Gaston 2009) and exist along a gradient of urban intensity (McDonnell & Hahs 2008). Recent work has used coarse binary classifications to discriminate between urban and non-urban environments (Aronson et al. 2014; Beninde, Veith & Hochkirch 2015) meaning cities that may vary considerably in terms of GI cover and urban intensity are compared like for like. This limits what can be inferred about how species respond to increasing impervious land cover and what biodiversity is supported by urban GI.

1.1.2 Ecoacoustics for Biodiversity Assessment

Information on biological systems is crucial for mitigating the negative ecological effects of anthropogenic pressures (Collen et al. 2013). Biodiversity assessment provides us with the information to understand the state of biodiversity (Goldsmith 1991), and identify species and ecosystems under threat (Spellerberg 2005). With limited funding available to conserve the species and ecosystems that are negatively impacted by anthropogenic pressures (Waldron et al. 2013) information from assessment is crucial to identify priorities for conservation action (Bottrill et al.

2008; Wiens, Goble & Scott 2012). Assessment is also a crucial element of understanding the impacts of conservation actions (Stem et al. 2005) and to inform adaptive management of conservation interventions (Salafsky, Margoluis & Redford 2016). Assessment and monitoring is crucial for the conservation of biodiversity in a world with ever increasing anthropogenic activity.

Traditional biodiversity assessment and monitoring methods are often costly and resource-intensive (Spellerberg 2005; McDonald-Madden et al. 2010), and do not lend themselves to the large-scale monitoring that is necessary for understanding urban ecosystems. Conventional biodiversity assessment techniques typically require experts to conduct taxonomic identification, which can be both costly and vulnerable to observer bias (Fitzpatrick et al. 2009). Most traditional methods do not produce a permanent record making it impossible to validate data in the future (Aide et al. 2013) and often rely on invasive methods such as trapping and collection (Greenwood & Robinson 2006). Urban environments present additional challenges in the form of access restrictions to private land which hinders large-scale assessment, teamed with safety and security issues for human surveyors and equipment (McIntyre, Knowles-Yánez & Hope 2000; Farinha-Marques et al. 2011).

Ecoacoustic surveying is a useful way of quantifying ecological communities and their habitats where acoustic measures are used as a proxy for measures of biodiversity by summarising the activity or diversity of sounds present in audio data (Towsey, Parsons & Sueur 2014; Merchant et al. 2015; Sueur & Farina 2015). Recent developments in passive acoustic recording technology have made it possible to collect acoustic information at large spatial and temporal scales (Blumstein et al. 2011; Towsey, Parsons & Sueur 2014). Ecoacoustics reduces the biases associated with human surveyors (Sauer, Peterjohn & Link 1994) and facilitates the collection and processing of biodiversity data at scales not currently possible with traditional methods of biodiversity assessment (Towsey, Parsons & Sueur 2014). Although ecoacoustics may provide a useful method to measure biodiversity, its use in acoustically complex urban habitats dominated by anthropogenic noise is not well understood.

A significant challenge of ecoacoustics is the extraction of meaningful information from the large volumes of audio data that are typically generated (Towsey, Parsons

& Sueur 2014). To tackle this challenge, Acoustic Indices (AIs) have been developed which facilitate the rapid calculation of acoustic measures from large volumes of audio data (Sueur et al. 2014). To date, the majority of ecoacoustic research has been conducted in less disturbed environments than cities (e.g. Boelman et al. 2007; Pieretti, Farina & Morri 2011; Gasc et al. 2013) and the effect of the wide range of non-biotic sounds that characterise cities on measures of biotic sound generated by AIs has not been thoroughly investigated. AIs typically measure a small number of acoustic features such as spectral entropy within defined frequency bands (Boelman et al. 2007; Villanueva-Rivera et al. 2011; Kasten et al. 2012) or entropy changes over time (Pieretti, Farina & Morri 2011) to generate measures such as acoustic activity, diversity or disturbance. Some common non-biotic sounds have been found to bias existing algorithms including road traffic (Fuller et al. 2015), human speech (Pieretti, Farina & Morri 2011) and wind (Towsey et al. 2014). To apply ecoacoustics in urban environments, the suitability of using AIs for measuring biotic sound in complex and high disturbed environments dominated by anthropogenic sound must be assessed.

1.1.3 Machine Learning

Machine learning is a computer science speciality, borne out of artificial intelligence, in which systems learn and improve on the performance of tasks without needing to be explicitly programmed by a human (Carbonell, Michalski & Mitchell 1983). Today, machine learning is commonly used to access and learn patterns in data to support tasks such as identifying objects in images, recognising songs in audio recordings and transcribing speech into text (LeCun, Bengio & Hinton 2015). Machine learning is being increasingly applied to biodiversity monitoring because it facilitates the detection and identification of patterns in the large volumes of audio data that ecologists are increasingly generating using new recording hardware technologies (Klein, McKown & Tershy 2015). Using annotated datasets of known biotic sounds, these machine learning algorithms are trained to recognise sounds based on a wide range of acoustic characteristics, or features, which are either defined beforehand (supervised) or chosen by the algorithm (unsupervised). Therefore, machine learning algorithms are likely to outperform AIs as they can utilise many more features in their calculations.

Machine learning algorithms have been developed to identify the vocalisations of a range of taxonomic groups, including bats (Walters et al. 2012), birds (Stowell & Plumbley 2014), and amphibians (Acevedo et al. 2009). However, these classification algorithms are limited to a small number of soniferous species, and typically do not provide information on the wider environment. Recently, machine learning algorithms have been developed that facilitate the detection and classification of biotic sounds in audio recordings to generate whole community measures of taxon-specific biotic sound analogous to the acoustic measures produced by AIs (Stowell et al. 2016; Grill & Schlüter 2017). However, these algorithms have not been tested on long and noisy audio data from the urban environment, and how these algorithms perform on recordings made in cities in comparison to AIs is yet to be tested.

1.1.4 Measuring the Environment with Ecoacoustics

The use of ecoacoustics for environmental assessment is based on the theory that acoustic characteristics can be used as proxy measures of biodiversity (Pijanowski et al. 2011a). There is some evidence that acoustic measures produced by AIs correlate with biodiversity including the abundance (Boelman et al. 2007; Pieretti, Farina & Morri 2011) and diversity (Sueur et al. 2008; Depraetere et al. 2012; Fuller et al. 2015) of soniferous species, in addition to the structure and composition of native vegetation (Fuller et al. 2015). However, there is evidence that these relationships can be affected by the context of the recording environment. For example, climatic conditions have been shown to bias measures of AIs (Depraetere et al. 2012) and it has been argued that certain relationships are restricted to tropical environments due to the characteristics of soniferous species in these habitats (Krause & Farina 2016). There is currently very little evidence on what relationships exist between acoustic and biodiversity measures in complex and acoustically disturbed urban environments.

1.2 UNDERSTANDING USERS REQUIREMENTS

The past decade has seen a shift within the UK building sector. Integrating biodiversity into the built environment is seen as an increasingly important element of sustainable business practice (eftec & Centre for Regional Economic and Social Research 2013; Natural England 2014). A variety of sustainability assessment tools exist that enable the built environment industry to quantify the sustainability of developments (Chehrzad et al. 2016) which commonly employ scoring systems to assess the ecological value of proposed or existing GI habitats. Commonly the size and type of habitats present on a site is used to calculate, based on a weighting applied to different habitat types, a simple metric to quantify the ecological value of GI developments (e.g. BRE 2011; Kruuse 2011; DEFRA 2012; Berlin Senate Department for Urban Development and the Environment 2013; Seattle Department of Planning and Development 2013). The data required by these tools is either generated from ecological surveys (BRE 2011; DEFRA 2012) or from information that built environment professionals should have access to such as aerial photos of sites, site plans and architectural drawings (Kruuse 2011; Berlin Senate Department for Urban Development and the Environment 2013; Seattle Department of Planning and Development 2013). An advantage of these systems is that they produce simple metrics that can be understood by built environment professionals who typically do not have the expertise to interpret results of ecological surveys (Tzoulas & James 2010). However, the current tools available to enable industry to work with biodiversity have numerous shortcomings (UK-GBC 2009). For example, the simplicity of these tools has been criticised for promoting ‘tokenistic’ investments that maximise the scores achieved but that do not necessarily provide valuable habitat for biodiversity (Kirkpatrick 2009; UK-GBC 2009).

This Engineering Doctorate (EngD) research project needed to be informed by both the academic research gaps and the needs of industry. Therefore, the requirements of the intended end users of this work, the UK built environment industry, were assessed at the beginning of the project. To understand the relationship between the current academic research gaps and the needs of industry, two half-day workshops were held with a wide range of built environment professionals. The first workshop was held during the UK Construction Group Environmental Forum for Biodiversity at Kier Construction plc, Sandy, on 11th January 2013 while the second workshop was held at University College London on 18th January 2013. In total the workshops were attended by 16 participants. The built environment roles represented included: sustainability managers, ecological consultants, local authority environmental managers and ecologists, green infrastructure developers, sustainability policy advisors, biological data managers, and landscape architects. Participants represented a range of organisations including government departments, local authorities, architecture firms, engineering consultancy firms, construction companies, wildlife conservation charities, green infrastructure consultancy firms, construction industry advisory organisations, and biological record centres. The objectives of the workshops were threefold:

1. To understand the challenges currently faced by built environment professionals when working with biodiversity.
2. To understand the knowledge gaps of industry in relation to biodiversity in the built environment and the design and management of urban GI.
3. To understand what is missing from existing sustainability assessment tools and define requirements for a new tool to facilitate measurement and reporting of biodiversity in the built environment.

Workshop participants were given an overview of the research project and the workshop objectives. Participants were then divided into groups, mixed by profession, and asked a series of questions to stimulate group discussion around the three objectives. During each round of group discussions, participants were encouraged to capture their comments on post-it notes, and share these comments with workshop participants, who then grouped comments into themes in order to stimulate discussion. The themes relevant to each objective that emerged from these discussions are described below.

Objective 1 – Current challenges

Workshop participants complained of a lack of ecological expertise in the professions most commonly involved in the design and management of GI habitats. Participants cited several examples of inappropriate designs of GI features by landscape architects, such as the use of non-native and invasive plant species such as *Buddleja davidii* (Booy, Wade & Roy 2015), because these professionals are not always ecologically trained. In addition, the professionals commonly in charge of GI habitat management such as facilities managers and grounds keepers rarely have the ecological expertise to manage GI features to maximise the biodiversity supported. These professionals are unable to conduct biodiversity assessment of GI habitats and the costs of contracting external ecological expertise to conduct biodiversity assessment acts as a barrier.

Objective 2 – Knowledge gaps

A lack of evidence on what works for biodiversity in terms of the design and management of urban GI was cited by participants as a significant barrier in their work. They stated that there was a lack of examples of project successes and failures due to a lack of assessment and reporting on the biodiversity supported by GI habitats. Participants complained that this lack of evidence base made it difficult to convince stakeholders to make investments in GI.

Objective 3 – Existing tools and design requirements

Participants discussed the shortcomings of existing sustainability assessment tools, in particular the Buildings Research Establishment's Environmental Assessment Method (BRE 2011), which was the most commonly used tool across the participants. Issues that were raised included a lack of built-in mechanisms for post-construction assessment of biodiversity on GI habitats. In particular because changes in biodiversity occur over long time periods, typically over several years after construction, participants claimed that long-term ecological impacts of GI investments were not being assessed. Participants raised concerns that the lack of long-term assessment confounds the issue of a lack of evidence base on how to design and manage urban GI for biodiversity.

1.3 RESEARCH AND DESIGN REQUIREMENTS

Informed by the outcomes of these workshops, combined with a review of the academic literature (Section 1.1), the following set of research and design requirements for the EngD project were identified.

1.3.1 Developing the evidence base on the biodiversity supported by urban GI

The research project needed to develop an improved evidence base on the biodiversity supported by GI in the built environment in order to inform the design and management of urban GI for biodiversity. Following these workshops, a scoping exercise was conducted to assess the available documented evidence on the biodiversity supported by GI in the built environment with the intention of synthesising existing evidence in a systematic review-style analysis (Centre for Evidence-Based Conservation 2010). In this scoping exercise, peer-reviewed academic literature was sourced from Web of Knowledge and Scopus databases and grey literature was sourced from industry reports and websites between 19/03/2013 and 16/04/2013. This scoping exercise revealed that the published literature was too scarce and study designs too heterogeneous to provide suitable data for a systematic review study. Therefore, it was decided that an alternative method needed to be used to develop the evidence base on the biodiversity supported by GI in the built environment.

1.3.2 Suitable for non-ecologists

For assessment and reporting of biodiversity on GI habitats, any tool developed needed to be suitable for use by the professionals that manage these habitats who typically do not have ecological expertise. To facilitate reporting, the information produced by the tool also needed to be interpretable by non-ecologists. Professionals such as planners, built environment professionals and urban designers need to make informed decisions about urban planning and land management but don’t have the expertise to interpret results from traditional ecological surveys themselves (Tzoulas & James 2010). Therefore, the tool needed to produce simple to understand metrics of biodiversity that could be understood by these sections of industry.

1.3.3 Operate over large scales

The tool needed to be able to be used over long time periods because changes in biodiversity occur slowly, typically over years. In addition, construction and development projects have a typical life span of several years, so the tool should be able to be used to measure biodiversity before, during and into perpetuity after projects are completed. Therefore the tool needed to be able to process large volumes of biodiversity data with relative speed and ease.

1.3.4 Produce meaningful ecological information

The tool needed to produce meaningful ecological information in order to ensure that investments in GI for biodiversity are valuable. Any measures of biodiversity produced by the tool need to be understandable in terms of what ecological measures they capture. It should enable users to make informed decisions about how to design and manage GI for biodiversity based on information inferred from assessments conducted using the tool.

1.4 AIMS AND OBJECTIVES

Based on the current academic research gaps and the needs of industry the aims of this thesis are twofold: 1. To improve our understanding of what biodiversity is supported by urban GI, and 2. To develop a tool for assessing and reporting on biodiversity in cities.

I focus on the following specific objectives:

1. To investigate the biodiversity supported by urban GI, and assess what types of urban GI mitigate the negative ecological effects of urban development.
2. To evaluate the suitability of ecoacoustics for surveying biodiversity in cities. In particular, to investigate the suitability of commonly used AIs for use in urban environments, by assessing the measures of biotic sound they capture and identifying the non-biotic sounds that bias them.
3. To develop machine learning algorithms for measuring biotic and anthropogenic sound in audio data that are robust to the wide range of non-biotic sounds in the urban environment, and compare their performance to the state-of-the-art algorithms for measuring biotic and anthropogenic sound.
4. To investigate the environmental measures of urban GI habitats that correlate with acoustic measures to assess whether ecoacoustics can be used to assess urban GI habitats.

1.5 THESIS OUTLINE

This thesis is structured as follows:

In **Chapter 2** I conduct a global analysis of 80 studies of biodiversity across cities combined with spatial analysis of GI land cover, which shows that overall biodiversity responses to increasing impervious land cover (my proxy for urban intensity) are negative, and that urban GI does not currently mitigate significantly against biodiversity losses in cities. This suggests that current approaches to urban GI design and management are not supporting high biodiversity, and that our understanding of how to support biodiversity with urban GI must be improved.

In **Chapter 3** I assess the performance of four commonly used AIs for measuring biotic sound in the urban environment. I measure the activity and diversity of sounds in both low (0-12 kHz) and high (12-96 kHz) frequency recordings to assess the measure of biotic sound captured by the AIs, and the non-biotic sounds which bias them. I show that the majority of AIs tested either do not measure urban biotic sound or are biased by a range of anthropogenic and geophonic sounds.

In **Chapter 4** I co-develop and test machine learning algorithms (CityNet) to automatically measure levels of biotic and anthropogenic acoustic activity in long and noisy audio data from the urban environment, and compare their performance to a suite of commonly used AIs and the state-of-the-art algorithm for measuring bird sound in audio data. I show that CityNet outperformed all the competing algorithms tested and is robust to a range of common anthropogenic and geophonic sounds, but is biased by mechanical sounds.

In **Chapter 5** I evaluate the use of ecoacoustic measures as proxies for environmental measures of urban GI habitats by investigating the relationship between acoustic activity and diversity with environmental measures of urban GI habitats. I show that biotic acoustic activity correlated positively with GI habitat complexity while biotic acoustic diversity correlated positively with GI habitat diversity, habitat size and the amount of GI in the surrounding landscape. This suggests that ecoacoustic measures may be suitable for assessing GI habitats in cities.

In **Chapter 6** I offer a discussion of the key findings and conclusions of this thesis.

CHAPTER 2

Existing green infrastructure in cities globally fails to mitigate the impact of urban development on biodiversity

2.1 ABSTRACT

Global urban land cover will increase dramatically in the coming decades, potentially severely negatively impacting wildlife populations and ecosystems. To ensure future cities are sustainable and liveable, biodiversity must be conserved within cities to support the numerous ecosystem services that improve urban environmental quality. Recent studies suggest that urban green infrastructure (GI) is important for biodiversity, but it is not known how urban GI mitigates the biodiversity losses caused by urban development. Here, I use a terrestrial biodiversity database of 3130 sites from 80 studies within and outside cities across the world, and land cover data, to assess: 1) the response of the total abundance and richness of species to increasing impervious land cover globally, and 2) how species responses are impacted by the size and type of urban GI. As expected, urban areas contain fewer species and lower total abundance than surrounding habitats (even agricultural habitat), although this pattern varied considerably. In contrast to previous work, I found species responses were consistent across ecological realms, but varied taxonomically in concordance with previous work. Surprisingly, large areas of forest, grassland or agricultural urban GI did not significantly mitigate against biodiversity losses in cities. This suggests that current approaches to urban GI design and management are not supporting high biodiversity, and that simply having GI in cities doesn't necessarily deliver measurable benefits for biodiversity. Interestingly, blue infrastructure (BI) maintained levels of total abundance and species richness comparable to habitats outside of cities. Urban planners and land managers across the world must improve the ecological performance of urban GI, by recognising that these multifunctional spaces are subject to a multitude of anthropogenic pressures which negatively impact biodiversity, such as predation by domestic animals, road mortality, light and noise pollution. Habitat restoration may

enable these underperforming habitats to support the biodiversity and ecosystem services required to support sustainable and liveable cities for future generations.

2.2 INTRODUCTION

By 2030, the world is projected to accommodate 1.1 billion additional people (UN-DESA 2015), the majority being born in cities (UN-DESA 2016). Cities face multiple environmental challenges including the control of pollution, disease, flooding, over-heating and lack of local resources, which can negatively impact the health and well-being of urban populations (Satterthwaite 2003). City administrations must find ways to tackle these problems while accommodating ever increasing numbers of people. Expanding the footprints of cities has been the predominant method of accommodating growing urban populations to date (Seto, Parnell & Elmqvist 2013), and by 2030 global urban land cover is projected to have tripled from 2000 levels (Elmqvist 2012; Seto, Güneralp & Hutyra 2012). This process of urban development has been shown to drive significant losses in biodiversity, the effect of which varies based on the species (Sushinsky et al. 2013; Soga et al. 2014) and location of study (Aronson et al. 2014). The global challenge is the development of sustainable cities of high urban environmental quality without increasing the already large burden that cities place on the natural environment (Forman & Wu 2016).

Biodiversity is an integral element of sustainable and liveable cities because it facilitates human contact with nature and provides valuable ecosystem services such as air purification, urban cooling, climate regulation and habitat for wildlife (Gómez-Baggethun & Barton 2013; Gómez-Baggethun et al. 2013). Urban green and blue infrastructure (GI and BI, respectively) are the natural and semi-natural areas of pervious land cover in cities which includes features such as parks, forests, cemeteries, lakes, canals, and reservoirs (Cvejić et al. 2015). These spaces are typically multifunctional and support a range of human activities including recreation, food production and sustainable urban drainage (Pauleit et al. 2011; European Commission 2012). City administrations are increasingly integrating the conservation of these spaces into environmental management plans as they are seen as providing multifunctional solutions to urban environmental problems (Bloomberg

& Holloway 2010; Greater London Authority 2017) while being cheaper than engineered solutions (Roberts et al. 2012).

Globally, many cities contain large areas of GI and BI. The results of a number of recent studies suggest that urban GI and BI are important for biodiversity in cities (Gagné & Fahrig 2010; Sushinsky et al. 2013; Aronson et al. 2014; Soga et al. 2014). However, these studies are limited by investigating only certain types of urban GI, such as remnant vegetation (Aronson et al. 2014), amenity land (Sushinsky et al. 2013), and forested habitat (Caryl et al. 2016). In reality, urban GI is heterogeneous in terms of the habitats it supports, including forest, grassland, and agricultural land (Cvejić et al. 2015). To date, there is little comparative evidence of what role the size and type of urban GI and BI play in mitigating the biodiversity losses caused by urban development globally. An additional limitation of recent work is the, often, coarse binary classifications used to discriminate between urban and non-urban environments (Aronson et al. 2014; Beninde, Veith & Hochkirch 2015), whereas in reality these environments exist along a gradient of urban intensity (McDonnell & Hahs 2008). In addition, the biodiversity supported by these urban habitats may be affected by the urban intensity of the environment in which they are embedded which is rarely accounted for. Finally, ecological responses to urban environments have been shown to vary taxonomically due to the ability of some species but not others to survive in cities (Francis & Chadwick 2012) and spatially due to the different human histories of world regions (La Sorte, McKinney & Pyšek 2007). However, the only global study of these patterns to date (Aronson et al. 2014) is limited by the shortcomings previously outlined including the binary classification of urban environments and the investigation of a single type of GI.

Here, I use a terrestrial species assemblage database of 3130 sites from 80 studies within and outside of cities around the world to investigate: 1) the response of the total abundance and richness of species (spatially and taxonomically) to increasing impervious land cover (my proxy for urban intensity), and 2) how species responses are impacted by the size and type of GI and BI in cities. I use open-source land cover data to estimate the amount of impervious land cover surrounding all the study sites in the terrestrial assemblage database, as well as four different types of urban GI and BI: agriculture, blue infrastructure, forest and grassland. I investigate overall responses to increasing impervious land cover, as well as taxonomic and spatial differences in responses. Finally I investigate the mitigating effect of urban GI and BI on biodiversity losses in cities. To do this I compare biodiversity at sites in cities of high and low GI and BI cover with reference levels of biodiversity at sites in the landscape surrounding cities to assess whether urban GI and BI mitigates the negative ecological effects of urban development.

2.3 MATERIALS AND METHODS

2.3.1 Data Collection

Data on site-level total species abundance and richness was collected from published studies (Table A.1). Studies were selected which had surveyed at least one site within an urban environment and one comparison non-urban site in the landscape surrounding the same city. I gathered site-level differences in species richness from the Projecting Responses of Ecological Diversity In Changing Terrestrial Systems (PREDICTS) database (Hudson et al. 2014), a collation of samples from existing spatial comparisons of local-scale biodiversity exposed to different intensities and types of anthropogenic pressures from terrestrial sites around the world, and from Matthews et al. (2014). This was supplemented by those sources found from a literature search using the Scopus database on 4/11/2013, using the search terms "species richness" AND 'urban*' AND 'gradient'. Of the resulting 182 studies I found in the literature search, only those that reported data from urban and comparison non-urban sites were included. Where the biodiversity recorded at each study site was not reported in the paper, authors were contacted requesting this information. Where possible I also calculated the site-level total abundance of all species for each study. All data were compiled into a database following the PREDICTS protocol whereby all study sites were assigned to a predominant habitat type according to Hudson et al. (2014) and Newbold (2015). When a published study reported data on more than one taxonomic group, the data were divided into separate studies for the purposes of analysis. Where papers in the database did not report accurate location data, maps and/or location details in the text of the paper were used to estimate coordinates using GoogleMaps (Google 2015). Taxonomic names followed those in the Integrated Taxonomic Information System (Integrated Taxonomic Reference System 2016). The database consisted of 1718 estimates of total abundance and 3977 estimates of species richness at 3130 sites (Figure 2.1) (2-

301 sites per study, median 22, Table A.1). These data, from 80 publications, represent 3796 species from 7 phyla and 13 of the 14 terrestrial biomes (Olson et al. 2001). In terms of taxonomic coverage, the majority of estimates were for species of the Arthropoda (1459) and Chordata (1211) phyla, followed by species of the Mollusca (507), Tracheophyta (317), Ascomycota (252), Basidiomycota (120), Bryophyta (106), and Annelida (5) phyla. In terms of ecological realm coverage, the majority of estimates were from the Palearctic (1899) and Nearctic (1201) realms, followed by the Australasia (304), Afrotropic (282), Neotropic (234) and Indo-Malay (57) realms.

2.3.2 Spatial Analysis

OpenStreetMap (OSM, openstreetmap.org) geospatial data were used to quantify the amount (m^2) of GI and BI in the landscape surrounding every study site in the database. OSM was used because it provides global coverage of urban land cover at a finer scale than any other open-source global land cover dataset; OSM resolution ranges between 1 cm to several meters in comparison with a 309 m resolution of GlobCover v.2, the highest resolution spatial dataset reviewed by Potere et al. (2009). OSM data were downloaded between 05/10/2015 and 12/01/2016 from multiple sources (http://www.geofabrik.de/, https://mapzen.com/ and https://www.openstreetmap.org).

The OSM land cover/use classes were grouped into four GI and BI classes: agricultural, blue infrastructure (e.g. rivers, lakes, reservoirs, canals), forest, and grassland, based on the land cover which has been shown to be of ecological importance in urban environments (see Table A.2 for groupings of OSM data and references to studies reporting ecological effects of urban land cover). I improve on previous broad characterisations of the environments within and surrounding cities, such as ‘urban’, ‘suburban’ and ‘rural’(Porter, Bulluck & Blair 2005; van Heezik, Smyth & Mathieu 2008; Sanford, Manley & Murphy 2009; Dures & Cumming 2010; McKinney, Raposa & Cournoyer 2011; Rubio 2012), by using the amount of impervious land cover surrounding sites to quantify levels of urban intensity to account for the heterogeneity of environments both within and across cities (McKinney 2008). To quantify the level of urban intensity of study sites, OSM data classified as containing built structures such as buildings and infrastructure were grouped into an impervious land cover class (Table A.2). Due to the open-source nature of OSM data, overlapping spatial data is a common feature of this dataset due to multiple users mapping similar areas multiple times (Figure). To avoid inflating measures of area cover, overlapping spatial data were replaced with non-overlapping data assigned to a single land cover class. The amount (m^2) of each land cover class within a 1 km radius of sites was extracted using ArcGIS v.10.3 (ESRI 2014). I recognise this spatial scale will not be optimal for all of the taxa in the database, but because the database was multi-taxonomic I used a 1 km scale as it is a value that is sensible for multiple taxa and is often used in multi-taxa type studies (Soga et al. 2014; Alberti et al. 2017). Finally, ecological realm data (Olson et al. 2001) were extracted based on the location of sites in relation to biogeographic data sourced from The Nature Conservancy (The Nature Conservancy 2009).

2.3.3 Statistical Analysis

To investigate the overall response of biodiversity to urban intensity, I fitted generalised linear mixed-effects (GLMER) random slope models in R v.3.1.2 (R Core Team 2014), with total abundance and species richness as response variables, with the amount (m^2) of impervious land cover within a 1 km radius of sites as a fixed effect nested within unique study identifier as a random effect. The abundance data was log transformed and this model was fitted with a Gaussian error structure using the 'lme4' v.1.1-7 (Bates et al. 2014) package, while the species richness model was fitted with a zero-inflated negative binomial error structure using the 'glmmADMB' v.0.7 (Skaug et al. 2011) package due to the zero-inflated nature of the data. The impervious land cover data was standardised and log transformed. Sites with less than 10% coverage of OSM data within a 1 km radius (1160 sites) were removed.

To investigate taxonomic and spatial differences in the response of biodiversity to urban intensity, the random effect coefficients generated by the GLMER models for each unique study were grouped separately by phyla and ecological realm. I used one-sample t-tests to investigate whether the response of each group was significantly different to zero i.e. no response to increasing impervious land cover.

To investigate the impact of the extent and type of urban GI and BI on biodiversity responses to urban intensity, I fitted GLMER models, with total abundance and species richness as response variables, with unique study identifier as a random effect, and the amount (m^2) of each GI and BI type within a 1 km radius of sites as fixed effects and fitted as interaction terms with the amount (m^2) of impervious land cover within a 1 km radius of sites. All predictor variables were standardised and fitted as quadratic polynomial continuous effects to accommodate potential non-linear relationships between biodiversity and increasing impervious land cover. I performed model averaging and selection using information theoretic model comparison and frequentist likelihood ratio tests similar to Dornelas and Connolly (2008) and Antão et al. (2017). Interaction terms were tested first, where models of all 15 possible combinations of interactions between impervious land cover and each GI or BI variable were fitted with the full set of main effects. Parameter estimates were averaged across models with ΔAICc < 2, and Akaike weights (AICc) were used to select and rank the most parsimonious models using the 'MuMIn' package v.1.12.1 (Bartoń 2012). The relative importance of predictor variables was computed as the sum of the Akaike weights (based on the corrected Akaike information criterion, AICc) for the variables included in the averaged models (Burnham & Anderson 2002). Next, the decision whether or not to retain main effect terms was based on likelihood ratio tests comparing the full model of main effects and interaction terms of importance >50%, with and without each main effect.

Next the top models were then used to compare the biodiversity at sites in cities with high and low GI and BI cover with the biodiversity at sites outside of cities. Sites within cities were defined as those surrounded by the upper 95% confidence interval (CI) of impervious land cover within 1 km radius (77.6% and 74.9% impervious and cover for the total abundance and species richness datasets, respectively). Sites outside of cities were defined as those surrounded by the lower 95% CI of impervious land cover within 1 km radius (0% for both datasets). Sites within cities with high GI or BI cover were defined as those surrounded by the upper 95% CI of either agriculture (total abundance dataset: 65.9% and species richness dataset: 65.6%), blue infrastructure (18.9% and 13.2%), forest (86.6% and 87.2%) or grassland (84.7% and 63.3%) within 1 km radius. Sites within cities with no GI or BI cover were defined as those surrounded by the lower 95% CI of agriculture, blue infrastructure, forest or grassland (0% in all cases). Sites outside cities that were used for this analysis were those surrounded by the upper 95% CI of each GI and BI type because these sites were assumed to be the least disturbed habitat so were likely to support the highest biodiversity and provide a reference level of biodiversity. Only sites surrounded by like for like GI or BI were compared, for example sites surrounded by forest GI within cities were only compared with sites surrounded by forest GI outside of cities, but not with sites surrounded by agriculture, blue infrastructure or grassland.

2.4 RESULTS

Responses of biodiversity to increasing impervious land cover (my proxy for urban intensity) were mixed (Figure 2.1, Figure 2.2) and I did not find a significant overall response of biodiversity to increasing impervious land cover (Table 2.1). The response of species richness was more consistent than total abundance, and it had less variance in the response to increasing impervious land cover.

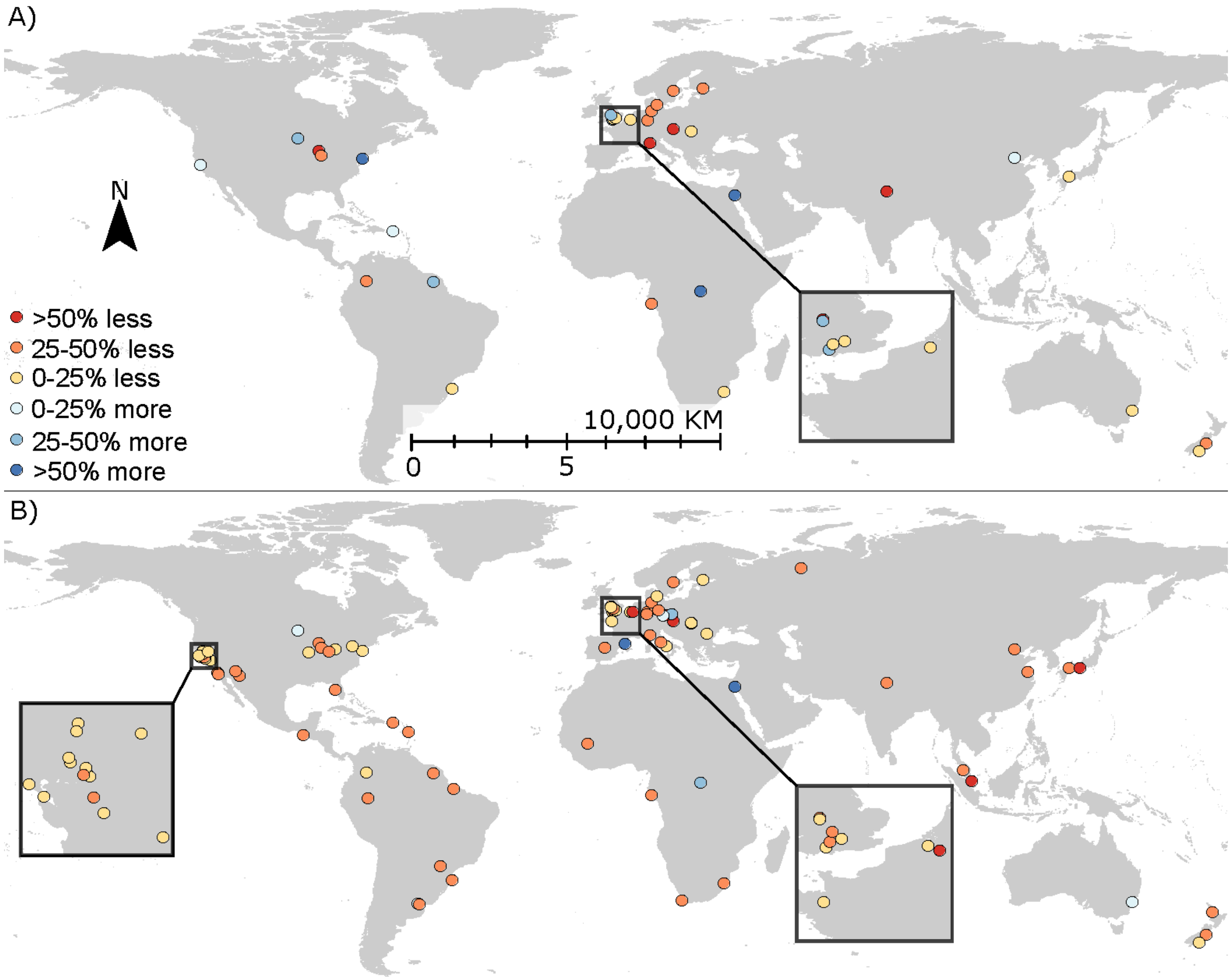


Figure 2.1 Response of biodiversity to increasing impervious land cover. Dots represent the locations of unique studies reporting total abundance (n = 42) (A) and species richness (n = 80) (B) in the database. Colours represent the percentage (%) change in biodiversity in response to increasing impervious land cover. Percentage change data is derived from the unique study random effect coefficients of GLMER models fit with total abundance and species richness as response variables, with the amount (m^2) of impervious land cover within a 1 km radius of sites as a fixed effect nested within unique study identifier as a random effect. Inset boxes show areas of high concentrations of studies.

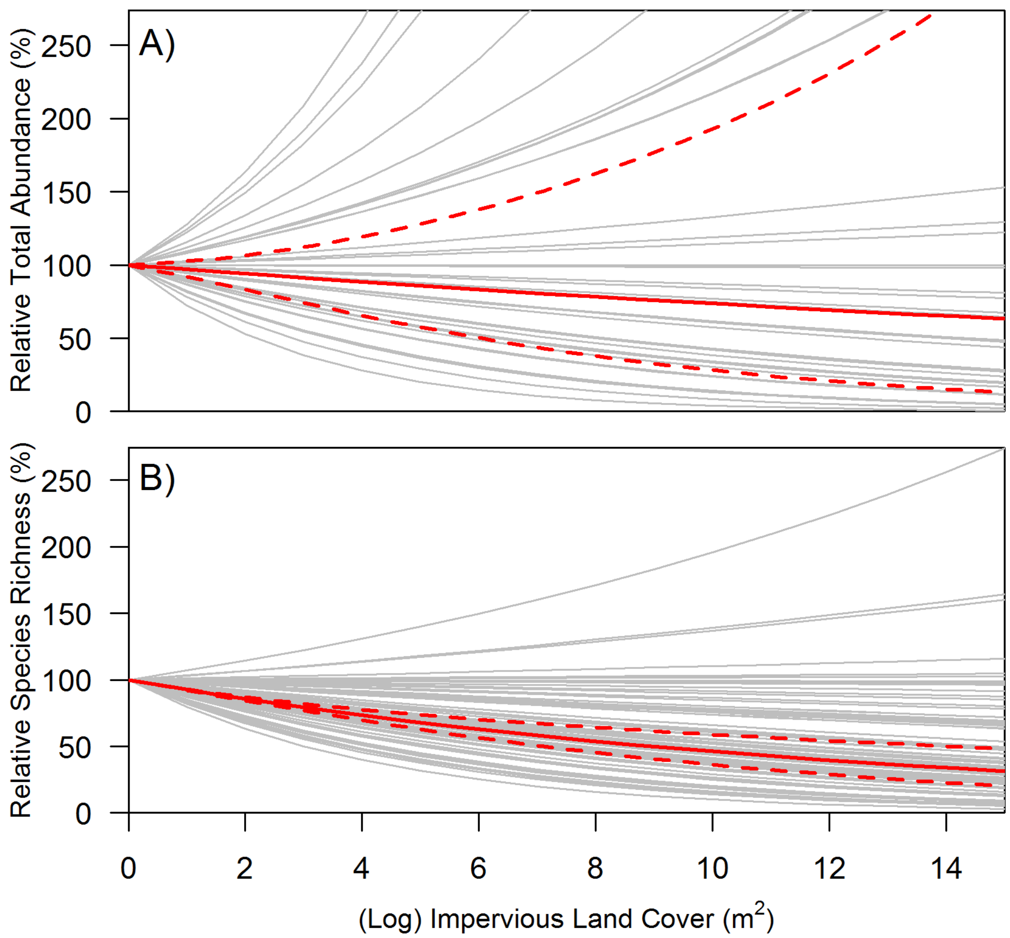


Figure 2.2 Relative response of biodiversity to increasing (log) impervious land cover. Grey solid lines indicate study-level total abundance (A) and species richness (B) responses (i.e. the unique study random effect coefficients of GLMER models fit with total abundance and species richness as response variables, with the amount (m^2) of impervious land cover within a 1 km radius of sites as a fixed effect nested within unique study identifier as a random effect). Average responses indicated by a solid red line, with dashed red line representing confidence intervals indicated. Only study-level random slopes falling within the 95% confidence interval are displayed.

Table 2.1 Random slope mixed-effects models describing the response of biodiversity to impervious land cover. The amount (m^2) of impervious land cover within a 1 km radius of sites is fitted as a fixed effect nested within unique study identifier as a random effect. Details include the model coefficient estimates, standard error and t-value.

Covariates	Estimate	Standard error	t-value
Total abundance (log)			
Intercept	4.23	0.38	11.09
Impervious (log)	-0.03	0.07	-0.46
Species richness			
Intercept	2.16	0.11	19.16
Impervious (log)	-0.08	0.02	-3.71

Biodiversity responses to increasing impervious land cover did not vary significantly across ecological realms. Species richness responses to increasing impervious land cover varied taxonomically, with the greatest declines found in the fungal phylum Ascomycota ($t=-3.27$ (3), $p=<0.05$) (Figure 2.3), but total abundance responses did not vary taxonomically.

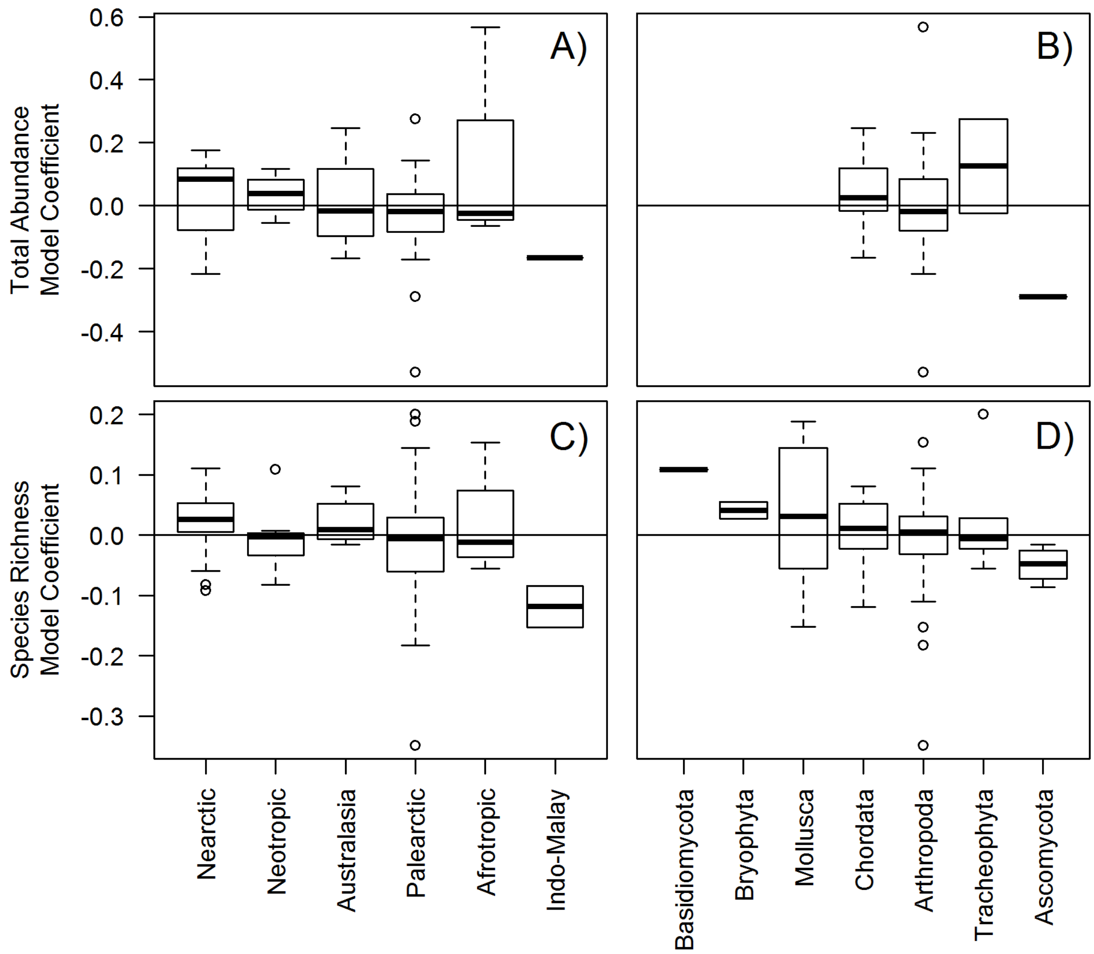


Figure 2.3 Spatial and taxonomic responses of biodiversity to increasing impervious land cover. Study-level responses of total abundance (A-B) and species richness (C-D) across ecological realms and phyla. Model-coefficients are derived from the unique study random effect coefficients of GLMER models fit with total abundance and species richness as response variables, with the amount (m^2) of impervious land cover within a 1 km radius of sites as a fixed effect nested within unique study identifier as a random effect. The average response is indicated by the solid line, which is equivalent to the average slope in Figure 2.2.

When comparing sites surrounded by high agricultural GI cover, the total abundance and richness of species was significantly lower at sites within cities in comparison to sites outside of cities (Figure 2.4, Table A.3). In addition, total abundance was significantly lower at sites with high forest cover within cities and species richness was significantly lower at sites with high grassland cover within cities, in comparison to sites outside of cities.

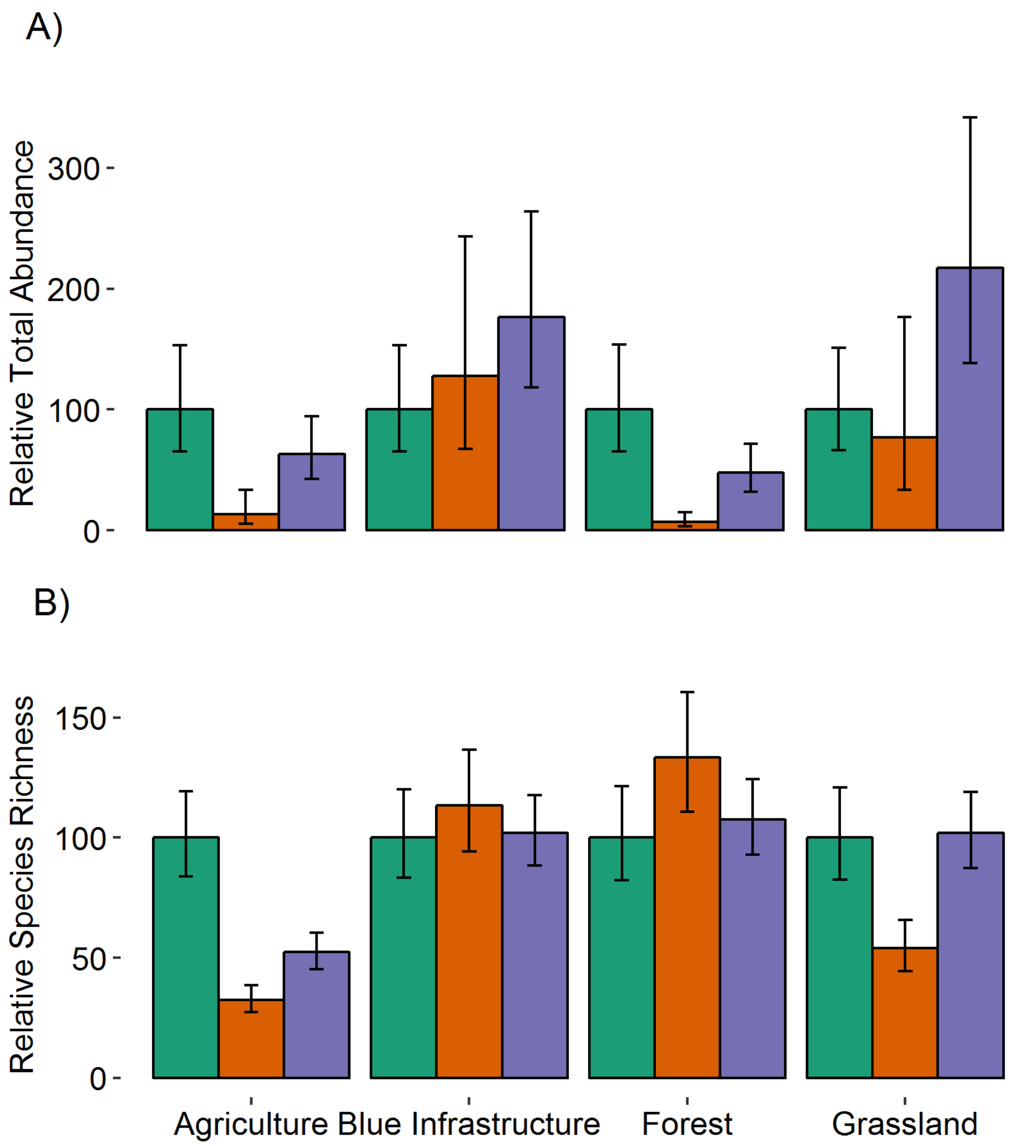


Figure 2.4 Mitigating effects of urban GI and BI on ecological responses to increasing impervious land cover. Biodiversity at sites outside cities (green) is used as a reference level (100%) of total abundance (A) and species richness (B) and biodiversity at sites with high (red) and low (blue) GI and BI cover within cities is reported as a percentage of the reference level. Error bars represent standard deviation and report the uncertainty in the model coefficients. Percentage change data are derived from predicting biodiversity levels at sites of the lower and upper 95% confidence intervals of impervious land cover, agriculture, blue infrastructure, forest and grassland. Predictions derived from GLMER models fitted with unique study identifier as a random effect, and the amount (m^2) of each land cover type within a 1 km radius of sites as fixed effects and fitted as interaction terms with the amount (m^2) of impervious land cover within a 1 km radius of sites (Table A.4-5).

2.5 DISCUSSION

This study advances knowledge by using biodiversity data from a global collection of cities, covering a wide range of taxa and biomes, to investigate the global biodiversity response to increasing impervious land cover and the biodiversity currently supported by different types of GI and BI in cities. I show that, in concordance with previous work, there is considerable variation around the overall trend in the response of biodiversity to increasing impervious land cover (McKinney 2008). In contrast with previous work (Aronson et al. 2014), I did not find that ecological responses to impervious land cover varied significantly across ecological realms, while in concordance with previous work (Sushinsky et al. 2013; Soga et al. 2014) I found that this response varies taxonomically. Surprisingly, I found that having large areas of urban agriculture, forest, or grassland did not mitigate significantly against biodiversity losses in cities. This finding is in contrast to previous work that suggests that the preservation of large areas of GI within cities is the best solution for urban biodiversity conservation (Gagné & Fahrig 2010; Sushinsky et al. 2013; Soga et al. 2014).

My findings suggest that there is great variation in the response of biodiversity to impervious land cover, particularly for total abundance, with several positive trends in the dataset in concordance with McKinney (2008). The response of total abundance was less negative than has been found previously (Newbold 2015), potentially because I included non-urban study sites of disturbed habitat rather than limiting the analysis to sites of undisturbed habitat. I report that these trends can be explained partly by taxonomic group of study, similar to Sushinsky et al. (2013) and Soga et al. (2014). Species of the fungal phylum Ascomycota responded consistently negatively to increasing impervious land cover suggesting that species of this phylum are particularly sensitive to urban development. Potentially, because these species uptake air-borne pollutants (Carreras et al. 2005) they are less able to persist in cities where air quality tends to be worse than in non-urban environments (Gerdol et al. 2002). In contrast, I found considerable variation in the response of species to increasing impervious land cover in several of the phyla tested, suggesting that the Mollusca, Chordata, Arthropoda and Tracheophyta phyla contain both synurbic (adapted to the urban environment) (Francis & Chadwick 2012) and urban sensitive species. Unfortunately I was unable to access species lists for the majority of studies in the dataset and therefore I was unable to test whether these patterns are driven by non-native species, which tend to respond well to urban conditions (Francis & Chadwick 2012). I found considerable variation in the response of biodiversity to increasing impervious land cover within most ecological realms, suggesting that the phenotypic plasticity required for species to adapt to survival in urban environments (Alberti et al. 2017) may not be associated with biogeographic factors.

My results suggest that cities characterised by large areas of agriculture, forest or grassland do not currently support more biodiversity than cities that are missing these large areas of GI habitat. This is in contrast to recent studies that argue for the conservation of large over small areas of urban GI for biodiversity conservation (Gagné & Fahrig 2010; Sushinsky et al. 2013; Soga et al. 2014) and suggests that the availability of GI habitat may be less important for mitigating biodiversity losses in cities than other environmental factors. For example, the survival of wildlife in cities is impacted by numerous factors including the connectivity of habitats (Hale et al. 2012; Beninde, Veith & Hochkirch 2015), predation by domestic animals (Baker et al. 2005), road mortality (Trombulak & Frissell 2000), artificial lighting (Hale et al. 2015) and noise pollution (Warren et al. 2006). Due to the multifunctional natural of urban GI, which provides among other things space for human recreation, food production and sustainable urban drainage, urban GI is often characterised by many of those factors which degrade habitats and negatively impact the survival of wildlife populations (Pauleit et al. 2011; European Commission 2012). Habitat restoration should be a key consideration for urban planners and land managers trying to improve the performance of urban GI for biodiversity conservation (Collas et al. 2017). If the management of large areas of urban GI is to be improved for biodiversity conservation, it may be necessary to look beyond simply the amount and type of habitat in cities and mitigate for the multiple anthropogenic pressures that impact biodiversity in these habitats.

My results highlight the importance of water habitat in cities for biodiversity, as blue infrastructure maintained non-urban levels of both total abundance and species richness within cities, the only land cover type tested here to do so. Access to water is a key concern for current and future urban populations (McDonald et al. 2014) and future urban expansion will have a big impact on biodiversity, especially in areas suffering from water scarcity (Güneralp et al. 2013). To meet future urban water demands, billions must be spent on improving urban water infrastructure (World Water Council 2003). The link between urban biodiversity and urban water infrastructure is recognised in the Convention on Biological Diversity (UNEP 2010) and future urban expansion is an opportunity to manage urban ecosystem services, including the supply of freshwater to urban populations. Multifunctional blue infrastructure that supports both biodiversity and water provision could achieve this. However, because my database was limited to terrestrial studies, the analysis would not have included aquatic species. Future work should investigate the role of BI habitat in mitigating the effects of urban development on aquatic biodiversity.

This study will have been limited by the use of OpenStreetMap geospatial data, as the open-source nature of these data meant it was spatially biased in terms of completeness towards Europe and N. America, and subjectively biased in terms of the land cover/use classes used by OSM contributors (Haklay 2010). However, the use of these data enabled me to analyse global urban natural land cover at a higher resolution than would have been possible with any other global urban land cover dataset (Potere et al. 2009). The GI and BI land cover classifications I used were quite broad and contained a wide range of different land cover and use types. Unfortunately this was necessary in order to have sufficient data within each land cover class to include the covariates in multivariate analysis. This may have made it difficult to detect the importance of some types of urban GI and BI for biodiversity. For example, the grassland class included highly disturbed habitats such as athletic fields and golf courses which are unlikely to support high biodiversity, as well as less disturbed habitats such as shrub and grassland which have greater potential to support high biodiversity. The OSM data did not include vertical green space features, such as green walls, which are being increasingly designed into cities to enhance the quality of urban environments (Cvejić et al. 2015). It is important that urban mapping projects begin to take account of these new vertical features of importance to biodiversity. I was unable to access species lists for many studies in the database which meant I was unable to investigate whether non-native species contributed to the patterns observed. I limited analysis of the landscape surrounding study sites to a 1 km radius which may have been a more relevant scale for some species investigated in this study than others. However, this is a commonly used scale for multi-taxa studies in urban ecological research (Soga et al. 2014; Alberti et al. 2017) and is relevant to a broad range of taxa. To provide a stark comparison of the biodiversity supported by GI and BI within and outside cities, only sites at the extreme ends (upper and lower 95% CI) of the urban intensity gradient were compared. Future analysis could investigate the biodiversity supported by GI and BI at other points along the urban intensity gradient.

2.5.1 Conclusions

Cities are complex and heterogeneous habitats that have the potential to support high biodiversity. Unfortunately my study demonstrates that, despite the availability of large areas of GI in many cities, these habitats are not currently being designed and managed to maximise the biodiversity supported. Further investigation is required that enables urban planners and land managers to make informed decisions about how to manage urban GI for biodiversity that supports sustainable and liveable cities in the future.

CHAPTER 3

Biases of acoustic indices measuring biodiversity in urban areas

3.1 ABSTRACT

Urban green infrastructure, GI (e.g., parks, gardens, green roofs) are potentially important biodiversity habitats, however their full ecological capacity is poorly understood, in part due to the difficulties of monitoring urban wildlife populations. Ecoacoustic surveying is a useful way of monitoring habitats, where acoustic indices (AIs) are used to measure biodiversity by summarising the activity or diversity of biotic sounds. However, the biases introduced to AIs in acoustically complex urban habitats dominated by anthropogenic noise are not well understood. Here I measure the level of activity and diversity of the low (0-12 kHz, $_l$) and high (12-96 kHz, $_h$) frequency biotic, anthropogenic, and geophonic components of 2452 hours of acoustic recordings from 15 sites across Greater London, UK from June to October 2013 based on acoustic and visual analysis of recordings. I used mixed-effects models to compare these measures to those from four commonly used AIs: Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Bioacoustic Index (BI), and Normalised Difference Soundscape Index (NDSI). I found that three AIs (ACI_l, BI_l, $NDSI_l$) were significantly positively correlated with my measures of $biotic_l$ activity and diversity. However, all three were also correlated with $anthropogenic_l$ activity, and BI_l and $NDSI_l$ were correlated with $anthropogenic_l$ diversity. All low frequency AIs were correlated with the presence of $geophonic_l$ sound. Regarding the high frequency recordings, only one AI (ACI_h) was positively correlated with measured $biotic_h$ activity, but was also positively correlated with $anthropogenic_h$ activity, and no index was correlated with $biotic_h$ diversity. The AIs tested here are therefore not suitable for monitoring biodiversity acoustically in anthropogenically dominated habitats without the prior removal of biasing sounds from recordings. However, with further methodological research to overcome some of the limitations identified here, ecoacoustics has enormous potential to facilitate urban biodiversity and ecosystem monitoring at the scales necessary to manage cities in the future.

3.2 INTRODUCTION

With over half of the world's human population now living in urban areas (UN-DESA 2016), the global challenge is to design sustainable and liveable cities (Elmqvist et al. 2013). A large body of evidence now exists for the multiple human benefits of biodiversity in urban areas through the provision of ecosystem services such as air filtration, pest regulation, storm water management and food provision (Gómez-Baggethun et al. 2013). In urban environments, the local provision of these services can reduce human reliance on external ecosystems and can be highly valuable both economically and socially (Gómez-Baggethun & Barton 2013). There is also an increasing amount of research showing that cities can support high biodiversity, including native endemic species (Aronson et al. 2014).

Urban green infrastructure (GI), the natural and semi-natural features and green spaces in cities (European Commission 2012), provides opportunities for biodiversity and ecosystems (Sadler et al. 2011; Murphy, Gunnell & Williams 2013). GI features and spaces vary widely and include, but are not limited to, parks, gardens, biodiverse roofs and walls, street trees, and sustainable urban drainage systems (Cvejić et al. 2015). Some cities have turned to increasing GI as a means of improving urban environmental quality, while being cheaper than traditional engineered solutions to urban environmental problems (Bloomberg & Holloway 2010; Roberts et al. 2012; Greater London Authority 2017). However, the suitability of this wide variety of urban GI to support biodiversity and ecosystems is often not well quantified (Pataki et al. 2011; European Commission 2012).

To understand how sustainable and liveable cities can be designed it is crucial to understand how biodiversity responds to different types of urban GI. Greater efforts must be put into monitoring the biodiversity and ecosystems supported by urban GI (Kremer et al. 2016) so that urban planning decisions can be informed by a strong evidence base. The use of ecoacoustics as a method of quantifying ecological communities and their habitats has received increasing attention (Towsey, Parsons & Sueur 2014; Merchant et al. 2015; Sueur & Farina 2015). Due to recent advances in passive acoustic recording technology, large volumes of acoustic data can be collected with relative ease (Blumstein et al. 2011; Towsey, Parsons & Sueur 2014). However, the extraction of meaningful information from these large datasets is very challenging. Species-specific acoustic monitoring efforts have focussed on the development of classification algorithms to automatically identify the sounds emitted by organisms (Walters et al. 2012; Aide et al. 2013; Stowell & Plumbley 2014) but they are limited to a small number of species and do not provide information on the wider environment. Acoustic indices (AIs) are novel methods that attempt to overcome these challenges of quantifying the biotic and anthropogenic sounds (Sueur et al. 2014) in the large volumes of data generated by ecoacoustic monitoring.

Although AIs may provide a useful method to measure biodiversity, their sources of bias in acoustically complex urban habitats dominated by anthropogenic noise is not well understood. Verification of the measures of biotic sound captured by AIs has tended to focus on less disturbed environments than cities, with the exception of Joo, Gage and Kasten (2011) where a positive relationship was reported between avian diversity and AI values along an urban-rural gradient. A range of sounds have been found to bias AIs including road traffic (Fuller et al. 2015), human speech (Pieretti, Farina & Morri 2011), rain and wind (Depraetere et al. 2012; Towsey et al. 2014). However, formal testing of the bias caused by non-biotic sounds has tended to group non-biotic sounds as 'background noise' rather than examine the effect of individual sound sources (Towsey et al. 2014; Gasc et al. 2015b), and the response of AIs to the full spectrum of sounds typical of the urban environment remains to be tested. Additionally, the application of AIs has been limited to the audible (20 Hz-20 kHz) spectrum, and testing has tended to focus on the bird ecoacoustic community using data from ornithological surveys (Boelman et al. 2007; Pieretti, Farina & Morri 2011) or from identifications of bird vocalisations within recordings (Farina, Pieretti & Piccioli 2011; Depraetere et al. 2012; Kasten et al. 2012). However there are a number of taxonomic groups common in cities, including bats and invertebrates, which use the ultrasonic spectrum (>20 kHz). Limiting the application of AIs to the lower frequency spectrum excludes entire taxonomic groups.

Here, I evaluate four AIs on their ability to measure biotic sound captured using low (0-12 kHz, $_l$) and high (12-96 kHz, $_h$) frequency sound recordings from 15 sites across Greater London, UK and investigate which non-biotic sounds are responsible for any bias in the AIs. The AIs tested include: Acoustic Complexity Index (ACI) (Pieretti, Farina & Morri 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al. 2011), Bioacoustic Index (BI) (Boelman et al. 2007), and Normalised

Difference Soundscape Index (NDSI) (Kasten et al. 2012). Of the multitude of AIs that exist (Sueur et al. 2014), I test these four as they are designed to be robust to anthropogenic noise based on assumptions regarding the characteristics of biotic and anthropogenic sound (Figure 3.1). Commonly used indices that have already been shown to be sensitive to 'background noise' were not tested here (Sueur et al. 2014; Gasc et al. 2015b). There have been varying definitions of the different sounds that constitute a soundscape. Following Pijanowski et al. (2011b), I define biotic as sounds generated by non-human biotic organisms, anthropogenic as sounds associated with human activities, and geophonic as non-biological ambient sounds e.g. wind and rain. I compare the activity and diversity of the biotic and non-biotic (anthropogenic and geophonic) components of my recordings to those values obtained by AIs.

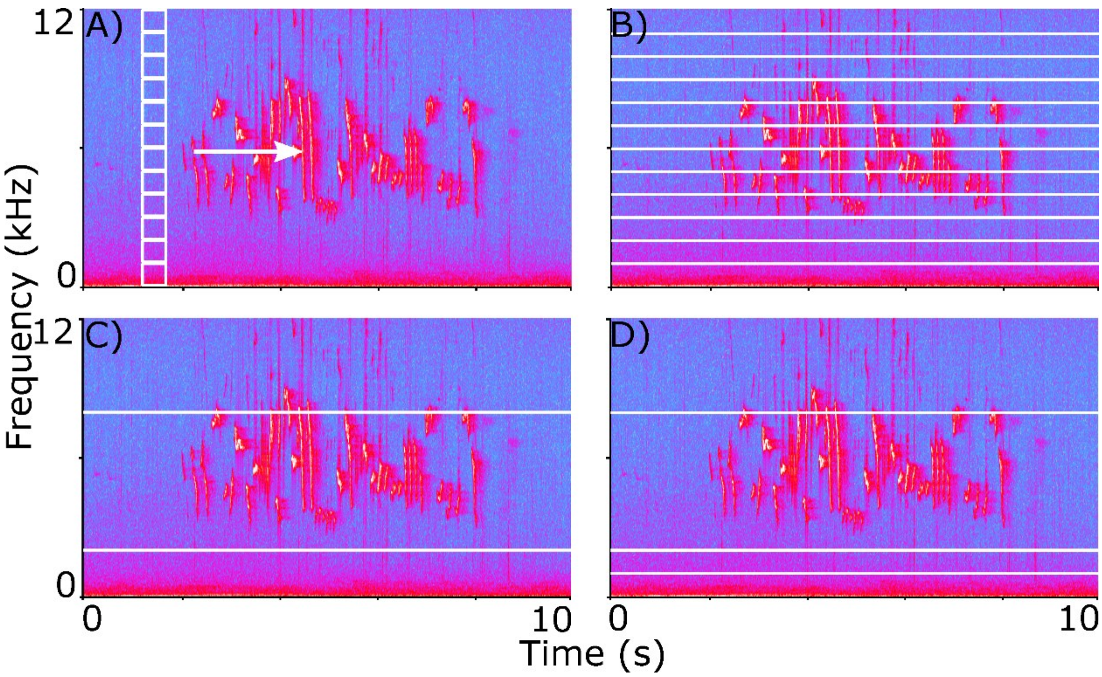


Figure 3.1 Calculation of four Acoustic Indices (AIs) on example ecoacoustic data. Data is represented in spectrograms (FFT non-overlapping Hamming window size=1024) where blue to yellow corresponds to increasing sound amplitude (dB). Spectrograms represent calculations of (A) Acoustic Complexity Index (ACI_l), (B) Acoustic Diversity Index (ADI_l), (C) Bioacoustic Index (BI_l), and (D) Normalised Difference Soundscape Index ($NDSI_l$). Frequency or temporal bins are indicated in white (see Table B.2 for specifications). ACI_l sums the absolute difference in signal power within frequency bins over time using a sliding window and defined temporal steps (indicated by arrow). ADI_l is calculated as the Shannon's diversity index for each recording based on the signal power occupancy of each 1

kHz frequency band. BI_l calculates the signal power within 2-8 kHz frequency band of recordings. $NDSI_l$ calculates the ratio of signal power in the frequency bands between 1-2 kHz and 2-8 kHz to measure the level of anthropogenic disturbance on the landscape.

3.3 MATERIALS AND METHODS

3.3.1 Data Collection

In order to maximise the variability in urban sounds with which to test the performance of the AIs, I selected 15 recording sites in habitats within and around Greater London, UK ranging from 995 to 14248 m^2 (Figure 3.2, Table B.1), and used a sampling protocol to capture the seasonal variability in the soundscape. In this analysis, I did not aim to test the effect of different habitats or environmental conditions on the performance of the AIs. GI selection was limited to churches and churchyards as they are spatially evenly distributed due to their legal protection in the UK (Department of Constitutional Affairs 1884). They also represent a wide range of urban environments that are similar to other types of urban GI due to the heterogeneity of management regimes. For example, some undergoing intensive maintenance similar to urban parks, others have large areas often left alone making them more similar to urban protected areas, and some sites that are managed by congregations are often characterised by ornamental planting making them quite similar to domestic gardens. Sites were classified using Google Earth (Google Earth 2012) into three size categories (including the building footprint): (i) small (<0.5 ha); (ii) medium (0.5-1.5 ha); and (iii) large (>1.5 ha); and three urban intensity categories based on the predominant land cover surrounding sites within a 500 meter radius: (i) high (typically contiguous multi-storey buildings); (ii) medium (typically detached and semi-detached housing); and (iii) low (typically fields and/or woodland) (Figure 3.2, Table B.1).

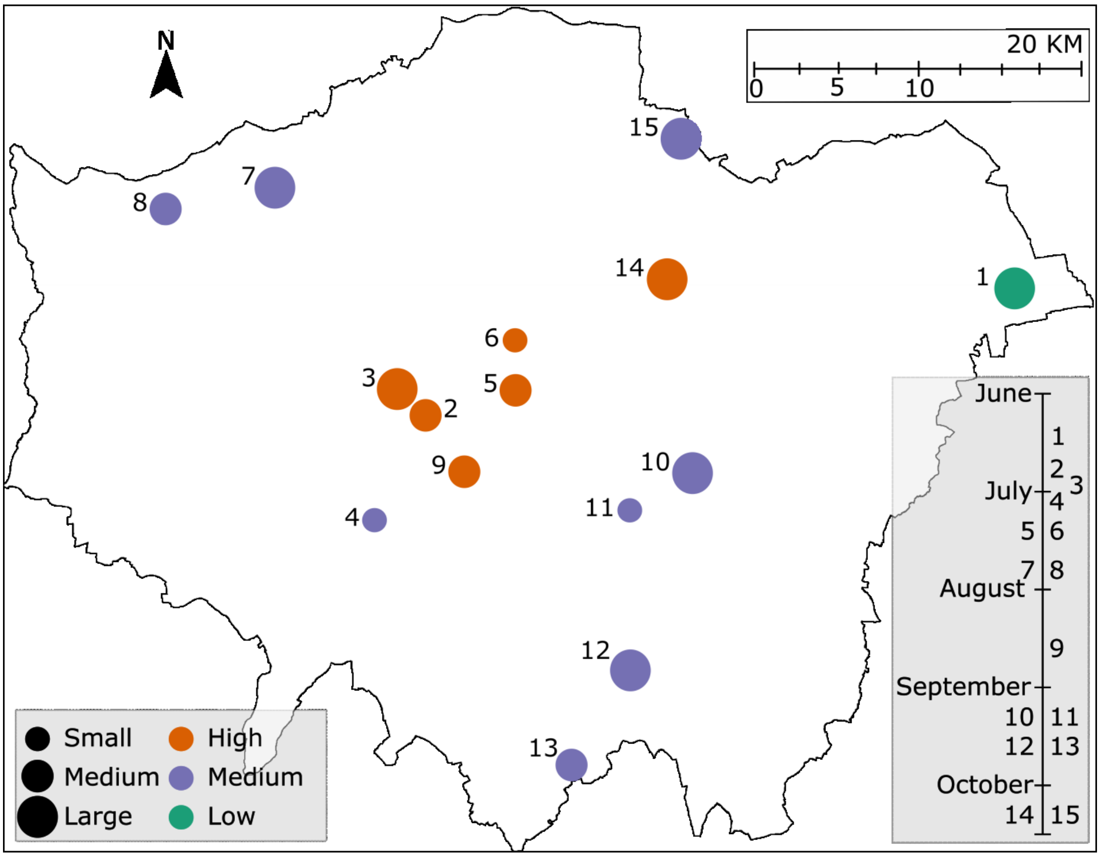


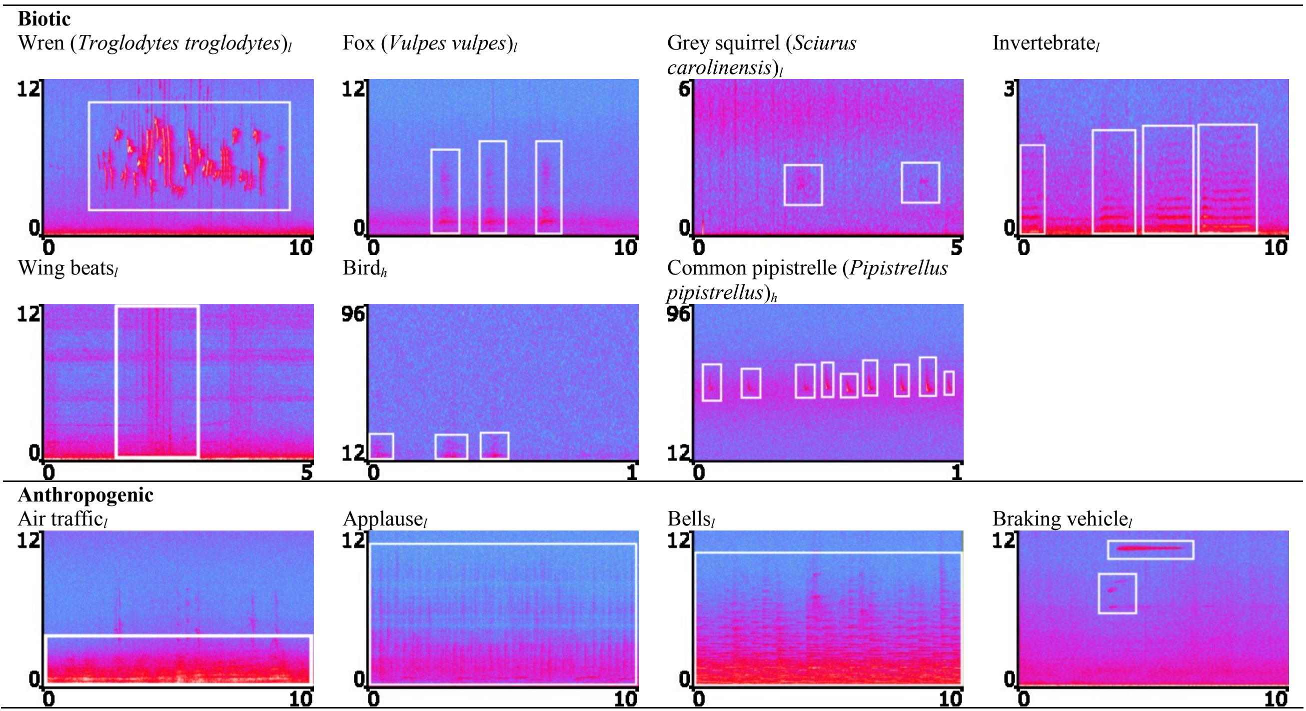
Figure 3.2 Locations and characteristics of 15 survey sites across Greater London, UK. Dots and numbers indicate sites. Relative site size indicated by dot size, urban intensity indicated by dot colour (red: high, blue: medium, green: low). Location of numbers along date scale indicates date of survey at each site. Boundary data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014).

Acoustic recordings were collected for 7 consecutive days at each site to capture the daily variability in activity across a week. In order to maximise the variability in the biotic sounds recorded, surveys were conducted between June and October 2013 which sampled both the avian breeding season (March-July) (Cramp 1994), and the peak in activity and diversity of a range of other taxonomic groups including bats (Kunz & Fenton 2003) and invertebrates (Chinery 1993; Tolman & Lewington 2009). Surveys were conducted in the summer when ecological activity is highest in the UK, rather than in winter when the variability of the soundscape is more limited to just anthropogenic and geophonic sounds. At each location, a Song Meter SM2+ and a SM2BAT+ digital audio field recorder (Wildlife Acoustics, Inc., Concord, Massachusetts, USA) were deployed, recording sound within the low (0-12 kHz, $_{l}$) and high (12-96 kHz, $_{h}$) frequency ranges. The AIs tested were developed using a range of upper spectral thresholds, i.e. 8 kHz for BI (Boelmann et al 2008) and NDSI (Kasten et al 2012), and 11-12 kHz for ADI (Villanueva-Rivera and Pijanowski 2016) and ACI (Pierretti et al 2011). For consistency, I tested all AIs using an upper threshold of 12 kHz. I acknowledge that this would have included frequencies above the thresholds of the BI and NDSI, but this is unlikely to affect my results as few sounds occur between 8 and 12 kHz (Figure 3.3). Each recorder was equipped with a single omnidirectional microphone (frequency response: -35±4 dB) oriented horizontally at a height of 1 meter. Files were saved in *.wav* format. SM2+ recordings were made in manageable chunks of 29 minutes of every half hour leading to a total of 146,160 minutes of recording (9,744 minutes for each of the 15 sites). SM2BAT+ recordings were made using an internal trigger for >12 kHz sounds and set to continue recording until no trigger was detected for a 2.0 second period, leading to a total of 474 minutes of high frequency recording (median 8.8, [5.4 and 24.8 the lower and upper 95% CI observations respectively] minutes per site).

Each 29-minute low frequency recording was divided into 1-minute audio files using Slice Audio File Splitter (NCH Software Inc. 2014) and each high frequency recording was reduced to 2-second audio files using Sound eXchange (Bagwell 2014). In order to maximise the variability of sounds with which to test the AIs, twenty-five 1-minute low frequency and 25 2-second high frequency recordings were randomly selected from each site resulting in a dataset of 375 minutes of low frequency and 12.5 minutes of high frequency audio recordings. I used a random sample rather than focussing on times of peak biotic activity, because anthropogenic sound tends to be lower at these times of day (i.e. dawn and dusk), which would have reduced the variability of anthropogenic sounds with which to test the AIs. A wide range of sampling protocols has been used in ecoacoustic studies to date. For example, Pieretti and Farina (2013) used 4 1-minute samples from 8 recording sites to investigate the effect of traffic noise on the relationship between the ACI and avian singing dynamics, while Towsey et al. (2014) used 60-minutes per day for 5 days from a single site to test the relationship between AIs and avian species richness. My sampling protocol is similar to that used by Fuller et al. (2015) who also investigated the performance of a suite of AIs in an anthropogenically-disturbed environment.

3.3.2 Acoustic Analysis

To compare the measures of biotic and non-biotic (anthropogenic and geophonic) components of my recordings to those values obtained by AIs, I generated three measures of acoustic data for each audio recording: acoustic activity (number of spectrogram pixels occupied by sound), acoustic diversity (number of unique sound types), and disturbance (ratio between biotic and anthropogenic acoustic activity). To generate these measures, I manually annotated spectrograms of each recording, computed as the log magnitude of a discrete Fourier transform (non-overlapping Hamming window size=720 samples=10 ms), using a bespoke software programme AudioTagger (available: https://github.com/groakat/AudioTagger). I then localised the time and frequency bands of discrete sounds by drawing bounding boxes as tightly as visually possible within spectrograms displayed on a Dell UltraSharp 61cm LED monitor with a Nvidia Quadro K600 graphics card. Types of sound, such as “invertebrate”, “rain”, and “road traffic”, by looking for typical patterns in spectrograms (Figure 3.3), and by listening to the audio samples represented in the annotated parts of the spectrogram. An urban transport expert provided support in the identification of the complex sounds produced by transport infrastructure. Electrical buzzes and crackles from the recording devices were classified as anthropogenic sound, and this electrical self-noise will vary depending on the recording devices used.



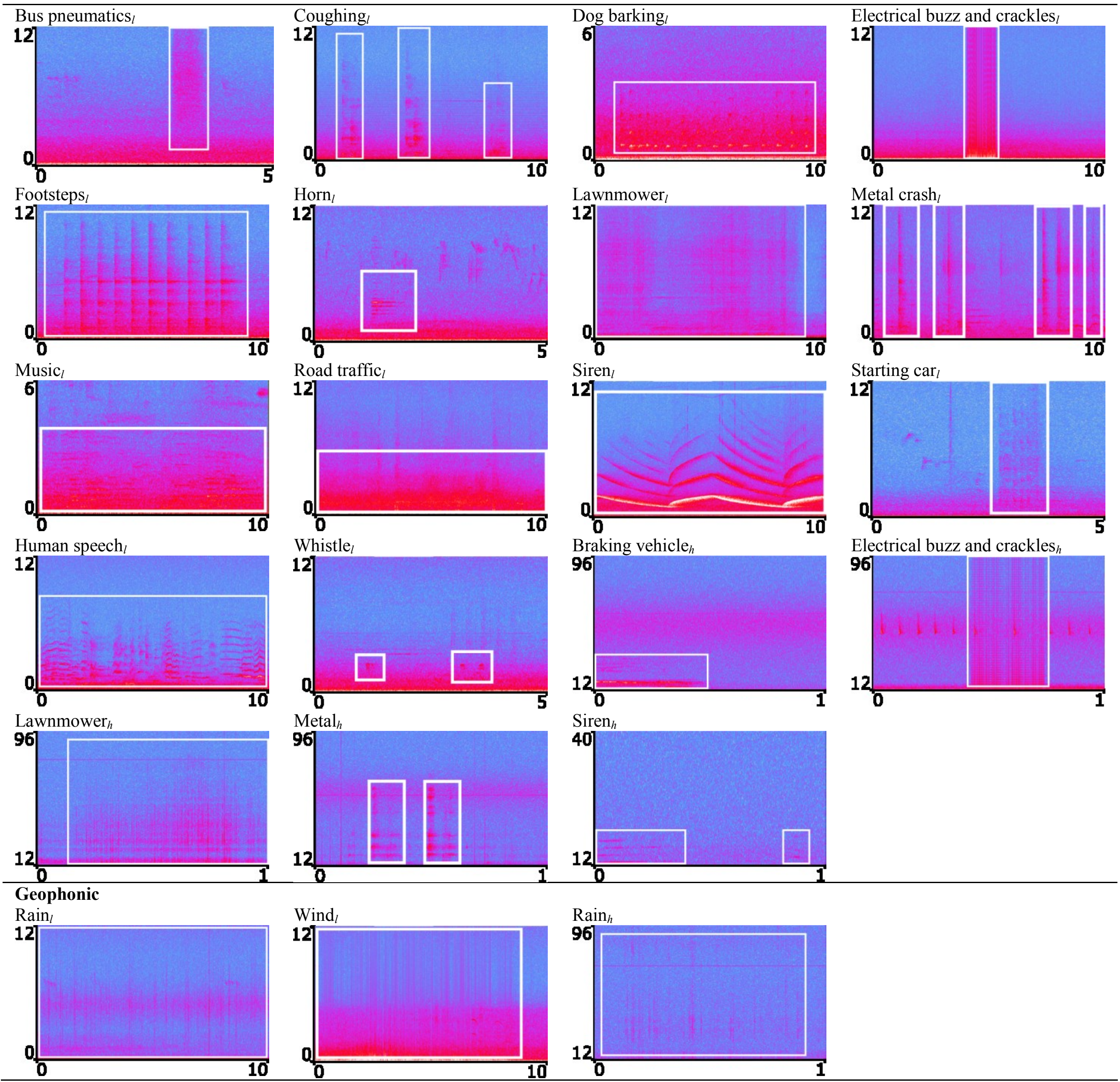


Figure 3.3 Examples of all sound types present in recordings. Bird and bat sounds were identified further to species with one example of each given here. Unidentified sounds not shown due to wide range of sound types within this group. Data is represented in spectrograms (FFT non-overlapping Hamming window size=1024) where blue to yellow corresponds to sound amplitude (dB). Frequency (kHz) and time (s) are represented on the y- and x-axes, respectively. Spectrograms represent biotic (sounds generated by non-human biotic organisms), anthropogenic (sounds associated with human activities including human speech) and geophonic sounds, where $_l$ and $_h$ denote low (<12 kHz) and high (>12 kHz) frequency sound, respectively.

3.3.3 Acoustic Activity

Acoustic activity within recordings was measured by the number of spectrogram pixels contained by the bounding boxes. This measurement was conducted by AudioTagger based on the x and y-coordinates of the corners of the bounding boxes. Sound types (n=68) (Figure 3.3) were grouped into four broad sound classes: (a) biotic (sounds generated by non-human biotic organisms, e.g. blue tit, common pipistrelle, n = 47 types); (b) anthropogenic (sounds associated with human activities including human speech, n = 18); (c) geophonic (rain and wind, n = 2); and (d) unidentifiable sounds (n = 1). The activity of each sound class within recordings was calculated as the sum of activity (number of spectrogram pixels contained by the bounding boxes) of all sound types within each class.

3.3.4 Acoustic Diversity

Acoustic diversity was measured by the number of unique sound types associated with the relevant sound class identified in each recording. For biotic diversity, sound types correspond directly to species scientific names. Where species identification was not possible, e.g. in the case of invertebrate sounds and harmonics of bird vocalisations in the high frequency recordings, these sounds were identified to one of two taxonomic groups: unidentified birds (3.2% of biotic sounds recorded) or unidentified invertebrates (0.3%). Low frequency biotic$_l$ sounds were identified and verified by two independent ecological experts; high frequency biotic$_h$ sounds were identified to species-level using Sonobat v.3.1.6p (Szewczak 2010) and iBatsID (Walters et al. 2012) which uses ensembles of artificial neural networks to probabilistically classify European bat calls. To minimise error, taxonomic classifications were manually validated using a classification probability threshold of >70%. Anthropogenic and geophonic diversity were calculated as the number of sound types associated with the anthropogenic and geophonic sound classes within each recording. Unidentified sound diversity was treated as a presence/absence as I did not differentiate between different types of unidentifiable sounds.

3.3.5 Disturbance

The NDSI$_l$ quantifies disturbance based on the ratio of biotic to anthropogenic sound in recordings (Figure 3.1) (Kasten et al. 2012). To test the NDSI$_l$ with its intended measure I calculated my own measure of disturbance (γ) using my observed activity measures as follows:

$$\gamma = \frac{\beta - \alpha}{\beta + \alpha} \qquad \text{Equation 1}$$

where β and α are the total biotic and anthropogenic acoustic activity in each recording, respectively. Observed geophonic and unidentified acoustic activity were used as additional measures of disturbance.

3.3.6 Acoustic Indices

Four AIs (ACI_l, ADI_l, BI_l and $NDSI_l$) were calculated for each low frequency recording and two AIs for each high frequency recording (ACI_h and ADI_h) in R v.3.1.2 (R Core Team 2014) using the 'soundecology' package v.1.1.1 (Villanueva-Rivera & Pijanowski 2014) (Figure 3.1, Table B.2). I did not test the BI and NDSI with high frequency data as this would require changing their biotic and anthropogenic frequency thresholds. Such adaptation would require investigation of the spectral characteristics of high frequency biotic and anthropogenic sounds which is beyond the scope of this study.

3.3.7 Statistical Analysis

To investigate the measures of biotic sound captured by the AIs and which non-biotic sounds are responsible for any bias, I fit generalised linear (GLMER) or linear (LMER) mixed-effects models in R using the 'lme4' v.1.1-7 (Bates et al. 2014) and 'glmmADMB' v.0.8.0 (Skaug et al. 2011) packages. To examine the measures of biotic sound captured by the AIs, models were fit with AIs as response variables, acoustic measures from acoustic and visual analysis of recordings as fixed effects, and site as a random effect. To investigate which non-biotic sounds were responsible for any bias, I fit the same models as above but with anthropogenic sound type as fixed effects. All variables were standardised prior to analysis to make them comparable as the measures of acoustic activity and diversity varied greatly across sound classes/types (Schielzeth 2010). I used GLMERs to fit ADI_l and ACI_h data with a Gaussian error structure and I applied a log link function and a Lambert-W transformation (Goerg 2011) to the ACI_l data to normalise its heavy-tailed distribution. Due to the bounded nature of the $NDSI_l$ (-1 to 1), the data was transformed according to the formula ($NDSI_l$ + 1) / 2 and fit with a beta error structure (Cribari-Neto & Zeileis 2009). All other data were normally distributed and were fit with LMERs. Full models were checked for assumption violation of mixed-effect models of correlation of fixed-effects, collinearity, homoscedasticity, residual normality and influence of outliers using linear regression and residual plots. In all multivariate analyses, the relative importance of predictor variables was computed as the sum of the Akaike weights (based on the Akaike information criterion, AIC) for the variables included in the averaged models (Burnham & Anderson 2002). Parameter estimates were averaged across models with ΔAIC < 4, and the corrected AIC was used to select and rank the most parsimonious models using the 'MuMIn' package v.1.12.1 (Bartoń 2012).

3.4 RESULTS

3.4.1 Urban Soundscape Composition

Most sites were dominated by both low and high frequency anthropogenic activity. Anthropogenic sound in my dataset was composed of a large variety of sound types, predominantly road traffic sounds, followed by human voices, electrical buzzes and crackles from the recorders and the environment, and air traffic (56.5%, 5.7%, 4.0% and 2.6% of total activity, respectively) (Figure 3.4). Biotic sound was mainly associated with birds and bats (9.3% and 2.3% of total activity, respectively). Other less common biotic sounds were produced by invertebrates, foxes (*Vulpes vulpes*) and grey squirrels (*Sciurus carolinensis*).

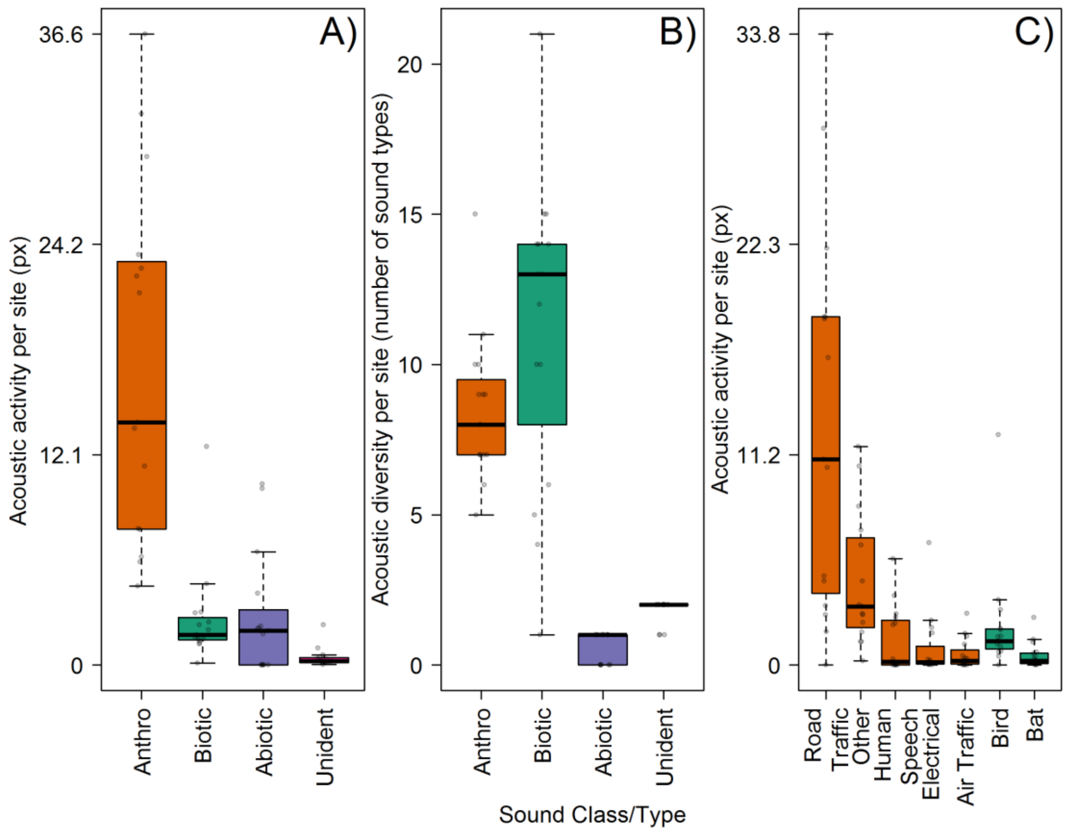


Figure 3.4 Average sound activity and diversity per site (n = 15) in Greater London. Information on each sound type is reported in A) and B), and C) reports the most common anthropogenic and biotic sound types. Acoustic activity reported as number of pixels (px, total = 75858750) occupied by each sound class/type in the spectrograms of the 25 1-minute low and 25 2-second high frequency recordings per site, where the x-axis is scaled to 10^6. Acoustic diversity reported as the number of sound types, where species are treated as unique sound types in the case of birds and bats, within each sound class. The bar indicates the median, the box indicates the inequality range, the whiskers indicate the range, and the points indicate the site data. 'Anthro' indicates anthropogenic sounds and 'Unident' indicated unidentifed sounds.

3.4.2 Acoustic Activity

Three AIs (ACI_l, BI_l, and $NDSI_l$) were significantly positively correlated with $biotic_l$ activity (Table 3.1, Table B.3), but two AIs (ACI_l, BI_l) were also correlated positively with $anthropogenic_l$ activity.

Table 3.1 Averaged mixed-effects models describing acoustic covariates of four Acoustic Indices (AIs), for sound class activity, diversity, and disturbance. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where l and h denotes low and high frequency versions, respectively. Models represent best (ΔAICc < 4) models from full candidate sets (Table B.3-5 for full models). Bold type indicates 95% significant covariates. Values represent regression slope (standard error, Z-value), relative importance of covariate across full candidate model set, and – represents covariates <50% of importance which were omitted.

			Acoustic Indices			
	Low frequency				***High frequency***	
Covariates	**ACI_l**	**ADI_l**	**BI_l**	**$NDSI_l$**	**ACI_h**	**ADI_h**
Activity						
Intercept	1801.70 (1.76, 1022.5)	0.20 (0.09, 2.3)	9.91 (1.29, 7.7)	-0.45 (0.17, 3.86)	-0.03 (0.01, 5.1)	2.15 (0.25, 8.6)
Biotic	**8.91 (0.78, 11.4), 1**	-	**2.11 (0.36, 5.9), 1**	**0.30 (0.04, 6.9), 1**	**0.04 (0.01, 15.2), 1**	-
Anthropogenic	**2.68 (1.25, 2.1), 0.69**	-0.09 (0.05, 1.7), 0.61	**3.52 (0.59, 5.9), 1**	**-0.23 (0.07, 3.1), 1**	**0.02 (0.01, 4.3), 1**	-
Geophonic	**7.18 (0.68, 10.5), 1**	**0.08 (0.01, 5.1), 1**	-	**0.19 (0.04, 5.2), 1**	-	**0.07 (0.04, 1.7), 0.63**
Unidentified	-	**-0.29 (0.14, 2.0), 1**	-	-	-	**0.14 (0.04, 3.4), 1**
Diversity						
Intercept	1800.56 (1.90, 945.0)	0.44 (0.08, 5.4)	11.14 (1.70, 6.6)	-0.20 (0.13, 1.5)	-0.01 (0.01, 0.7)	2.35 (0.27, 8.7)
Biotic	**4.16 (0.43, 9.6), 1**	-	**0.95 (0.20, 4.8), 1**	**0.09 (0.02, 4.0), 1**	-	**-0.26 (0.13, 2.1), 0.78**
Anthropogenic	0.96 (0.65, 1.5), 0.51	**-0.13 (0.02, 6.7), 1**	**0.71 (0.30, 2.3), 0.93**	**-0.20 (0.04, 5.6), 1**	-	**-0.23 (0.12, 2.1), 0.74**
Geophonic	**26.25 (2.59, 10.1), 1**	**0.21 (0.05, 3.8), 1**	**2.45 (1.16, 2.1), 0.79**	**0.46 (0.13, 3.5), 1**	-	-
Unidentified	3.29 (1.87, 1.8), 0.62	-0.24 (0.06, 3.9), 1	-	-	-	**0.38 (0.19, 2.0), 0.77**
Disturbance						
Intercept				0.02 (0.11, 0.1)		
Disturbance				**0.73 (0.07, 10.0), 1**		
Geophonic				**0.14 (0.04, 3.8), 1**		
Unidentified				-		

$NDSI_l$ was significantly negatively correlated with $anthropogenic_l$ activity. All except one AI (BI_l) was correlated positively with $geophonic_l$ activity. In the high frequency recordings, ACI_h was significantly positively correlated with both $biotic_h$ and $anthropogenic_h$ activity, while being unbiased by $geophonic_h$ activity. ADI_h was not correlated with either $biotic_h$ or $anthropogenic_h$ activity, and was positively correlated with $geophonic_h$ activity.

3.4.3 Acoustic Diversity

Three AIs (ACI_l, BI_l, and $NDSI_l$) were significantly positively correlated with $biotic_l$ diversity (Table 3.1, Table B.4). However, BI_l was positively correlated with $anthropogenic_l$ diversity, while ADI_l and $NDSI_l$ were negatively correlated. All AIs were significantly positively correlated with the diversity of $geophonic_l$ sound. ACI_h was not correlated with any of the acoustic diversity covariates, while ADI_h was negatively correlated with both $biotic_h$ and $anthropogenic_h$ diversity and positively with the diversity of $geophonic_h$ sound.

3.4.4 Disturbance

$NDSI_l$ was significantly positively correlated with both $anthropogenic_l$ (γ) disturbance, and $geophonic_l$ activity (Table 3.1, Table B.5).

3.4.5 Acoustic Sound Bias

All AIs were significantly correlated with the presence of one or more anthropogenic sounds in recordings (Table 2, Table B.6). Human speech was correlated with all four low frequency indices: positively with ACI_l and BI_l and negatively with the ADI_l and $NDSI_l$. Braking vehicles, road traffic and electrical sounds were negatively correlated with the ACI_l, ADI_l and $NDSI_l$. ACI_h was significantly positively correlated with electrical and braking vehicle sounds, and ADI_h was negatively correlated with the sound of braking vehicles.

Table 3.2 Averaged mixed-effects models describing acoustic covariates of four Acoustic Indices (AIs), for the presence of anthropogenic sound types. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where l and h denotes low and high frequency versions, respectively. Models represent best (ΔAICc < 4) models from full candidate sets (Table B.6 for full models). Bold type indicates 95% significant covariates. Values represent regression slope (standard error, Z-value), relative importance of covariate across full candidate model set, and – represents covariates <50% of importance which were omitted.

	Acoustic Indices			
	Low frequency			
Covariates	**ACI*l***	**ADI*l***	**BI*l***	**NDSI*l***
Intercept	1814.02 (3.06, 591.5)	0.50 (0.09, 5.8)	10.32 (1.65, 7.9)	0.07 (0.14, 0.5)
Air Traffic	-	**-0.20 (0.06, 3.2), 1**	-	**-0.42 (0.11, 3.7), 1**
Beep	-	-	-	-
Braking vehicle	-3.23 (2.14, 1.5), 0.52	**-0.15 (0.07, 2.1), 0.84**	-	**-0.17 (0.10, 1.7), 0.61**
Electrical	**-5.19 (2.03, 2.5), 0.92**	**-0.25 (0.05, 4.9), 1**	-	**-0.17 (0.09, 1.8), 0.66**
Road traffic	**-7.03 (2.32, 3.0), 1**	**-0.21 (0.05, 4.4), 1**	-	**-0.48 (0.11, 4.5), 1**
Human Speech	**10.85 (2.24, 4.8), 1**	**-0.20 (0.06, 3.2), 1**	**3.19 (0.89, 3.6), 1**	**-0.31 (0.11, 2.9), 1**
	High frequency			
	ACI*h*	**ADI*h***		
Intercept	-0.01 (0.01, 0.4)	2.27 (0.22, 10.2)		
Braking vehicle	**-0.03 (0.01, 2.3), 0.90**	**-0.76 (0.19, 1.0), 1**		
Electrical	**0.04 (0.01, 2.4), 0.93**	-		
Metal	-	-		

3.5 DISCUSSION

This is the first examination of the performance of a suite of AIs in the urban environment. My acoustic data indicates that the urban environment is dominated by a much wider range of anthropogenic sounds than has been dealt with by research into AIs to date. My results reveal that in terms of both biotic activity and diversity, this subset of published AIs either do not measure biotic sound or are biased by non-biotic sound in recordings. In only a few cases, could the AIs be used reliably to measure biotic sound in the urban environment during appropriate weather conditions: the ACI*l* could be used to measure low frequency biotic*l* diversity while the NDSI*l* could be used to measure the ratio of biotic*l* to anthropogenic*l* activity as a proxy for disturbance.

If AIs are to be used in the urban environment, they must be improved to be robust to the high diversity of anthropogenic sounds in this environment. My recordings were dominated by road traffic sound and also contained a large number of other anthropogenic sounds. The BI*l* was biased by the fewest anthropogenic sound types being affected only by human speech. However, I found several anthropogenic sounds bias the other AIs tested here, this is in concordance with previous studies (Pieretti & Farina 2013; Towsey et al. 2014; Fuller et al. 2015). Common methods for dealing with these sounds prior to analysis using AIs include the use of filters to remove low frequency sound from recordings (Sueur et al. 2008; Towsey et al. 2014; Pieretti et al. 2015) and the manual identification and removal of recordings containing biasing sounds (Gasc et al. 2013; Rodriguez et al. 2014). The former method is not suitable for the urban environment as many of the anthropogenic sounds recorded here occupy the same frequencies as biotic sound (Figure 3.3). The latter is impractical when considering the large volumes of data typically generated by ecoacoustic monitoring (Towsey, Parsons & Sueur 2014). Our challenge is to find better ways of reducing the bias caused by these sounds. Automated methods for identifying multiple sound types, such as the machine learning techniques used for species identification (Walters et al. 2012; Stowell & Plumbley 2014), could be used to identify and remove biasing sounds prior to the application of AIs. For example, if the BI_l was used in combination with a detection algorithm for human speech it could be a suitable AI for use in the urban environment. The identification of sounds from within the large datasets typical of ecoacoustics is a valuable area of future research.

It is difficult to interpret the negative bias caused by road traffic in my dataset as the actual amount of biotic sound in the environment might be depressed due to an effect of traffic noise on species. For example, signal-generating organisms have been shown to respond to traffic noise in multiple ways, including changing the amplitude (Pieretti & Farina 2013) and pitch (Lampe et al. 2012) of acoustic signals, to altering habitat use (McClure et al. 2013), and foraging behaviour (Schaub, Ostwald & Siemers 2008). Simulation techniques such as those employed by Gasc et al. (2015b) that control the amount of biotic sound in recordings while manipulating traffic noise may help to clarify whether the bias of traffic sound is a methodological shortcoming of AIs or a product of the ecological effects of traffic noise on biodiversity.

Geophonic sounds have been shown to bias AIs (Towsey et al. 2014; Gasc et al. 2015b) and my results reveal that this rule holds in the urban environment. However, the heterogeneity of the urban environment (Grimm et al. 2008) may greatly influence the strength of this relationship across a city. For example, a green roof located on top of a ten-storey building is more exposed to wind and rain events than an urban park sheltered by buildings and mature trees. Therefore, the suitability of using AIs in the urban environment may be highly site specific. Commonly used methods for reducing the bias of geophonic sounds are similar to those used for anthropogenic sounds including low frequency filters (Sueur et al. 2008; Pieretti et al. 2015) and manual identification and exclusion of recordings (Boelman et al. 2007; Gasc et al. 2013; Rodriguez et al. 2014). However the same issues that limit the use of these methods for anthropogenic sounds also apply for geophonic sounds: spectral overlap with biotic sounds and large volumes of recordings. Methods must be developed that are robust to the characteristic broad frequency ranges and modulations of geophonic sound.

In this study I did not test the effect of environmental factors on the performance of the AIs, but such research is required to understand what can be inferred about urban habitats from AIs. Research in non-urban habitats has revealed that environmental factors do impact the performance of AIs, for example in temperate woodlands the correlation between biodiversity and AIs weakens with increasing anthropogenic disturbance (Depraetere et al. 2012). However, the fundamental relationship between the acoustic and physical environments requires further investigation. In spite of suggestions about how biodiversity may relate to spectral diversity (Krause & Farina 2016), it remains unclear what can be inferred about the physical environment from the soundscape. In addition, species have highly variable acoustic detection probabilities (Wiley & Richards 1978), and it is not clear what can be inferred about communities from measures that are derived solely from the species which emit sound at sufficient volume (dB) to be detected by acoustic sensors. Until these relationships are better understood, ecoacoustic monitoring should be used whilst understanding the limitations of the approach.

This study could be improved by including more than one type of urban land use. Using church and churchyard green space will have limited the sounds recorded to those of the biotic communities and physical environments associated with these areas (Irvine et al. 2009). However, my use of sites that represent a range of sizes and levels of urban intensity spread widely across the city would have maximised the range of potential soundscapes recorded on this type of GI. Data collection was also limited to a single city in a single country. Cities may be characterised by unique acoustic profiles (Aiello et al. 2016) due to factors such as industries present, modes of public transport and spatial configurations of the built environment which impact the propagation of sound through the city (Piercy, Embleton & Sutherland 1977). Conducting my study in a large and heterogeneous city such as London meant I was able to record soundscapes that characterise a wide range of urban environments. Due to the lack of automated tools for sound detection and identification, I was unable to test the AIs on my entire dataset as manual acoustic data processing is highly time-consuming. The use of 25 low and high frequency recordings per site was based on practicality and is similar to previous work on AIs from disturbed environments (Fuller et al. 2015). Sites were not sampled systematically across the survey period in terms of urban intensity and size due to site access restrictions, which resulted in a slight bias towards sampling low urban intensity sites in spring, and no sampling over winter periods. However, because I was testing the performance of AIs by maximising variation in soundscapes recorded, rather than comparing the AIs across sites, I do not believe that my sampling design would have had an impact on the overall conclusions of the study. For example, I found all AIs to be biased by non-biotic sound despite sampling during the times when biotic sound would have been at its highest, therefore this finding would have remained consistent if I had also sampled during times such as winter when biotic sound is lower and non-biotic sound dominates the urban environment. Recordings were randomly selected within sampling weeks between the months of June-October so I was unable to investigate the effect of seasonality or daily variation on the acoustic components investigated. Due to power and storage constraints, my use of the SM2BAT+ trigger to record high frequency sounds means that I was unable to test the AIs on silent high frequency recordings. Finally my use of a human to detect, classify and measure sounds in the recordings, would have introduced error and bias into my data (Kershenbaum et al. 2014). For example, using bounding boxes for detecting sounds presumes that the extent of the sound can be accurately quantified, and the activity of sounds that did not completely fill the shape of the box may have been inflated. Development of machine learning algorithms for the detection and classification of urban sounds in audio recordings (Salamon & Bello 2015) could reduce the subjectivity of using humans to identify and annotate sounds in the future.

3.5.1 Application

There is growing recognition from government, industry and the environmental sector that urban GI is not currently monitored sufficiently to fulfil one of its key roles of supporting urban biodiversity and ecosystems (UK-GBC 2009; European Commission 2012; UK Parliament 2013). It is being increasingly recognised that there is a positive link between human well-being and biodiversity in the urban environment (HM Government 2010; UNEP-WCMC 2010; Dale et al. 2011), and government, industry and the environmental sector are hungry for new methods to make urban biodiversity monitoring easier and more reliable. If AIs are to be used, biasing sounds must be removed from recordings, prior to the calculation of AIs, such as has been done in marine environments to remove anthropogenic seismic exploration signals from recordings prior to the calculation of AIs (Parks, Miksis-Olds & Denes 2014). With this pre-processing the AIs could be used to measure a range of biotic factors in urban areas: activity could be monitored using the ACI_l, BI_l, $NDSI_l$, and ACI_h, while diversity of organisms could be monitored using the ACI_l, BI_l, $NDSI_l$ and ADI_h. The $NDSI_l$ which was designed to measure disturbance (Kasten et al. 2012) could be used to monitor long-term trends in human disturbance at individual sites. However, I do not recommend the use of AIs on recordings without the prior removal of biasing sounds. The use of automated methods such as machine learning algorithms to detect and identify biasing sounds could make this pre-processing feasible with large ecoacoustic datasets. The effect of this pre-processing on AI measures must be tested before AIs can be used in the urban environment. As the global human footprint increases (UN-DESA 2015), ecoacoustic scientists and practitioners need to be increasingly aware of the range of anthropogenic sounds that human activity generates such as those identified here, and take steps to reduce their effect on ecoacoustic measures of biodiversity.

3.5.2 Conclusions

Ecoacoustics presents a promising tool to facilitate urban biodiversity monitoring by making it possible to collect and process the volumes of data required to monitor cities at large spatial and temporal scales. By testing the application of existing AIs to measure biotic sound in this highly complex and anthropogenically disturbed environment, I show that there is potential in this field but much area for improvement. With the development of better methods for measuring urban biotic sound that are robust to the quantity and diversity of non-biotic sounds in this environment, ecoacoustics could lead the way in smart nature monitoring of future cities.

CHAPTER 4

CityNet – A deep learning tool for urban ecoacoustic assessment

4.1 ABSTRACT

Cities support unique and valuable ecological communities, but understanding urban wildlife is limited due to the difficulties of monitoring biodiversity. Ecoacoustic surveying has emerged as a useful way of assessing habitats, where biotic sound measured from audio recordings is used as a proxy measure of biodiversity. However, existing automated methods for measuring biotic sound in ecoacoustic data have been shown to be biased by non-biotic sounds in recordings, typical of urban environments. I co-develop CityNet, an automated deep learning system using convolutional neural networks (CNNs), to measure low-frequency (0-12 kHz) biotic (CityBioNet) and anthropogenic (CityAnthroNet) acoustic activity in urban environments. The CNNs were trained on a large set of noisy annotated audio recordings collected across Greater London, UK. Using a held out test dataset, I compare the precision/recall of CityBioNet and CityAnthroNet separately to the best available alternative approaches: four commonly used acoustic indices (AIs): Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Bioacoustic Index (BI), and Normalised Difference Soundscape Index (NDSI), and a state-of-the-art bird call detection CNN algorithm (bulbul). I also compare the effect of non-biotic sounds on the accuracy of CityBioNet and bulbul. Finally I apply CityNet to investigate acoustic patterns of the urban soundscape. In terms of precision and recall, CityBioNet was the best performing algorithm for measuring biotic activity, followed by bulbul, while the AIs performed worst. CityAnthroNet outperformed the NDSI, but by a smaller margin than CityBioNet achieved against the other competing algorithms. The accuracy of CityBioNet was decreased by mechanical sounds and the accuracy of bulbul was decreased by air traffic and wind sounds. I show that CityNet produced realistic daily patterns of biotic and anthropogenic acoustic activity from urban audio data. I show that, using CityNet, it is possible to automatically measure biotic and anthropogenic acoustic activity in real-

world urban environments from noisy audio recordings. If embedded within an autonomous assessment system, CityNet could produce environmental data for cites at large-scales and facilitate investigation of the impacts of anthropogenic activities on wildlife.

4.2 INTRODUCTION

Over half of the world's human population now live in cities (UN-DESA 2016) and urban biodiversity provides urban populations with a multitude of health and well-being benefits including improved physical (Takano, Nakamura & Watanabe 2002; De Vries et al. 2003) and psychological health (Fuller et al. 2007; Barton & Pretty 2010). Cities can support high biodiversity including native endemic species (Aronson et al. 2014), and act as refuges for biodiversity that can no longer persist in intensely managed agricultural landscapes surrounding cities (Hall et al. 2016). However, our understanding of urban biodiversity remains limited (Faeth, Bang & Saari 2011; Beninde, Veith & Hochkirch 2015). One reason for this is the difficulties associated with biodiversity assessment, such as gaining repeated access to survey sites and the resource intensity of traditional methods (Spellerberg 2005; McDonald-Madden et al. 2010). This inhibits our ability to conduct the large-scale assessment that is necessary for understanding urban ecosystems.

Ecoacoustic surveying has emerged as a useful method of large-scale quantification of ecological communities and their habitats (Towsey, Parsons & Sueur 2014; Merchant et al. 2015; Sueur & Farina 2015). Passive acoustic recording equipment facilitates the collection of audio data over long time periods and large spatial scales with fewer resources than traditional survey methods (Digby et al. 2013; Towsey et al. 2014). A number of automated methods have been developed to measure biotic sound in the large volumes of acoustic data that are typically produced by ecoacoustic surveying (Towsey, Parsons & Sueur 2014; Sueur & Farina 2015). For example, Acoustic Indices (AIs) use the spectral and temporal characteristics of acoustic energy in sound recordings to produce whole community measures of biotic sound (Sueur et al. 2014). However, several commonly used AIs have been shown to be biased by non-biotic sounds (Towsey et al. 2014; Fuller et al. 2015; Gasc et al. 2015a; Huijbers et al. 2015), and are not suitable for use in the urban environment without the prior removal of certain non-biotic sounds from recordings (Fairbrass et al. 2017).

Machine learning is being increasingly applied to biodiversity assessment and monitoring because it facilitates the detection and classification of ecoacoustic signals in audio data (Acevedo et al. 2009; Walters et al. 2012; Stowell & Plumbley 2014). Using audio datasets of annotated recordings of soniferous species, a machine learning model can be trained to recognise biotic sounds based on multiple acoustic characteristics, or features, and to associate these features with taxonomic classifications, enabling them to assign a probabilistic classification to sounds within recordings. AIs use a limited number of acoustic features in their calculations, typically just one or two such as spectral entropy within defined frequency bands (Boelman et al. 2007; Villanueva-Rivera et al. 2011; Kasten et al. 2012) or entropy changes over time (Pieretti, Farina & Morri 2011), and the relationship between the features and the algorithm outputs are chosen by a human, rather than learned automatically from a labelled dataset. On the other hand, machine learning algorithms can utilise many more features in their calculations, and the relationship between inputs and outputs is determined automatically based on the training data provided. Deep learning is a subset of machine learning where multiple layers of parameterised mathematical functions are used to infer the final prediction (LeCun, Bengio & Hinton 2015). They are typically given a raw input (e.g. a spectrogram) and allowed to choose, based on the annotations in the training dataset, the acoustic features that best discriminate different classifications of sounds. One advantage of deep learning systems compared to earlier machine learning methods is that they can take advantage of large quantities of training data. As more labelled data become available for researchers to use, the ability of deep learning to outperform human defined algorithms increases.

Species-specific machine learning algorithms have been developed to automatically identify the sounds emitted by a range of soniferous organisms including birds (Stowell & Plumbley 2014), bats (Walters et al. 2012; Zamora-Gutierrez et al. 2016), amphibians (Acevedo et al. 2009) and invertebrates (Chesmore & Ohya 2004). However, current classification algorithms are limited to a small number of species, or more recently, particular clades where algorithms that detect bird sounds in audio recordings from the UK and the Chernobyl Exclusion Zone have been developed through the 2016-7 Bird Audio Detection challenge (Stowell et al. 2016) and these algorithms have not been tested on noisy audio data from urban environments. There are currently no machine learning algorithms that produce whole community measures of biotic sound that are known to be suitable for use in acoustically complex urban environments.

Here, I developed the CityNet acoustic analysis system, which uses two deep learning Convolutional Neural Networks (CNNs) for measuring biotic (CityBioNet) and anthropogenic (CityAnthroNet) acoustic activity in low frequency (0-12 kHz) noisy audio recordings from urban environments. The CNNs were trained using CitySounds2017, a new annotated dataset of urban sounds collected across Greater London, UK, and tested using a held out dataset by comparing the precision/recall of CityNet to four commonly used AIs: Acoustic Complexity Index (ACI) (Pieretti, Farina & Morri 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al. 2011), Bioacoustic Index (BI) (Boelman et al. 2007), Normalised Difference Soundscape Index (NDSI) (Kasten et al. 2012), and to bulbul, a state-of-the-art algorithm for detecting bird sounds in order to summarise avian acoustic activity (Grill & Schlüter 2017). Because the main focus of the study was the development of algorithms for ecoacoustic assessment of biodiversity in cities, I conducted further analysis on the two best performing algorithms for measuring biotic sound, CityBioNet and bulbul, by investigating the effect of non-biotic sounds on the accuracy of the algorithms. Finally, I applied CityNet to investigate daily patterns of biotic and anthropogenic sound in the urban soundscape.

4.3 MATERIALS AND METHODS

CityNet was created to generate measures of biotic and anthropogenic sounds from long and noisy audio recordings. The CityNet system consisted of two convolutional neural network models, CityBioNet and CityAnthroNet, which generate measures of biotic and anthropogenic sound, respectively. The CityNet pipeline (Figure 4.1) consisted of 7 main steps as follows:

(1) *Record audio*: Low frequency (0-12 kHz) *.wav* audio recordings were made using a passive acoustic recorder.

(2) *Audio conversion to Mel spectrogram:* Each audio file was automatically converted to a Mel spectrogram representation with 32 frequency bins, represented as rows in the spectrogram, using a temporal resolution of 21 columns per second of raw audio. Before use in the classifier, each spectrogram *S* was converted to a log-scale representation, using the formula log(A + B * S). For biotic sound detection the parameters A = 0.001 and B = 10.0 were used, while for anthropogenic sound detection the parameters A = 0.025 and B = 2.0 were used.

(3) *Extract window from spectrogram:* A single input to the CNN comprised a short spectrogram chunk *Ws,* 21 columns in width, representing 1 second of audio.

(4) *Apply different normalisation strategies:* There are many different methods for pre-processing spectrograms before they are used in machine learning; for example whitening (Lee et al. 2009) and subtraction of mean values along each frequency bin (Aide et al. 2013). CNNs are able to accept inputs with multiple channels of data, for example the red, green and blue channels of a colour image. This was exploited to give as input to the CNN a four-channel spectrogram, where each channel was pre-processed using a different strategy (see Supplementary Methods in Appendix C). This gave considerable improvements to network accuracy above any single normalisation scheme in isolation. After applying different normalisation strategies, the input to the network consisted of a 32 x 21 x 4 tensor.

(5) *Apply CNN classifier:* As described above, classification was performed with a CNN, whose parameters were learned from training data. The CNN comprised a series of layers, each of which modified its input data with a parameterised mathematical operation. During training, the parameters of the layers were modified to optimise classification performance. The final layer produced the prediction of presence or absence of biotic or anthropogenic sound. The ordering and types of layers used in the CNN is described in the Supplementary Methods in Appendix C.

(6) *Make prediction for each moment in time:* At test time, steps (3)-(5) were repeated every 1 second throughout the audio file, to give a measure of biotic or anthropogenic activity throughout time. Predictions for each chunk of audio were made independently.

(7) *Summarise:* Where appropriate, the chunk-level predictions were summarised to gain insights into trends over time and space. For example, predicted activity levels for each half-hour window could be averaged to inspect the level of biotic and anthropogenic activity at different times of day.

The machine learning pipeline was written in Python v.2.7.12 (Python Software Foundation 2016) using Theano v.0.9.0 (The Theano Development Team et al. 2016) and Lasagne v.0.2 (Dieleman et al. 2015) for machine learning and librosa v.0.4.2 (McFee et al. 2015) for audio processing.

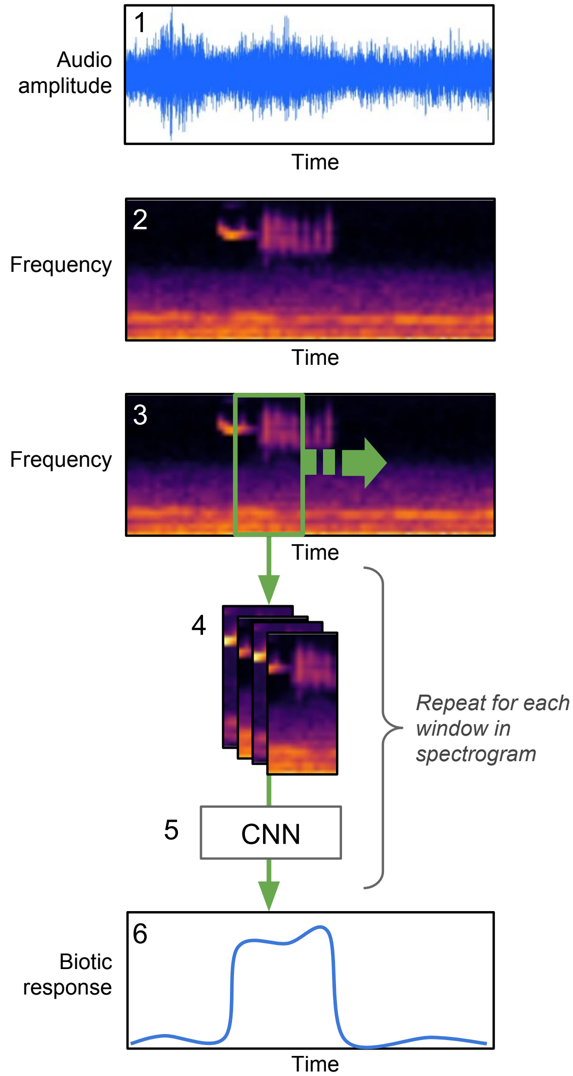


Figure 4.1 An overview of how CityNet is used to measure biotic and anthropogenic acoustic activity. Raw audio (1), recorded in the field, is converted to a spectrogram representation (2). A sliding window is run across the time dimension, and a window of the spectrogram extracted at each step (3). This spectrogram window is pre-processed with four different normalisation strategies, and the results concatenated. This stack of spectrograms is passed through a CNN (5), which was trained on CitySounds2017$_{train}$. The CNN gives, at each 1-second time step, a prediction of the presence/absence of biotic or anthropogenic acoustic activity (6).

4.3.1 Acoustic Training Dataset

I selected 63 green infrastructure (GI) sites in and around Greater London, UK to collect audio data to train and test the CityNet algorithms. These sites represent a range of GI in and around Greater London in terms of GI type, size and urban intensity. Each site was sampled for 7 consecutive days systematically across the months of May to October between 2013 and 2015 (Figure 4.2, Table C.1). At each location, a Song Meter SM2+ digital audio field recorder (Wildlife Acoustics, Inc., Concord, Massachusetts, USA) was deployed, recording sound between 0 and 12 kHz as this frequency range contains the majority of sounds emitted by audible soniferous species in the urban environment (Fairbrass et al. 2017). The recorder was equipped with a single omnidirectional microphone (frequency response: -35±4 dB) oriented horizontally at a height of 1 metre. Files were saved in *.wav* format. Recordings were made in computationally manageable chunks of 29 minutes of every 30 mins (23.2 hours of recording per day), which were divided into 1-minute audio files using Slice Audio File Splitter (NCH Software Inc. 2014), leading to a total of 613,872 discrete minutes of audio recording (9,744 minutes for each of the 63 sites).

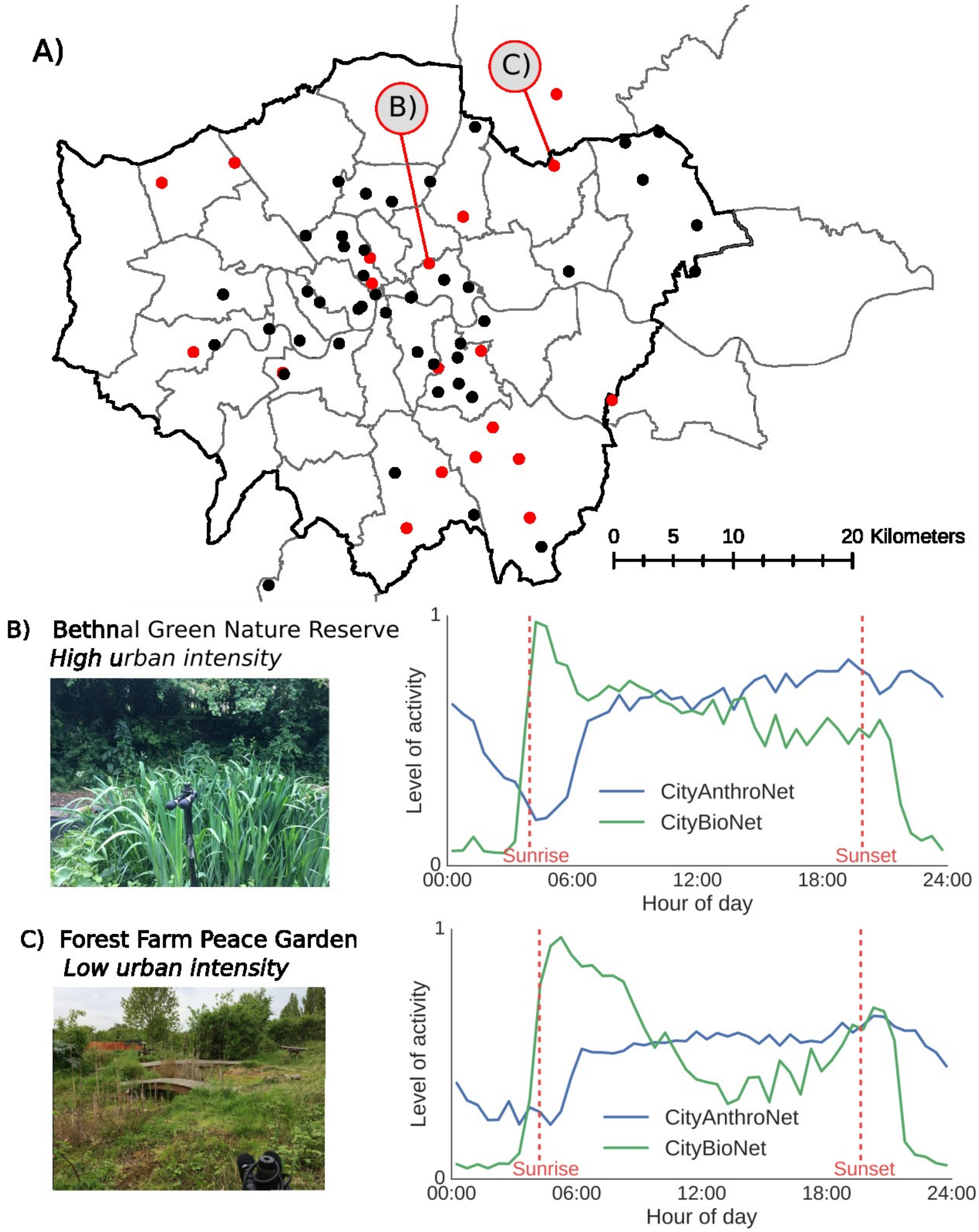


Figure 4.2 Location of study sites and average daily acoustic patterns at two sites along an urbanisation gradient. Points in (A) represent locations used for the training dataset, CitySounds2017$_{train}$ (black) and testing dataset, CitySounds2017$_{test}$ (red). Here CityNet was run across the entire 7 days of recording at two sites of high (B) and low (C) urban intensity to predict the presence/absence of biotic and anthropogenic sound at each second of the week using a 0.5 probability threshold. The predicted number of seconds containing biotic and

anthropogenic sound for each half-hour period was averaged over the week to produce average daily patterns of acoustic activity. Greater London boundary indicated with bold line. Boundary data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014).

I developed an urban audio dataset, CitySounds2017, by randomly sampling twenty-five 1-minute recordings from each site resulting in a dataset of 1575 minutes of audio recordings. I randomly selected 1100 recordings from 44 sites to create the training dataset (CitySounds2017$_{train}$), and I manually annotated the spectrograms of each recording, computed as the log magnitude of a discrete Fourier transform (non-overlapping Hamming window size=720 samples=10 ms), using AudioTagger (available at https://github.com/groakat/AudioTagger). To annotate the spectrograms I localised the time and frequency bands of discrete sounds by drawing bounding boxes as tightly as visually possible within spectrograms displayed on a Dell UltraSharp 61cm LED monitor. Types of sound, such as “invertebrate”, “rain”, and “road traffic”, were identified by looking for typical patterns in spectrograms (Figure), and by listening to the audio samples represented in the annotated parts of the spectrogram. Categories of sounds were then grouped into biotic, anthropogenic and geophonic classes. Following Pijanowski et al. (2011b), I define biotic as sounds generated by non-human biotic organisms, anthropogenic as sounds associated with human activities, and geophonic as non-biological ambient sounds e.g. wind and rain.

4.3.2 Acoustic Testing Dataset and Evaluation

To evaluate the performance of the CityNet algorithms, I created a testing dataset (CitySounds2017$_{test}$) by selecting 40 recordings from CitySounds2017 from 19 sites which contained a range of both biotic and anthropogenic acoustic activity. Audio data in the training and testing datasets were sampled from different recording sites to show that the CityNet algorithms generalise to sounds recorded at new site locations (Figure 4.2, Table C.1). To optimise the quality of the annotations in this testing dataset, five human labellers separately annotated the sound types within the audio recordings. These annotations were used to guide the annotation of the CitySounds2017$_{test}$ dataset, whereby I copied the annotations of the five labellers to create a single annotated dataset. Where labellers had classified the same annotated sound differently, the most commonly used classification was used, except in cases where there was no majority, in which case I used my own judgement on the most suitable classification.

The CitySounds2017$_{test}$ dataset was annotated differently to the CitySounds2017$_{train}$ dataset making it unsuitable to evaluate the CityNet algorithms using k-folds cross validation (Refaeilzadeh, Tang & Liu 2009). Instead, using the CitySounds2017$_{test}$ dataset, I separately assessed the performance of the two CityNet algorithms, CityBioNet and CityAnthroNet, using two measures: precision and recall. The CityBioNet and CityAnthroNet algorithms gave a probabilistic estimate of the level of biotic or anthropogenic acoustic activity for each 1-second audio chunk as a number between 0 and 1. Different thresholds could be used to convert these probabilities into sound category assignments (e.g. 'sound present' or 'sound absent'). At each threshold, a value of precision and recall was computed, where precision was the fraction of 1-second chunks correctly identified as containing the sound according to the annotations in CitySounds2017$_{test}$, and recall was the fraction of 1-second chunks labelled as containing the sound which was retrieved by the algorithm under that threshold. As the threshold was swept between 0 and 1, the resulting values of precision and recall were plotted as a precision-recall curve. Summary statistics of the average precision under all the threshold values were also computed, and the recall when the threshold chosen gave a precision of 0.95. Using a threshold of 0.5 on the predictions, confusion matrices were calculated showing how each moment of time was classified relative to the annotations. These analyses were conducted in Python v.2.7.12 (Python Software Foundation 2016) using Scikit-learn v.0.18.1 (Pedregosa et al. 2011) and Matplotlib v.1.5.1 (Hunter 2007).

4.3.3 Competing Algorithms

Using the CitySounds2017$_{test}$ dataset I compared the performance (precision/recall)of CityBioNet to acoustic measures produced by four AIs: Acoustic Complexity Index (ACI) (Pieretti, Farina & Morri 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al. 2011), Bioacoustic Index (BI) (Boelman et al. 2007), and Normalised Difference Soundscape Index (NDSI) (Kasten et al. 2012). The NDSI generates a measure of anthropogenic disturbance according to the formula

$$NDSI = \frac{\mathrm{NDSI}bio - \mathrm{NDSI}anthro}{\mathrm{NDSI}bio + \mathrm{NDSI}anthro} \qquad \text{Equation 1}$$

where NDSI_{bio} and NDSI_{anthro} are the total biotic and anthropogenic acoustic activity in each recording, respectively. Rather than compare CityNet to the NDSI, I compared the biotic (NDSI_{bio}) and anthropogenic (NDSI_{anthro}) elements of the NDSI to the measures produced by CityBioNet and CityAnthroNet, respectively, as these were more comparable. All AIs were calculated in R v.3.4.1 (R Core Team 2017) using the 'seewave' v.1.7.6 (Sueur, Aubin & Simonis 2008) and 'soundecology' v.1.2 (Villanueva-Rivera & Pijanowski 2014) packages.

As the AIs are all designed to give a summary of acoustic activity for an entire file, they were analysed on the $\mathrm{CitySounds2017}_{test}$ dataset by treating each 1-second chunk of audio as a separate sound file to enable direct comparisons to CityNet. The AI measures do not have a natural threshold for classification into biotic/non-biotic sound, meaning I could not calculate confusion matrices. However, a threshold between their lowest value and their highest value was used in combination with the range of precision and recall values to form precision-recall curves. The performance (precision/recall) of CityBioNet was also compared to bulbul (Grill & Schlüter 2017), a bird sound measurement algorithm for detecting avian sounds in entire audio recordings in order to summarise avian acoustic activity which was the winning entry in the 2016-7 Bird Audio Detection challenge (Stowell et al. 2016). Like CityNet, bulbul is a CNN-based classifier which uses spectrograms as input. However, their system does not use the same normalisation strategies as CityNet, and it was not trained on data from noisy, urban environments. Bulbul was applied to each second of audio data in $\mathrm{CitySounds2017}_{test}$, using the pre-trained model provided by the authors together with their code.

4.3.4 Impact of Non-Biotic Sounds

As the main focus of this study was the development of algorithms for ecoacoustic assessment of biodiversity in cities, I conducted additional analysis on the non-biotic sounds that affect the accuracy of CityBioNet and bulbul, because they were found to be the best performing algorithms for measuring biotic sound in terms of precision/recall. I only compared CityBioNet to the four AIs in terms of precision/recall and not the non-biotic sounds that affect the accuracy of the AIs because my analysis showed that the AIs performed so much worse than CityBioNet that it wasn't worthwhile investigating their utility further. To identify the non-biotic sounds that affect the accuracy of the algorithms, I created subsets of the CitySounds2017$_{test}$ dataset comprising all the seconds that contained a range of non-biotic sounds, e.g. a road traffic data subset containing all of the seconds in CitySounds2017$_{test}$ where the sound of road traffic was present. I then compared the accuracy of the measures produced by the algorithms on the full CitySound2017$_{test}$ dataset with the accuracy of the measures on the non-biotic sounds data subsets. The proportion of seconds correctly classified by each algorithm in the full and subset datasets were compared for significant differences using a Chi-squared test and the Cramer's V statistic was used to assess the effect size of differences (Cohen 1992). These analyses were conducted in R v.3.4.1 (R Core Team 2017).

4.3.5 Ecological Application

To investigate the acoustic patterns of the urban soundscape, CityNet was used to generate daily average patterns of biotic and anthropogenic acoustic activity for two study sites (E29RR and IG62XL, Table C.1). These sites were chosen to provide a comparison of the soundscape at sites of low (IG62XL) and high (E29RR) urban intensity while controlling for the date of recording; both sites were surveyed between May and June 2015. To create daily patterns of acoustic activity, CityNet was run over the entire 7 days of recordings from each site to predict the presence/absence of biotic and anthropogenic sound for every 1-second audio chunk. Measures of biotic and anthropogenic activity were created for each half hour window between midnight and midnight by averaging the predicted number of seconds containing biotic or anthropogenic sound within that window over the entire week. For example, the single average value of biotic and anthropogenic activity for the period 00:00 to 00:29 was formed by averaging the 12,180 1-second predictions during that time period over the seven days. Finally, the presence of sound in recordings may impact the predictions of CityNet, for example high anthropogenic sound may negatively bias the predictions of CityBioNet. To investigate this, the correlation between the predictions of CityBioNet and CityAnthroNet was tested using the average daily activity data and a Spearman's rank correlation test.

4.4 RESULTS

4.4.1 Acoustic Performance

Both CityNet algorithms outperformed the AIs in terms of precision and recall (Table 4.1, Figure 4.3).

Table 4.1 Average precision and recall results for CityNet and competing algorithms for each 1-second audio clip in the CitySounds2017$_{test}$ dataset. Recall results are presented at 0.95 precision. Higher values are better for both metrics. The highest values in each section are shown in bold. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI$_{bio}$ and NDSI$_{anthro}$ biotic and anthropogenic Normalised Difference Soundscape Index respectively.

Acoustic Measures	Recall at 0.95 precision	Average precision
Biotic		
CityBioNet	**0.710**	**0.934**
Bulbul	0.398	0.872
ACI	0.000	0.663
ADI	0.001	0.439
BI	0.002	0.516
NDSI$_{biotic}$	0.000	0.503
Anthropogenic		
CityAnthroNet	**0.858**	**0.977**
NDSI$_{anthro}$	0.815	0.975

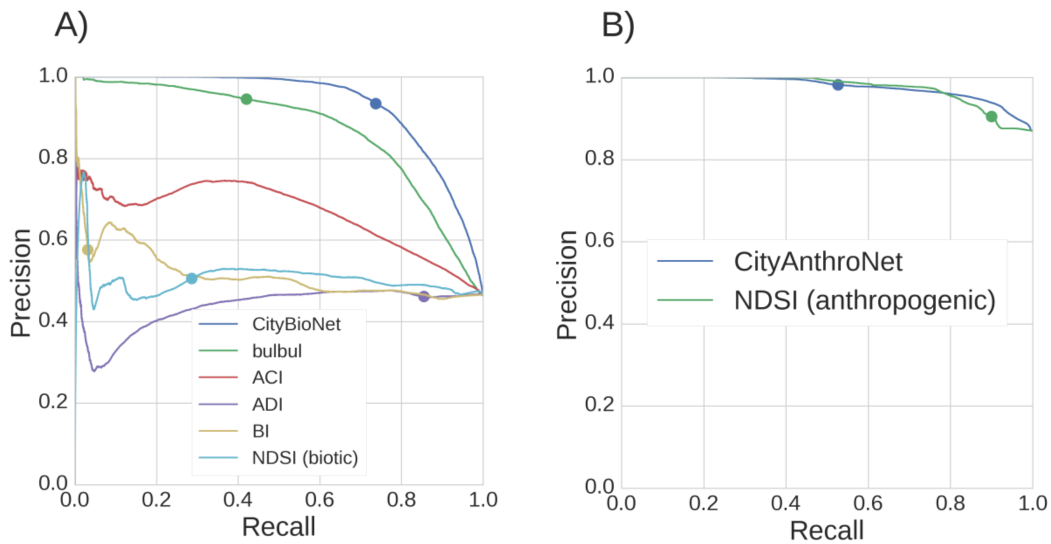


Figure 4.3 Precision-recall curves for CityNet and competing algorithms predicting A) biotic and B) anthropogenic acoustic activity for each 1-second audio clip in the CitySounds2017$_{test}$ dataset. Dots indicate the precision and recall values at a threshold value of 0.5. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI$_{bio}$ and NDSI$_{anthro}$ biotic and anthropogenic Normalised Difference Soundscape Index, respectively.

CityBioNet had an average precision of 0.934 and recall of 0.710 at 0.95 precision, while CityAnthroNet had an average precision of 0.977 and recall of 0.858 at 0.95 precision. In comparison to CityBioNet, the ACI, ADI, BI and NDSI$_{bio}$ had a lower average precision (0.663, 0.439, 0.516, and 0.503, respectively) and lower recall at 0.95 (all less than 0.01). In comparison to CityAnthroNet, the NDSI$_{anthro}$ had a lower average precision (0.975) and lower recall at 0.95 (0.815). CityBioNet also outperformed bulbul which had an average precision of 0.872 and recall at 0.95 of 0.398 (Table 4.1, Figure 4.3). Inspection of the confusion matrices (Figure 4.4) confirms that when biotic sound was present in recordings, CityBioNet correctly predicted the presence of biotic sound (True Positives) in a greater proportion of audio data than bulbul (33.2% in comparison with 18.5% respectively). However, CityBioNet failed to correctly predict the presence of biotic sound (False Negatives) in 1.7% of recordings in comparison with 1.0% incorrect predictions by bulbul. When biotic sound was absent from recordings, CityBioNet correctly predicted the absence of biotic sound (True Negatives) in 51.6% of the audio data in comparison with 52.6% for bulbul, and CityBioNet failed to correctly predict the absence of biotic sound (False Positives) in 13.5% of audio data in comparison with 20.0% incorrect predictions by bulbul.

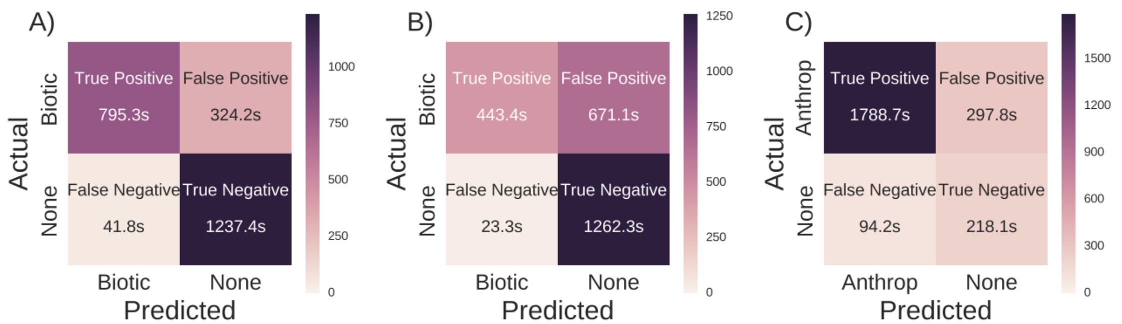


Figure 4.4 Confusion matrices comparing the predicted acoustic activity of A) CityBioNet, B), bulbul, and C) CityAnthroNet for each 1-second audio clip in the CitySounds2017$_{test}$ dataset. Numbers in each cell report the proportion of 1-second audio clips in the CitySounds2017$_{test}$ dataset predicted either correctly (True Positives and True Negatives) or incorrectly (False Positives and False Negatives) as containing biotic (A and B) or anthropogenic (C) sound. To create the confusion matrices, the probabilistic predictions from the classifiers are converted to binary classifications using a threshold that gives a precision of 0.95.

4.4.2 Impacts of Non-Biotic Sounds

CityBioNet was strongly (Cramer's V effect size >0.5) negatively affected by mechanical sounds (28.60% less of the data was accurately classified as containing biotic sound when mechanical sounds were also present) (Table 4.2). Bulbul was moderately (Cramer's V effect size 0.1-0.5) negatively affected by the sounds of air traffic and wind (5.34% and 6.93% less of the data was accurately classified as containing biotic sound when air traffic and wind sounds were also present in recordings respectively). The accuracy of neither of the algorithms was affected by the sound of road traffic, sirens or rain.

Table 4.2 Impact of non-biotic sounds on the accuracy of biotic activity measures produced by CityBioNet and bulbul. Values represent percentage change in classifier accuracy between the full CitySound2017$_{test}$ dataset (40 minutes) and the subset datasets (size in time indicated in left-hand column) of all 1-second audio clips containing the non-biotic sound (chi-squared test statistic for difference in proportions of successes in each dataset, and Cramer's V effect size measure). Effect sizes indicated as <0.1 (*), 0.1-0.3 (**) and >0.5 (***).

Sound Type	CityBioNet	bulbul
Anthropogenic		
Air traffic (9m 4s)	-2.11 (30.35, 0.05)*	-5.34 (162.73, 0.12)**
Mechanical (11s)	-28.60 (134.38, 0.77)***	0.02 (0.01, 0.01)*
Road traffic (29m 15s)	0.79 (10.15, 0.02)*	1.41 (27.67, 0.03)*
Siren (1m 21s)	2.28 (5.73, 0.06)*	3.70 (12.95, 0.09)*
Geophonic		
Rain (2m 44s)	-0.77 (1.29, 0.02)*	-1.51 (4.17, 0.04)*
Wind (53s)	0.76 (0.47, 0.02)*	-6.93 (33.11, 0.17)**

4.4.3 Ecological Application

CityNet produced realistic patterns of biotic and anthropogenic acoustic activity in the urban soundscape at two study sites of low and high urban intensity (Figure 4.2). At both sites, biotic acoustic activity peaked just after sunrise and declined rapidly after sunset. A second peak of biotic acoustic activity was recorded at sunset at the low urban intensity site but not at the high urban intensity site. At both sites anthropogenic acoustic activity rose sharply after sunrise, remained constant throughout the day and declined after sunset. Finally, I found no correlation between the predictions of CityBioNet and CityAnthroNet on the daily average activity data (r_s = 0.02, p = 0.81).

4.5 DISCUSSION

Both CityBioNet and CityAnthroNet outperformed the competing algorithms on the CitySound2017$_{test}$ dataset. CityBioNet performed better than bulbul on noisy recordings from the urban environment; it was robust to more non-biotic sounds, including road traffic, air traffic and rain. Being robust to the sound of road traffic supports the suitability of CityBioNet for use in cities, as the urban soundscape is dominated by the sound of road traffic (Fairbrass et al. 2017) which has been shown to bias several of the commonly used AIs tested here (Fuller et al. 2015; Fairbrass et al. 2017). The sound of rain has also been shown to bias several AIs (Depraetere et al. 2012; Gasc et al. 2015b;

Fairbrass et al. 2017) and the development of a method that is robust to this sound is a considerable contribution to the field of ecoacoustics. The urban biotic soundscape is dominated by the sounds emitted by birds (Fairbrass et al. 2017), and the good performance of bulbul, an algorithm for measuring exclusively bird sounds, on the CitySounds2017$_{test}$ dataset, confirms this. Birds are used as indicator species in existing urban biodiversity monitoring schemes (Kohsaka et al. 2013) using data collected from traditional forms of biodiversity survey. The algorithms developed here could be used to support such existing schemes by making it easier to collect data on these indicator taxa.

CityNet is the only method currently available for measuring both biotic and anthropogenic acoustic activity using a single system in noisy audio data from urban environments. There is increasing evidence that anthropogenic noise affects wildlife in a variety of ways including altering communication behaviour (Lampe et al. 2012; Gil & Brumm 2014) and habitat use (Deichmann et al. 2017). However, these investigations are limited in scale by the use of resource intensive methods of measuring biotic and anthropogenic sound in the environment (Brumm 2004; Grace & Anderson 2015) or from audio data (Hanna et al. 2011; Grace & Anderson 2015), or rely on AIs (Pieretti & Farina 2013) which have been shown to be unreliable in acoustically disturbed environments (Fairbrass et al. 2017). CityNet could facilitate the investigation of the impacts of anthropogenic activities on wildlife populations in cities at scales not currently possible with traditional acoustic analysis methods.

CityBioNet clearly outperformed all the AIs tested, but the difference in performance between CityAnthroNet and the competing algorithm for measuring anthropogenic acoustic activity (NDSI$_{anthro}$) was much less marked. These results suggest that the measurement of biotic sound in noisy audio data from urban environments is more difficult and requires more sophisticated algorithms than the measurement of anthropogenic sound. One reason for this may be that anthropogenic sounds may be more easily separable from other sounds in frequency space, a theory which is the basis of a number of AIs (Boelman et al. 2007; Kasten et al. 2012), enabling the use of hand-tuned heuristic algorithms such as NDSI$_{anthro}$. Whereas, because biotic sounds occur in a frequency space shared with anthropogenic and geophonic sounds (Fairbrass et al.

2017), algorithms such as AIs which only use a small number of spectral features to discriminate sounds are not sufficient for use in cities. Therefore, machine learning algorithms which are able to utilise large numbers of features to discriminate sounds, such as the CNNs implemented in the CityNet system, are better able to detect biotic sounds in recordings that also contain non-biotic sounds at overlapping frequencies. A recent unsupervised method developed by Lin, Fang and Tsao (2017) to separate biological sounds from long recordings could be used as a pre-processing step to further improve CityNet's performance.

Low cost acoustic sensors and algorithms for the automatic measurement of biotic sound in audio data is facilitating the assessment and monitoring of biodiversity at large temporal and spatial scales (Towsey, Parsons & Sueur 2014), but to date this technology has only been deployed in non-urban environments (e.g. Aide et al. 2013). In cities, the availability of mains power and Wifi connections is supporting the development of the urban Internet of Things with low cost sensors integrated into existing infrastructure, monitoring environmental factors including air pollution, noise levels, and energy use (Zanella et al. 2014; Mydlarz, Salamon & Bello 2017). The CityNet system could be integrated into an Internet of Things-style assessment pipeline of audio data capture and analysis which could facilitate large-scale urban environmental monitoring. The algorithms developed here would be an essential element of an autonomous urban environmental assessment system by generating measures of biodiversity and human acoustic activity from the large volumes of audio data that would be captured by such a system. Large-scale deployment of algorithms such as this requires low power usage and fast running times. One way to help to achieve this aim would be to combine the two networks (CityBioNet and CityAnthroNet) into one CNN which predicts both biotic and anthropogenic acoustic activity simultaneously. A combined network could produce two predictions using the same number of operations inside the network as it currently performs to produce one, thereby halving the time taken by the system. The challenge is making one network learn to give both answers at once.

Many stakeholders in cities are interested in simple to understand measures of biodiversity that can be interpreted without ecological knowledge to inform decisions about urban land management (Tzoulas & James 2010). I have shown that the CityNet system can be used to process large volumes of audio data from urban environments and produce simple measures of biotic and anthropogenic acoustic activity which could be used by a range of stakeholders such as planners, urban designers, and sustainability managers. The biodiversity data currently collected in cities tends not to be suitable for assessing the impacts of urban land management policies because the resource intensity of traditional biodiversity monitoring makes it difficult to collect long-term temporal data (Greenspace Information for Greater London CIC 2017). Embedded within an autonomous urban acoustic environmental assessment system, CityNet could produce the data necessary for policy-makers to assess long-term impacts of urban land management decisions such as the environmental impacts of investments in urban GI.

An expansion of CityNet to ultrasonic frequencies would increase the generality of the tool as it could be used to monitor species in cities that emit sounds at frequencies higher than 12 kHz such as bats and some invertebrates. Bats are commonly used as ecological indicators because they are sensitive to environmental changes yet are hard to monitor due to their cryptic nature (Walters et al. 2013). Acoustic monitoring is commonly used to monitor bat populations with passive ultrasonic recorders creating large volumes of audio data. In this way, the bat monitoring field faces the same challenges as the field of ecoacoustics in terms of the extraction of meaningful information from large volumes of audio data. The development of automated methods for measuring bat calls in ultrasonic data has focused to date on the identification of bat species calls and many algorithms are proprietary (e.g., Szewczak 2010; Wildlife Acoustics 2017). The development of an open-source algorithm that produces community-level measures of bats would be a valuable addition to the toolbox of bat researchers and conservationists. In addition, bats have been found to be sensitive to anthropogenic noise (Bunkley et al. 2015), of which there are numerous non-biotic sounds which occupy the same frequencies as bat calls (Fairbrass et al. 2017). If developed for use on ultrasonic frequencies, CityNet could facilitate future research into the impact of ultrasonic anthropogenic noise on bat populations.

Retraining CityNet with labelled audio data from other cities would make it possible to use the system to monitor urban biotic and anthropogenic acoustic activity more widely. However, as London is a large and heterogeneous city, CityNet has been trained using a dataset containing sounds that characterise a wide range of urban environments. The task of annotating large audio datasets from acoustically complex urban environments is highly resource intensive, a problem which has been recently tackled with citizen scientists to create the UrbanSounds and UrbanSound8k datasets using audio data from New York city, USA (Salamon, Jacoby & Bello 2014). These comprise short snippets of 10 different urban sounds such as jackhammers, engines idling and gunshots. This is not suitable for the purpose of this research project for three reasons. Firstly, they assume only one class of sound is present at each time, while in fact multiple sound types can be present at one time (consider a bird singing while an aeroplane flies overhead). Secondly, they only include anthropogenic sounds, while I analyse both anthropogenic and biotic sounds. Finally, each file in their dataset has a sound present, while city soundscapes contain many periods of silence or geophonic sounds, two important states which are not present in UrbanSounds8k. This highlights the need for an internationally coordinated effort to create a consistently labelled audio dataset from cities to support the development of automated urban environmental assessment systems with international application.

4.5.1 Conclusions

The CityNet system for measuring biotic and anthropogenic acoustic activity in noisy urban audio data significantly outperformed the state-of-the-art algorithms for measuring biotic and anthropogenic sound in entire audio recordings. Integrated into a pipeline for recording and analysing audio data in cities it could facilitate urban environmental assessment at greater scales than has been possible to date using traditional methods of surveying urban biodiversity. On publication of these results I plan to make the CityNet system available open source in combination with the expertly annotated urban soundscape dataset, CitySounds2017, to facilitate future research development in this field.

CHAPTER 5

Ecoacoustic activity and diversity describe urban green infrastructure habitat characteristics

5.1 ABSTRACT

As cities and human populations in urban areas continue to grow, interest is increasing about using green infrastructure (GI) to support sustainable and liveable cities. Due to the difficulties of quantifying the GI habitats, how to design and manage urban GI is poorly understood. Ecoacoustics provides a potential new opportunity for assessing and monitoring urban GI, where acoustic methods could be used as a proxy for environmental measures of GI habitats by summarising the activity or diversity of sounds present at the sites. However, how well ecoacoustic measures capture the environmental characteristics of urban GI is not well understood. Here, I measure the level of activity, diversity and daily activity patterns of biotic and anthropogenic components of 10,584 hours of acoustic recordings made at 63 GI sites across Greater London, UK from May to October between 2013 and 2015, and compare these acoustic measures to a suite of local and landscape habitat and abiotic environmental factors. I show that the daily activity patterns of acoustic activity and the diversity of biotic and anthropogenic sound were highly variable across the study sites. Biotic activity was significantly positively correlated with GI habitat complexity, while biotic diversity was significantly positively correlated with GI habitat diversity, habitat size, and the amount of GI in the surrounding landscape in London. My results suggest that there is a credible justification for using acoustics as proxy measures for GI habitats, and that even in intensely urban environments, habitats that are managed to support high vegetation diversity and habitat complexity can support rich and abundant communities of soniferous species. Biotic sound promotes human well-being, and the results presented

here could inform the design of urban environments that support abundant and rich biotic soundscapes that promote improved health for urban populations.

5.2 INTRODUCTION

By 2030, the world is projected to accommodate 1.1 billion additional people (UN-DESA 2015), the majority being born in cities (UN-DESA 2016). Cities face multiple environmental challenges including the control of pollution, disease, flooding, over-heating and lack of local resources, which negatively impact the health and well-being of urban populations (Satterthwaite 2003). City administrations are increasingly including urban green infrastructure (GI), the natural and semi-natural features and green spaces in cities such as parks, cemeteries, green roofs and protected areas (European Commission 2012), in strategies for tackling multiple urban environmental problems (Bloomberg & Holloway 2010; Roberts et al. 2012; Greater London Authority 2017). These spaces are typically multifunctional and cheaper than engineered solutions to environmental problems (Pataki et al. 2011; European Commission 2012).

To design sustainable and liveable cities it is crucial to understand how urban GI can be used to maximise environmental quality in cities. My research has shown that urban GI is currently not supporting high abundance or diversity of species (see Chapter 2) suggesting that there is a need for greater understanding of how urban GI habitats should be designed and managed to maximise the biodiversity supported. Unfortunately, the habitats of urban GI is difficult to quantify due to the difficulties of conducting ecological assessment in cities; individuals and organisations managing urban GI typically do not have the ecological expertise to conduct habitat surveys (see Chapter 1) and private land restrictions make it difficult to conduct the repeated visits required to control for seasonal fluctuations in vegetation (McIntyre, Knowles-Yánez & Hope 2000; Farinha-Marques et al. 2011).

Ecoacoustics is being increasingly used to monitor the environment at large temporal and spatial scales (Towsey, Parsons & Sueur 2014). Due to recent advances in passive acoustic recording technology, large volumes of acoustic data can now be collected with relative ease (Blumstein et al. 2011; Towsey, Parsons & Sueur 2014). Machine learning algorithms have been developed that facilitate the detection and classification of biotic (Grill & Schlüter 2017) and anthropogenic (Salamon & Bello 2015) sound in audio recordings, as well as the measurement of biotic and anthropogenic acoustic activity in long and noisy audio data from the urban environment (see Chapter 4). If the acoustic measures produced by these algorithms could be used as a proxy for environmental measures of GI habitats, ecoacoustics could be used to assess and monitor changes in urban GI habitats over large scales.

The use of ecoacoustics for environmental assessment and monitoring is based on the assumption that acoustic characteristics can be used as proxies of environmental factors, such as the measurement of biotic sound levels to represent biodiversity (Pijanowski et al. 2011a). A number of studies have investigated the correlation between environmental measures and measures produced by acoustic indices (AIs), algorithms that calculate whole community measures of the biotic sound in entire audio recordings based on the spectral and temporal characteristics of acoustic energy in sound recordings (Sueur et al. 2014). AI measures have been shown to correlate with the abundance (Boelman et al. 2007; Pieretti, Farina & Morri 2011) and diversity (Sueur et al. 2008; Depraetere et al. 2012; Fuller et al. 2015) of soniferous species, in addition to the structure and composition of native vegetation (Fuller et al. 2015). However, AIs have already been shown to be biased by common non-biotic sounds, such as road traffic and rain, in the urban environment (Fairbrass et al. 2017, see Chapter 3), so the investigation of these relationships in cities requires the use of better acoustic measures.

There remains uncertainty about how consistent the relationships between acoustic and environmental measures are in different environments and how they are affected by different factors. Much of the evidence for the relationship between acoustics and the environment come from relatively undisturbed environments characterised by low levels of anthropogenic disturbance in comparison with cities (Boelman et al. 2007; Sueur et al. 2008; Pieretti, Farina & Morri 2011; Depraetere et al. 2012; Fuller et al. 2015). For example, Fuller et al. (2015) report a correlation between the structure and composition of native vegetation and AI measures, potentially because diverse and complex habitats provide more niches to support a greater diversity of species (Hortal et al. 2009). However, non-native vegetation was excluded from this study which means this relationship may not hold in cities where non-native plant species are common (Aronson et al. 2014). The importance of the size of habitat patches and the landscape habitat surrounding sites in shaping the characteristics of the soundscape has not been investigated. Many soniferous species in the urban environment are also those with high dispersal abilities and large habitat requirements due to being able to fly, such as birds and invertebrates, or being large bodied, such as foxes. Larger habitat patches and more vegetated urban landscapes may facilitate dispersal through the urban environment (Mörtberg & Wallentinus 2000; Mörtberg 2001; Hale et al. 2012) allowing soniferous species to access urban habitats, and for species with larger habitat requirements to persist in cities. Depraetere et al. (2012) report that temperature may affect the strength of the relationship between acoustic and environmental measures, potentially due to the positive effect of increasing temperature on biological activity in temperate environments. The biotic soundscape may be strongly shaped by seasonal conditions. For example, in the UK the summer months coincide with periods of increased ecological activity of soniferous species such as the avian breeding season (March-July) (Cramp 1994) and peaks in activity and diversity of invertebrates (Chinery 1993; Tolman & Lewington 2009). In conclusion, it remains unknown whether relationships between acoustic and environmental measures exist in complex and acoustically disturbed urban environments and what role local and landscape habitat and abiotic environmental factors play in shaping the urban soundscape.

Here, I investigate the relationship between a suite of acoustic and environmental measures from data captured at 63 urban GI sites across Greater London, UK from May to October between 2013 and 2015 to assess the use of ecoacoustics as a proxy for measure for environmental measure of urban GI habitats. Conducting this study in a large and heterogeneous city such as London meant I was able to record soundscapes that characterise a wide range of urban environments. Using machine learning algorithms (CityNet) (see Chapter 4) and acoustic and visual analysis, I measure the activity, diversity and daily activity patterns of the biotic and anthropogenic components of 10,584 hours of acoustic recordings, and compare these acoustic measures to a suite environmental measures of GI habitats including vegetation diversity, habitats complexity in terms of the successional vegetation stages and water habitat present, habitats size, the amount of GI habitat in the surrounding landscape at the 1 km scale, temperature and seasonality.

5.3 MATERIALS AND METHODS

5.3.1 Data Collection

I selected 63 urban GI sites in Greater London, UK to collect audio and environmental data. These sites represented a range of GI in Greater London in terms of GI type, size and urban intensity (Figure 5.1, Table D.1). To survey a range of environments, site selection focussed on four different types of GI: churches and churchyards, green roofs and walls, allotments and community gardens, and nature reserves, which were sampled across the months of May to October over three years (2013-15). These months were surveyed because they coincide with periods of increased ecological activity of soniferous species in the UK including the avian breeding season (March-July) (Cramp 1994) and peaks in activity and diversity of invertebrates (Chinery 1993; Tolman & Lewington 2009). A wide range of land management styles are employed both within and among these groups of GI, leading to a wide range of environments being supported by them. Church and churchyard sites were randomly selected as described in (Fairbrass et al. 2017, see Chapter 3). All sites were classified using Google Earth (Google Earth 2012) into three urban intensity categories based on the predominant land cover surrounding sites within a 500m radius: (i) high (contiguous multi-storey buildings); (ii) medium (detached and semi-detached housing); and (iii) low (fields and/or woodland). Sites were sampled to ensure that each urban intensity class was surveyed within each month between May to October.

Acoustic recordings were collected for 7 consecutive days at each site to capture the daily variability in activity across a week. At each location, a Song Meter SM2+ digital audio field recorder (Wildlife Acoustics, Inc., Concord, Massachusetts, USA), equipped with a single omnidirectional microphone (frequency response: -35±4 dB) oriented horizontally at a height of 1m, was deployed recording sound within the 0-12 kHz frequency range. In order to maximise the detection space of the recorder, recording locations within sites were chosen to minimise the presence of vegetation and built structures surrounding the microphones as advised by Darras et al. (2016). Files were saved in *.wav* format. Recordings were made in manageable chunks of 29 minutes of every 30 minutes leading to a total of 613,872 minutes of recording (9,744 minutes for each of the 63 sites).

5.3.2 Acoustic Measures

To test the relationship between acoustics and environmental measures of GI habitats I generated six acoustic measures: acoustic activity, acoustic diversity and daily acoustic activity patterns of biotic and anthropogenic sound. There have been varying definitions of the different sounds that constitute a soundscape. Following Pijanowski et al. (2011b), I define biotic as sounds generated by non-human biotic organisms, and anthropogenic as sounds associated with human activities. The machine learning algorithms of CityNet (Chapter 4) were used to generate average daily patterns of the biotic and anthropogenic acoustic activity at each study site. To do this, CityNet was run over the entire 7 days of recordings from each site to predict the presence/absence of biotic and anthropogenic sound for every 1-second audio chunk. Measures of biotic and anthropogenic activity for each half hour window between midnight and midnight were created by averaging the 1-second predictions within that window over the entire week. For example, the single average value of biotic and anthropogenic activity for the period 00:00 to 00:29 was formed by averaging the 12,180 1-second predictions during that time period over the seven days. To capture the daily acoustic activity patterns as a scaler value to use as a response variable in multivariate analysis, activity measures were averaged across the 7 days of recording at each site to produce an average acoustic activity value for each site.

To generate measures of acoustic diversity I annotated a subset of the audio recordings manually using a bespoke software programme (AudioTagger, available: https://github.com/groakat/AudioTagger) (Fairbrass et al. 2017, see Chapter 3). A subset of recordings was used rather than the full dataset, due to the resource-intensity of manually annotating audio data using human labellers. To identify the sample size required to represent the data adequately, I conducted an analysis to identify the number of recordings necessary to identify the majority of soniferous species at each site. Species were identified from 90 randomly selected 1-minute recordings from each of six sites chosen to represent a range of anthropogenic disturbance and time of year. Using the 'vegan' package v.2.2-0 (Oksanen et al. 2016) in R v.3.3.3 (R Core Team 2017) I estimated the total species at each of these six sites based on data from fourteen different sample sizes (25 to 90 minutes from each site in 5 minute increments). The density distribution of estimates produced from 1000 iterations at each sample size were compared to select 45 1-minute audio recordings at each site as the minimum sample size beyond which gains in estimate precision and accuracy were small (Figure D.1). This resulted in a dataset of 2835 randomly selected 1-minute audio recordings (45 minutes from each of the 63 sites) which was used to produce the acoustic diversity measures. I used a random sample rather than focussing on times of peak biotic activity, because anthropogenic sound tends to be lower at these times of day (i.e. dawn and dusk), which would have reduced the variability of audio data with which to test the relationship between acoustic and environmental measures.

In each of the 45 randomly selected 1-minute recordings from each site, all biotic an anthropogenic sounds where visually and audibly identified by looking for typical patterns in spectrograms of the recordings (Figure) which were annotated with the identified sounds using AudioTagger. Spectrograms of the audio data were first computed as the log magnitude of a discrete Fourier Transform (non-overlapping Hamming window size=720 samples=10 ms). I then localised the time and frequency bands of discrete sounds by drawing bounding boxes as tightly as visually possible within spectrograms. For biotic diversity, sound types were identified and verified by two independent ecological experts and correspond directly to species scientific names. Where species identification was not possible, e.g. in the case of invertebrate sounds, these sounds were classified as unidentified invertebrates (0.5%). Anthropogenic diversity was calculated as the number of sound types associated with the anthropogenic sound classes within each recording.

5.3.3 Site Characteristics

To characterise the diversity and complexity of the local habitat at each study site, I conducted walking vegetation surveys on the first day of sound recording where all plant, shrub and tree species were identified to species according to Rose, O'Reilly and Collings (2006) and Johnson and More (2004). To ensure that the entire area of the site was walked during the vegetation survey, parallel transects separated by 1 m were walked at a steady speed across the entire site. Site diversity was measured as the total number of vegetation species recorded, and site complexity was measured as the number of successional stages of vegetation (plant, shrub and tree) present on the site in addition to the presence of waterbodies (Krebs 1972). Surveys were conducted on the area defined by the administrative site boundary. In most cases the administrative boundary constituted a discrete patch of GI within a landscape of built land cover. In a small number of cases, the administrative boundary was bordered by other forms of GI e.g., a nature reserve surrounded by agricultural land. In these cases, I limited the surveys to the site administrative boundary, as the habitat characteristics of the GI site were likely to be very different to those of the neighbouring GI. Site size was defined as the area, including the footprint of any buildings within the site administrative boundary and was measured using the Google Maps Area Calculator Tool (Daftlogic 2016).

5.3.4 Landscape Characteristics

To characterise the landscape habitat surrounding each study site, I measured the amount of GI land cover within a 1 km radius. I limited the analysis of the landscape surrounding study sites to a 1 km radius because this is a commonly used scale for multi-taxa studies in urban ecological research (Soga et al. 2014; Alberti et al. 2017), and is relevant to a broad range of taxa. GI cover data for the Greater London area was provided by GiGL in the form of a public open space dataset (GiGL 2016b) and a domestic gardens dataset (GiGL 2016a). This data was displayed in ArcMap v.10.3 (ESRI 2014) and the area (m^2) of open space and domestic garden land cover surrounding each site at the 1 km scale was extracted using an ArcMap model. The area of open space and domestic garden land cover surrounding each site was then summed to generate a measure of GI land cover surrounding each site at the 1 km scales. Meteorological data collected at the Met Office Heathrow meteorological recording station was used to calculate average temperature for the 7-day recording period at each site.

5.3.5 Analysis

To investigate the relationship between the acoustic and environmental measures, I fitted beta regression and generalised linear (GLM) models in R v.3.3.3 (R Core Team 2017) using the 'lme4' v.1.1-13 (Bates et al. 2015) and 'beta-reg' v.3.1-0 (Cribari-Neto & Zeileis 2010) packages. Models were fit with average acoustic activity and total acoustic diversity as response variables and environmental measures as fixed effects. All variables were standardised prior to analysis to make them comparable as the acoustic and environmental measures varied greatly (Schielzeth 2010). I used beta regression models to fit acoustic activity data with a logit link function due to the bounded nature of this data (0 to 1), and GLMs to fit acoustic diversity data with a Poisson error structure due to the count nature of this data. Full models were checked for assumption violation of regression models of correlation of fixed-effects, collinearity, homoscedasticity, residual normality and influence of outliers using linear regression and residual plots. In all multivariate analyses, the relative importance of predictor variables was computed as the sum of the Akaike weights (based on the Akaike information criterion, AIC) for the variables included in the averaged models (Burnham & Anderson 2002). Parameter estimates were averaged across models with ΔAIC < 2, and the corrected AIC was used to select and rank the most parsimonious models using the 'MuMIn' package v.1.15.6 (Bartoń 2016).

5.4 RESULTS

Average daily patterns of acoustic activity and acoustic diversity were highly variable across the study sites. Most sites were dominated by anthropogenic sound throughout the day (Figure 5.1), but there were a number of sites where biotic activity peaked above anthropogenic activity, typically around dawn and dusk, and where biotic diversity was greater than anthropogenic diversity (Figure 5.2).

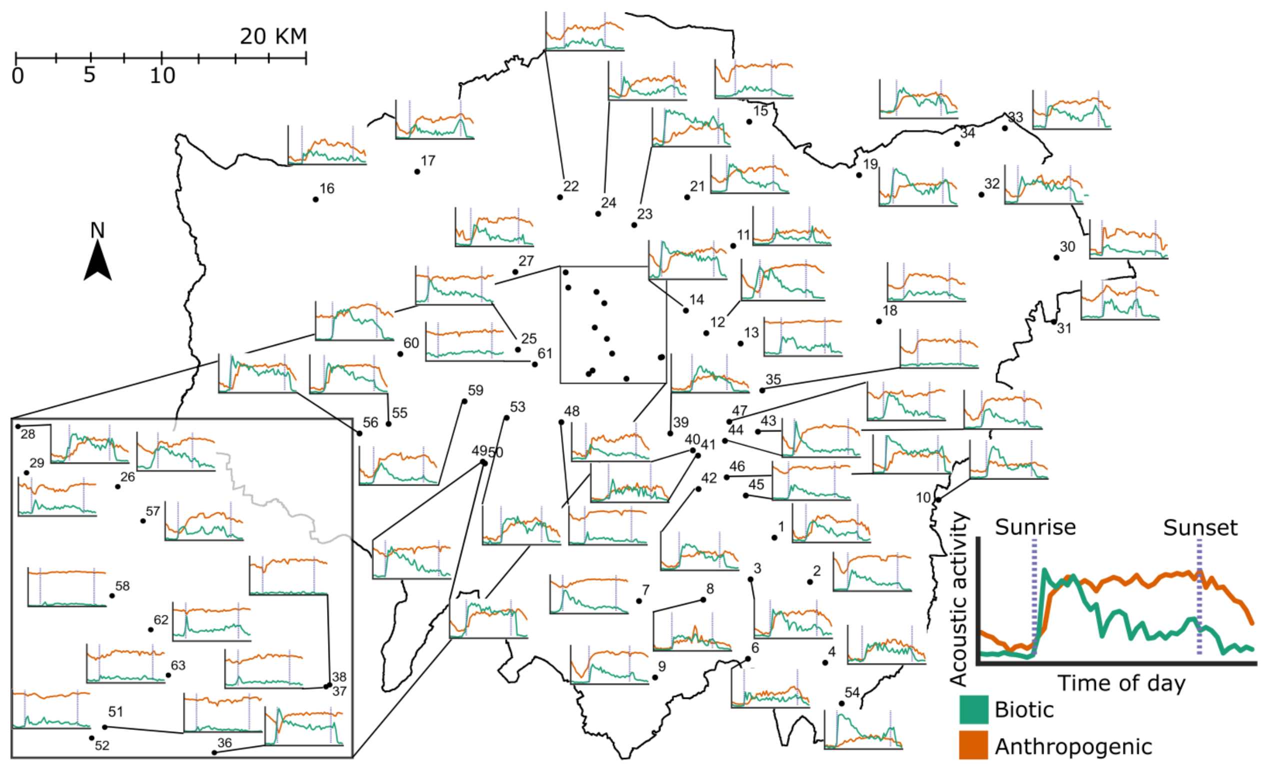


Figure 5.1 Average daily patterns of acoustic activity across the 7 days of recording between 2013 and 2015 at 63 study sites, identified and measured by CityNet. Average daily patterns of biotic and anthropogenic acoustic activity are displayed with green and red lines, respectively. Acoustic activity is standardised so patterns are directly comparable across sites. Greater London boundary indicated using data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014). Sites are numbered and indicated by black dots (see Table D.1 for description of each site). Inset boxes show areas of high concentrations of sites.

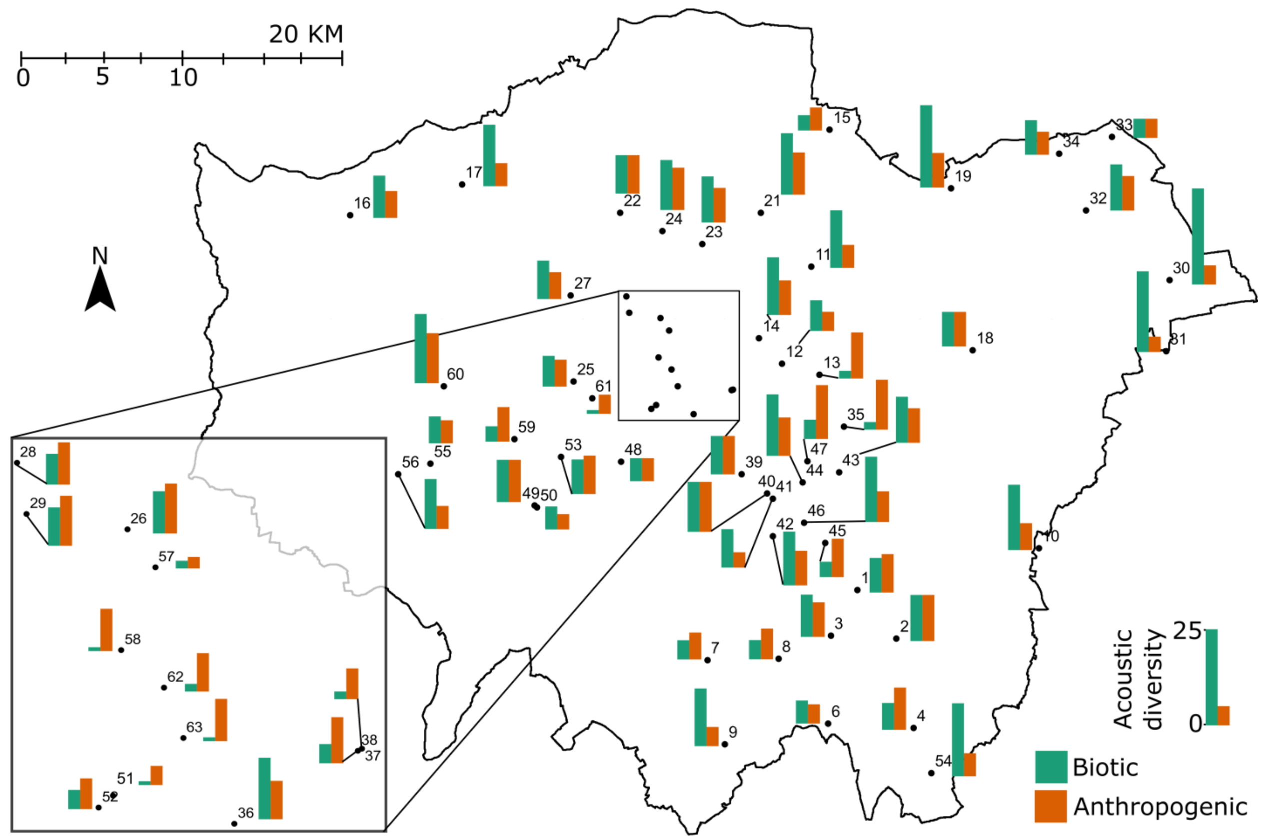


Figure 5.2 Amounts of total acoustic diversity across the 7 days of recording between 2013 and 2015 at 63 study sites, measured by identifying and annotating sounds using AudioTagger. Total biotic and anthropogenic acoustic diversity are displayed with green and red bars, respectively. Greater London borough boundaries indicated using data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014). Sites are numbered and indicated by black dots (see Table D.1 for description of each site). Inset boxes show areas of high concentrations of sites.

5.4.1 Correlates of Acoustic Activity and Diversity

Average biotic acoustic activity was significantly positively correlated with local habitat complexity (Table 5.1). Total biotic acoustic diversity was significantly positively correlated with local habitat diversity, the size of the local habitat, and the amount of GI within 1 km of the site. Average anthropogenic acoustic activity was significantly negatively correlated with local habitat diversity, as well as the amount of GI within 1 km of the site (Table 5.1). Total anthropogenic acoustic diversity was not significantly correlated with any of the variables in the models.

Table 5.1 Averaged multivariate models describing environmental covariates of biotic and anthropogenic average acoustic activity and total diversity. Models represent best (ΔAICc < 2) models from full candidate sets (Table D.2-3 for full models). Bold type indicates 95% significant covariates. Values represent regression slope (standard error, Z-value), relative importance of covariate across full candidate model set, and – represents covariates <50% of importance which were omitted.

Covariates	**Biotic**		**Anthropogenic**	
	Activity	*Diversity*	*Activity*	*Diversity*
Local				
Intercept	**-2.07 (0.35, 6.00)**	**1.53 (0.21, 7.25)**	**1.48 (0.24, 6.04)**	**2.33 (0.13, 18.13)**
Habitat Diversity	-	**0.29 (0.08, 3.74), 1**	**-0.35 (0.14, 2.47), 1.00**	-0.13 (0.10, 1.25), 0.74
Habitat Complexity	**0.73 (0.24, 3.00), 1**	-	-	-
Habitat Size	-	**0.12 (0.03, 3.26), 1**	-	-
Landscape				
Green Space 1km	0.30 (0.20, 1.47), 0.85	**0.46 (0.10, 4.36), 1**	**-0.72 (0.21, 3.49), 1**	-
Abiotic				
Mean Temperature	-	-	-	-
Survey Start Month	-	-	-	-

5.5 DISCUSSION

The acoustic measures tested here correlated with a number of environmental measures of urban GI habitats, suggesting that a relationship does exist between the soundscape of a habitat and its physical characteristics. Biotic acoustic activity was positively correlated with the complexity of the local GI habitat, which may be explained by these habitats providing more potential niches (Hortal et al. 2009) for a greater abundance of soniferous species than GI habitats composed for fewer successional stages and waterbodies. Previous work has noted that the sound emitted by particularly noisy soniferous species, such as cicadas, can dominate soundscapes (Sueur et al. 2008; Farina, Pieretti & Piccioli 2011; Towsey 2013). A small number of very vocal avian species, such as ring-necked parakeets (*Psittacula krameri*) and feral pigeons (*Columba livia*), are highly urban-adapted and were commonly recorded in this study. It would be interesting to investigate whether these species were responsible for the high acoustic activity recorded at some sites in this study. Biotic acoustic diversity correlated with the diversity of the GI habitat which suggests that biotic acoustic diversity could be used as an indicator of habitat diversity. Biotic acoustic diversity was also positively correlated with the size of GI habitat, which suggests that larger habitat areas not only support more total species (Triantis, Guilhaumon & Whittaker 2012) but also more soniferous species. The amount of GI habitat within the surrounding landscape also correlated positively with biotic acoustic diversity, potentially because a more vegetated urban landscape facilitates dispersal through the urban environment (Mörtberg & Wallentinus 2000; Mörtberg 2001; Hale et al. 2012) allowing soniferous species to access urban GI sites, and for species with larger range requirements to persist in the city. These results also indicate that the diversity of soniferous species supported by a GI habitat is determined by environmental factors at both the local and landscape scales (White et al. 2005). Anthropogenic acoustic activity was lower at sites of high habitat diversity and with more GI in the surrounding landscape, potentially because urban GI attenuates noise propagation through the landscape (Leonard & Parr 1970). This result supports the use of urban GI as a noise reduction strategy in cities to improve urban liveability (Faculty of Public Health 2010).

Many sites were characterised by typical daily acoustic patterns, with anthropogenic acoustic activity peaking during the morning rush hour and declining towards the end of the day, and with biotic acoustic activity peaking around dawn and dusk, which is typical of avian calling behaviour (Cramp 1994). A number of the most intensely urban sites (i.e. those surrounded by the least GI) where dominated by anthropogenic acoustic activity that remained constant throughout the 24 hour period with variability in the presence of biotic sound at these sites (Figure 5.1). Noisy sites with minimal biotic sound tended to be green roof sites (e.g. sites 35, 38, 51, 58, and 63), which often lacked any shrub or tree vegetation that would provide roost habitat for urban birds, whereas noisy sites which were still characterised by a peak of biotic acoustic activity at sunrise (e.g. sites 13, 25, 45, 48, and 62) were churchyards which typically supported more complex habitats. Future analysis could investigate differences between GI types in terms of how well they mitigate for any effects of decreasing landscape GI (as a measure of increasing urban intensity) on acoustic patterns.

The daily patterns of acoustic activity revealed by CityNet were highly variable across the city. It is interesting to note some marked differences between the acoustic characteristics of highly urban sites i.e. those surrounded by very little GI habitat (Figure 5.3). For example, site 36 is an urban agricultural site with a diverse and complex habitat (Table D.1) which is managed to promote biodiversity. Despite being dominated by anthropogenic acoustic activity throughout most of the day, it was characterised by a peak of biotic activity that rose above the anthropogenic noise at dawn. In addition, I recorded a greater diversity of biotic sounds than anthropogenic sounds at this site. In contrast, site 58 is a green roof site of similar size with lower habitat diversity and complexity (Table D.1). It was dominated by constant high levels of anthropogenic activity and very little biotic activity, as well as higher anthropogenic than biotic acoustic diversity.

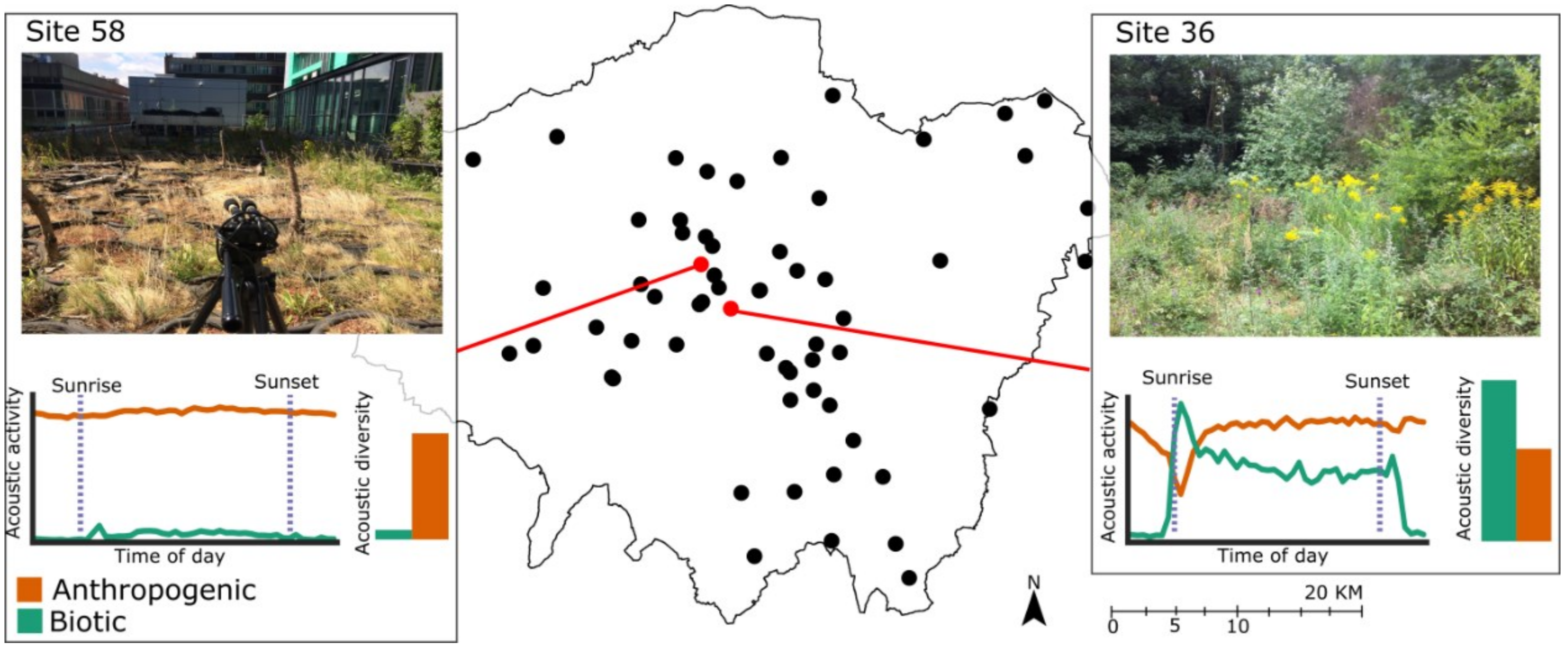


Figure 5.3 Average daily patterns of acoustic activity and amounts of total acoustic diversity of biotic (green) and anthropogenic (red) sound at two sites of similar urban intensity but different local habitat diversity and complexity. Dots indicate locations of 63 study sites. Sites are of similar size and surveys were conducted at similar times of year (site 58: 191 m^2, June 2015, site 36: 111 m^2, June 2014, Table D.1). Acoustic activity is standardised so patterns are directly comparable between sites. Greater London boundary indicated using data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014).

Wildlife in cities has been shown to be adaptable to these acoustically complex environments (Warren et al. 2006), and this comparison suggests that soniferous species are able to persist at highly acoustically disturbed sites if there is suitable habitat. There is growing evidence that biotic sound has a positive impact on human well-being by improving stress recovery (Alvarsson, Wiens & Nilsson 2010; Annerstedt et al. 2013) and attention restoration (Zhang, Kang & Kang 2017). The design and management of urban GI habitats to promote biotic acoustic activity and diversity could be a promising strategy for improving public health in cities. The results of this study could be a useful resource for the professionals involved in the design and management of urban GI such as architects, urban designers, landscape architects and ecologists to inform the development of urban habitats with abundant and rich biotic sounds that promote human well-being.

This study could be improved by treating the average acoustic activity data at each site as circular temporal data in the analysis (Jammalamadaka & Sengupta 2001), rather than using the average value across each site, as this is a very coarse value for summarising what is very detailed temporal data produced by CityNet (Figure 5.1). This would enable me to capture the temporal characteristics of the acoustic activity which may reveal more interesting relationships between acoustic activity and the environment than I have presented here. The connectivity of urban GI to the wider network of GI in the landscape has been shown to be an important predictor of habitat use by urban biodiversity (Mörtberg & Wallentinus 2000; Mörtberg 2001; Hale et al. 2012). Including a measure of connectivity of the study sites to the wider GI network may have improved the study, although the measure of the amount of GI in the surrounding landscape used here is similar to measures of landscape connectivity that have been used by others (Zeller, McGarigal & Whiteley 2012) so it could be argued that I did include a simplistic measure of connectivity in this study.

Future work should focus on the development of automated methods of measuring acoustic diversity in long and noisy audio recordings, to compliment the CityNet system. These automated methods facilitate processing of the large volumes of data generated by ecoacoustic monitoring with speed and relative ease; 10,584 hours of acoustic data was processed by CityNet in 9 days to reveal high resolution temporal acoustic patterns across an entire city, something that would be highly resource-intensive using manual annotation of audio data by humans. My results reveal that acoustic biotic diversity is a useful measure for quantifying the environmental characteristics of urban GI habitats, and the development of automated methods for measuring acoustic biotic diversity is a high priority. My analysis was spatially limited due to the use of high quality GI cover data provided by GiGL, which meant two sites were that are located outside of the Greater London area were excluded from the analysis. A national GI land cover dataset is due for imminent release from the UK Ordnance Survey, which could be used to repeat this analysis with the full dataset.

5.5.1 Conclusions

Ecoacoustics presents a promising tool to facilitate the assessment of GI habitats in urban environments. By testing the relationship between acoustic measures and the local and landscape-scale environments of urban GI across a large and heterogeneous capital city, I show that there is a credible justification for using ecoacoustics as a proxy for environmental measure of urban GI habitats. With the development of automated methods for measuring acoustic diversity in noisy audio data that complement existing automated methods for measuring acoustic activity, ecoacoustics could provide a valuable tool to inform the design and management of urban GI habitats which will be essential if future cities are to be sustainable and liveable.

CHAPTER 6

Discussion and Conclusions

In this thesis I tackled two aims: 1. To improve our understanding of what biodiversity is supported by urban green infrastructure (GI), and 2. To develop a tool for assessing and reporting on biodiversity in cities. To achieve these aims I first investigated the biodiversity supported by urban GI habitats in cities globally, and assessed whether urban GI mitigates the biodiversity losses cause by urban development. I went on to assess the suitability of existing ecoacoustic tools for measuring biotic sound in the urban environment by investigating the acoustic measures captured by Acoustic Indices (AIs) and the non-biotic sounds that bias them. Next I co-developed CityNet, a machine learning tool to quantify the biotic and anthropogenic sound in long and noisy audio data from the urban environment. Finally I investigated the relationship between the acoustic and environmental measures of urban GI habitats to assess whether ecoacoustics can be used as a proxy for assessing GI habitats in cities.

6.1 SUMMARY OF KEY FINDINGS

To assess the biodiversity currently supported by urban GI globally, I compiled a database of total abundance and richness of species recorded at urban GI sites and comparison non-urban GI sites from 80 publications covering all non-polar continents. I used a global open-source land cover dataset (OpenStreetMap, https://www.openstreetmap.org/) to place study sites along a gradient of surrounding impervious land cover (my proxy for urban intensity) to investigate ecological responses to increasing impervious land cover and taxonomic and spatial differences in responses. I also compared the biodiversity at sites in cities of low and high urban GI cover to investigate whether urban GI significantly mitigates against biodiversity losses in cities. I showed that, as expected, urban areas contain fewer species and lower total abundance than surrounding habitats (even agricultural habitat), although this pattern varied considerably. I found species responses were consistent across ecological realms, but varied taxonomically. Surprisingly, large areas of agriculture, forest, or grassland habitat did not significantly mitigate against biodiversity losses in cities. This suggests that current approaches to urban GI design and management are not supporting high biodiversity, and that simply having GI in cities doesn't necessarily deliver measurable benefits for biodiversity. To improve our understanding of how urban GI can be designed and managed to maximise the biodiversity it supports, we need improved methods of assessing these spaces to understand what works for wildlife in cities.

Unfortunately, biodiversity monitoring is difficult due to being highly-resource intensive (Spellerberg 2005; McDonald-Madden et al. 2010) making it prohibitive to conduct at large-scales, particularly in cities (McIntyre, Knowles-Yánez & Hope 2000; Farinha-Marques et al. 2011). The field of ecoacoustics (Sueur & Farina 2015) offers potential tools that could reduce the resource requirements of large-scale biodiversity assessment and monitoring in cities, but to date its application to acoustically complex urban habitats is not well understood. I tested a suite of AIs, algorithms which facilitate the rapid measurement of biotic and anthropogenic sound in large audio datasets (Sueur et al. 2014), by comparing measures of biotic acoustic activity, diversity and disturbance generated by the AIs with acoustic measures generated from the human annotation of 382.5 minutes of audio data randomly selected from 2452 hours of audio data collected from 15 urban GI sites in Greater London, UK. Sounds in the data were visually and audibly identified and annotated on spectrograms using a bespoke audio annotation software that I co-developed called AudioTagger (https://github.com/groakat/AudioTagger). The data produced by AudioTagger was used to generate measures of biotic, anthropogenic and geophonic acoustic activity, diversity and disturbance in the audio dataset, which I used to demonstrate that the AIs tested are not suitable for use in the acoustically complex urban environment without the prior removal of non-biotic sound from audio data.

I then went on to co-develop a new ecoacoustic tool, CityNet, which overcomes the shortcoming of the AIs tested by facilitating the rapid measurement of biotic and anthropogenic sound in long and noisy audio data from the urban environment, while being robust to many common non-biotic sounds in the urban environment. Using an audio dataset of 10,584 hours of audio data from 63 urban GI sites in Greater London, UK I annotated the biotic and anthropogenic sounds in 1575 randomly selected minutes of audio data using AudioTagger. This annotated audio dataset was used to train CityNet, a pair of Convolutional Neural Networks (CNNs), to generate measures of the acoustic activity of biotic (CityBioNet) and anthropogenic (CityAnthroNet) sound from long and noisy audio recordings from the urban environment. I compared CityNet's performance in terms of precision and recall to the best available alternative approaches: four commonly used acoustic indices (AIs): Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Bioacoustic Index (BI), and Normalised Difference Soundscape Index (NDSI), and a state-of-the-art bird call detection CNN algorithm (bulbul). In addition I compared the effect of non-biotic sounds on the accuracy of CityBioNet and bulbul, and used CityNet to investigate acoustic patterns of the urban soundscape. CityNet outperformed all the competing algorithms tested, and I demonstrated that CityNet can be used to reveal daily patterns in biotic and anthropogenic sound in cities.

Finally I investigated the validity of using ecoacoustic measures to assess GI habitats in cities. The use of ecoacoustics to quantify the environment is based on the theory that acoustic measures can be used as proxies of environmental factors, but there is little evidence that this theory holds in urban environments. To investigate the relationship between acoustic and environmental measures of urban GI habitats, I compared the level of activity, diversity and daily patterns of biotic and anthropogenic components in 10,584 hours of audio data from 63 urban GI sites in Greater London, UK, to a suite of local and landscape habitat characteristics and abiotic environmental factors of the study sites. I conducted local habitat surveys and spatial analysis of the landscape surrounding study sites to generate measures of local GI habitat diversity, habitat complexity, habitat size and the amount of GI in the surrounding landscape. I found that daily patterns of acoustic activity and the diversity of biotic and anthropogenic sound were both highly variable across the study sites. Biotic activity was significantly positively correlated with habitat complexity while biotic diversity was significantly positively correlated with habitat diversity, habitat size, and the amount of urban GI in the surrounding landscape. These findings suggest that a relationship between acoustic and environmental measures does exist in the urban environment, and that ecoacoustics may be a suitable tool for the assessment of GI habitats in cities.

6.2 RESEARCH IMPLICATION

The ecoacoustics field has developed to enable ecologists to take advantage of the increasing accessibility of passive acoustic recording hardware (Sueur & Farina 2015). This hardware has inundated ecologists with audio data and AIs were developed to enable ecologists to extract information about the biotic sounds recorded in these large volumes of data (Sueur et al. 2014). Unfortunately, it is my opinion that in the excitement of developing these new ecoacoustic tools, AIs were utilised without researchers questioning whether they were appropriate for assessing biodiversity in environments beyond those in which they were developed. For example, at the 2014 Meeting of the International Society of Ecoacoustics in Paris, several researchers presented work using AIs without assessing the sources of non-biotic sounds in their study environments or considering how this might affect measures produced by AIs. However, I do believe that there is growing scepticism in the ecoacoustics community about how easily AIs can be used in new study systems, thanks to the research presented here (Fairbrass et al. 2017, see Chapter 3) and other work (Gasc et al. 2015b). I hope this research will increase awareness in the ecoacoustics community of the short-comings of AIs, so that their suitability for use in new environments and potential sources of bias are assessed before they are used for scientific research or to inform conservation management.

The machine learning algorithms presented here (see Chapter 4) offer an opportunity to utilise passive acoustic recording hardware to apply ecoacoustics in the urban environment. This creates exciting opportunities because the availability of power and data connections in cities makes it feasible to deploy the Internet of Things (IoT) networks of sensors that are increasingly being deployed to monitor the urban environment (Zanella et al. 2014). The high resolution information that can be created by IoT systems dwarfs in detail the resolution of the biodiversity data that is currently produced by traditional methods of ecological survey. Use of IoT systems could create opportunities for urban biodiversity researchers to conduct biodiversity assessment and monitoring at high spatial and temporal scales. Urban researchers often struggle with getting access, especially repeated, to study sites in cities, which restricts the spatial and temporal coverage of urban biodiversity research (Farinha-Marques et al. 2011). Using machine learning algorithms embedded within IoT systems, some of these issues could be overcome, if access to a site was only required once to install an acoustic sensor. However, there could be drawbacks in the use of these systems if they reduce the requirements of ecologists to visit study sites. With less site visits researchers may lack the contextual understanding of their study system required to interpret results of biodiversity surveys. I believe that new technology is creating very exciting opportunities for biodiversity research, but we should be aware that the use of technology may distance us from the realities of the environments that we study.

An advantage of ecoacoustics is that it produces more biodiversity data with less resources than would be required using traditional ecological survey techniques. However, I don't believe that ecoacoustics can replace traditional ecological surveys because there remains uncertainty about how acoustic measures map to the biodiversity measures produced by traditional biodiversity survey techniques, such as species abundance, diversity and richness (Magurran 2004; Spellerberg 2005). There is evidence that acoustic measures correlate with measures of avian abundance (Boelman et al. 2007) and species richness (Pieretti & Farina 2013) from ornithological surveys. However, whether these relationships hold in urban environments remains unknown. In this thesis I show that acoustic measures correlate with environmental measures of urban GI habitats generated using traditional habitat survey techniques (see Chapter 5), but I did not investigate whether acoustic measures correlate with measures of faunal species in the recording environment. Measures of acoustic activity are vulnerable to being skewed by the presence of very noisy species, such as ring-necked parakeets (*Psittacula krameri*), which are common in the urban environment (Booy, Wade & Roy 2015). Future work should investigate the relationship between community composition of soniferous species and acoustic activity in urban environments to improve our understanding of how skewed the measure of acoustic activity is by the presence of certain noisy species.

6.3 IMPLICATIONS FOR INDUSTRY

At the outset of this EngD research project the academic research gaps and needs of industry were used to define a set of research and design requirements for the project. These requirements fed into the definition of four aims for the research. I will now discuss how the results presented here meet these aims and satisfy the defined research and design requirements.

6.3.1 Developing the evidence base on the biodiversity supported by urban GI

Urban GI is being increasingly integrated into urban management strategies to tackle persistent environment problems in cities (Bloomberg & Holloway 2010; Greater London Authority 2017). Unfortunately, the findings presented here (see Chapter 2) suggest that GI habitats are not currently supporting high biodiversity cities. Within the urban GI strategies that are being developed by city administrations there needs to be a mechanism for biodiversity assessment that informs the adaptive management of these habitats. The ecoacoustic tools presented in this thesis (see Chapter 4) could be appropriate for assessing the habitats of these spaces (see Chapter 5). To ensure that cities in the future foster an improved quality of life for urban populations, it is crucial that the biodiversity supported by new and existing GI habitats is assessed in the long-term and that results are reported. This will enable industry to develop the evidence base needed to effectively design and manage urban GI to maximise its potential environmental benefits.

6.3.2 Suitable for non-ecologists

The built environment professionals who manage urban GI habitats, typically facilities managers and grounds keepers, need to be able to operationalise the research and tools developed here. In addition, the professionals that design, plan and manage urban environments need to be able to interpret results produced by the CityNet tool. These professionals typically do not have the ecological expertise to conduct ecological surveys or interpret biodiversity information produced by traditional survey techniques (see Chapter 1). Consultation needs to be conducted about whether the research and tool can be used and interpreted by these professionals.

6.3.3 Operate over large scales

Industry desires a tool for conducting monitoring over long time periods which requires the generation of large volumes of biodiversity data. The CityNet tool developed here has been shown to be able to process large volumes of biodiversity data to produce information on ecological patterns (see Chapter 5). Industry needs to be able to use this information to assess the ecological effects of GI investments. This would require that changes over time can be detected using the data produced by CityNet. In this study I only monitored for up to 7 days at each site, and I did not test whether the acoustic measures could be used to detect changes in the environment. Future research should investigate whether the ecoacoustic measures produced by CityNet can be used to detect environmental changes, for example before and after the creation of new urban GI habitats.

6.3.4 Produce meaningful ecological information

There remains uncertainty about how acoustic measures map to ecological measures generated by traditional faunal biodiversity survey techniques. Therefore, I would advise that the tools developed here should not be used as a replacement for traditional faunal ecological surveys. However, the results of Chapter 5 suggest that acoustic activity and diversity correlate with several environmental measures of urban GI habitats. Therefore, I would suggest that these acoustic measures are suitable for the assessment of urban GI habitats. The build environment professionals typically involved in the management of urban GI habitats cannot conduct biodiversity assessments themselves because traditional habitat survey techniques require ecological expertise. I would suggest that the ecoacoustic tools developed in this thesis could be used by urban GI manager to conduct habitat assessments, while information on the faunal communities that are supported by urban GI continues to be generated using ecological experts.

6.3.5 Operationalising this research

To operationalise the research presented in this thesis, the CityNet algorithms need to be easy to implement and the costs of use need to be understood. One option for making them easy to use would be to embed them within an autonomous assessment pipeline (Figure 6.1), in which acoustic sensors deployed in the environment generate acoustic data, which is processed by CityNet and the results produced by CityNet are reported to the user.

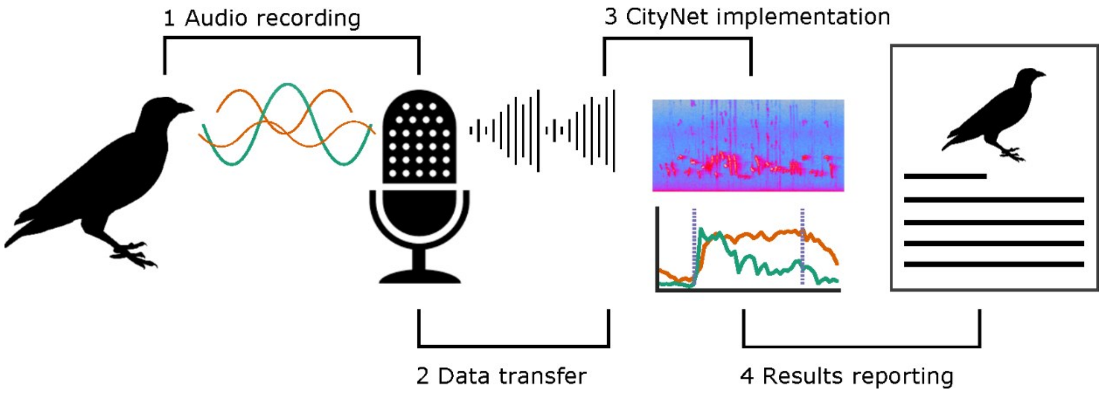


Figure 6.1 Autonomous ecoacoustic monitoring pipeline. Acoustic sensors record audio data (1) which is transferred to the CityNet algorithms (2) is transferred to an external server. CityNet is implemented to measure the acoustic biotic and anthropogenic activity in the audio data (3) which is reported to the user (4).

There are multiple options for how such a pipeline could work, including:

- Sensors: Low-cost sensors such as the AudioMoth (https://www.openacousticdevices.info/) which use an internal power supply could collect and store but not process data due to their computational limitations. Higher-cost sensors such as the Intel Edison have been used to monitor urban bat populations (https://naturesmartcities.com/about/) and would be computationally powerful enough to implement CityNet on-board, removing the requirement to transfer audio data to an external server. However, these sensors require an external power source which currently limits their application.
- Audio data storage: Whether the raw audio data should be stored is a major consideration. Data storage is costly but facilitates the post-hoc analysis of data. This may be desirable when data verification and reanalysis is desired.
- Reporting: What information is reported and the reporting medium used is a key consideration. The temporal and spatial scale of interest may vary for different users. For example, yearly trends may be desirable for a GI company monitoring the long-term environmental impact of a green roof. Alternatively, daily ecoacoustic patterns may be of interest to a land manager who wants to understand the environmental impact of activities such as mowing. Some users may require personalised reports of results, others may

require an online reporting system while others may desire real-time data to be displayed on the sensors.

- Privacy: The location of sensors must be considered in terms of the privacy of human users of a site as the sensors may record conservations. This would be a motivation for not storing the audio data where this is of anthropogenic origin.
- Provision of support: How support for the system would be provided must be considered.

6.4 LIMITATIONS OF THE CURRENT WORK

A limitation of the research in this thesis is that it was conducted in a single city, which means the findings and methods are not generalizable to other environments outside of Greater London. The majority of future urban development is projected to occur in the developing world (Seto et al. 2011; McPhearson et al. 2016; UN-Habitat 2016) and there is a need to develop ecoacoustic methods that are suitable for use in these regions. Improved assessment tools would support the study of biodiversity in these regions. With improved understanding of the biodiversity supported by cities in these regions, decisions about how to mitigate the negative ecological impacts of urban development in these regions could be better informed.

The research presented in Chapter 2 was conducted at a global scale which is in contrast to the single city scale of the research presented in the rest of this thesis. To even out the spatial scales of the chapters, the thesis could have been focussed on the UK scale. However, only seven studies that were suitable for inclusion in the analysis of Chapter 2 were conducted in the UK which would not have provided enough data to conduct the mixed-effects multivariate analysis presented in Chapter 2. On the other hand, it would have been very difficult to conduct the research presented in Chapters 3-5 at a national scale. The costs of the passive acoustic recording hardware that was available at the time that the fieldwork was conceived meant that only a small number of audio recorders could be purchased, limiting the scope of fieldwork. In the past few years, there have been exciting develops in low-cost passive audio recorders, such as the AudioMoth (https://www.openacousticdevices.info/) which would make it much more feasible to conduct this research at a large spatial scale.

The findings of this thesis suggest that ecoacoustics can be used to quantify GI habitat quality in cities. However, I did not investigate the relationship between ecoacoustic measures and faunal biodiversity in this thesis. There are many end-users that will value a simple metric, such as those produced by CityNet, that can create accurate descriptions of urban habitats in a manner that is understandable with minimal effort by non-ecologists (Tzoulas & James 2010), including planners, urban designers, architects, construction and development professionals. However, for ecological consultants the ability to identify species or facilitate the generation of species lists will be of significantly greater interest. The use of species call classification algorithms such as those available for British birds (warblr: https://warblr.net/) and European bats (Walters et al. 2012) could be applied and as these are refined and improved over time so their use alongside CityNet will become of increasing value and interest to professionals such as ecological consultants. Alternatively, future testing of the relationship between acoustic measures and measures of faunal species generated by traditional survey methods may make the acoustic measures generated by CityNet more robust as a proxy for biodiversity and thereby increasing interest from consultant ecologists.

6.5 FUTURE RESEARCH

There are a number of uncertainties that remain about the suitability of the tools developed here for use by industry. These include whether CityNet can be used and interpreted by non-ecologists, whether CityNet can be used to detect changes in biodiversity over long time scales, whether the measures produced by CityNet correlate with measures of faunal biodiversity, the logistics of integrating CityNet within an automated urban biodiversity assessment system (Figure 6.1) and to costs associated with operating such a system on an urban GI site. In collaboration with industry these uncertainties could be explored through the deployment of a pilot assessment system. The pilot could be deployed prior to the construction of new GI habitat and maintained for several years post-construction, during which time the habitat could be manipulated to determine whether the CityNet measures can be used to detect environmental changes. Comprehensive ecological surveys of a wide range of taxonomic groups and environmental factors could be conducted alongside the assessment system and measures compared to investigate the relationship between the acoustic measures and measures of faunal biodiversity as well as investigating the environmental factors that affect these relationships. A pilot deployment would develop understanding of the practicalities of operationalising an automated biodiversity assessment system in the urban environment. For example, the deployment of the world's first autonomous sensing network for surveying urban bat populations at the Queen Elizabeth Olympic Park, UK has provided valuable insight into the challenges of deploying acoustic biodiversity sensing systems 'in the wild' (Gallacher et al. Submitted). Importantly a pilot deployment could facilitate the assessment of associated costs and a comprehensive costing of the system would allow potential end-users to incorporate the system into project budgets and encourage uptake. The successful deployment of a pilot project would demonstrate the performance of the system to potential end-users which would encourage uptake. Potential funding sources and stakeholder collaborators for a pilot deployment of the proposed system need to be sought.

6.6 CONCLUSIONS

Cities provide important habitat for species and ecosystems that currently face monumental challenges, while urban biodiversity improves urban environmental quality and plays a key role in ensuring that cities are sustainable and liveable. High quality city-scale environmental data is required to inform the planning and management of cities that support biodiversity and ecosystems in order to improve the quality of life of urban populations in the future (UN-Habitat 2016). This study highlights the potential of ecoacoustics as a tool for generating this environmental data, by generating and processing audio data from the urban environment at scales appropriate for the planning and management of cities. If the tools and findings of this study are developed into an autonomous urban ecoacoustic assessment system, the information produced could be used to inform decisions about how to maximise the environmental potential of sustainable and liveable cities in the future.

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Appendices

Appendix A

Table A.1 Description of the source papers, including: phylum, reported response, country and ecological realm. In terms of ecological response investigated, TA denotes total abundance, SR denotes species richness, and TA & SR indicates where data on both responses were reported by the study. Full references follow the table.

Dataset	Phylum	Response	Country	Ecological Realm
Ackley et al. (2009)	Chordata	SR	Dominica	Neotropic
Amaral et al. (2012)	Tracheophyta	SR	Brazil	Neotropic
Atchison and Rodewald (2006)	Chordata	SR	U.S.A.	Nearctic
Basset et al. (2008)	Arthropoda	TA & SR	Gabon	Afrotropic
Bates et al. (2011)	Arthropoda	TA & SR	U.K.	Palearctic
Bolger et al. (1997)	Chordata	SR	U.S.A.	Nearctic
Bolger, Alberts and Soule (1991)	Chordata	SR	U.S.A.	Nearctic
Buczkowski (2010)	Arthropoda	TA & SR	U.S.A.	Nearctic
Buczkowski and Richmond (2012)	Arthropoda	TA & SR	U.S.A.	Nearctic
Cane (2006)	Arthropoda	SR	U.S.A.	Nearctic
Castelletta, Thiollay and Sodhi (2005)	Chordata	SR	Singapore	Indo-Malay
Chapman and Reich (2007)	Chordata	TA & SR	U.S.A.	Nearctic
Christian (2004)	Arthropoda	TA & SR	Austria	Palearctic
Croci et al. (2008)	Arthropoda; Chordata; Tracheophyta	SR	France	Palearctic
Crooks et al. (2001)	Chordata	SR	U.S.A.	Nearctic
Crooks (2002)	Chordata	SR	U.S.A.	Nearctic
Darvill, Knight and Goulson (2004)	Arthropoda	TA & SR	U.K.	Palearctic
Delabie et al. (2009)	Arthropoda	TA & SR	France	Neotropic
Dickman (1987)	Chordata	SR	U.K.	Palearctic
Diekötter et al. (2006)	Arthropoda	TA & SR	Germany	Palearctic
Dures and Cumming (2010)	Chordata	SR	South Africa	Afrotropic
Elek and Lövei (2007)	Arthropoda	TA & SR	Denmark	Palearctic
Fernández-Juricic (2000)	Chordata	SR	Spain	Palearctic
Fiera (2008)	Arthropoda	SR	Romania	Palearctic
Fierro et al. (2012)	Arthropoda	TA & SR	Mexico	Neotropic
Fowler (2015)	Arthropoda	TA & SR	U.K.	Palearctic
Gaublomme et al. (2008)	Arthropoda	SR	Belgium	Palearctic
Ge et al. (2012)	Annelida	TA & SR	China	Palearctic
Giordani (2012)	Ascomycota	TA & SR	Italy	Palearctic
Giordano et al. (2004)	Bryophyta	SR	Italy	Palearctic
Gottschalk et al. (2007)	Arthropoda	TA & SR	Brazil	Neotropic
Granjon and Duplantier (2011)	Chordata	TA & SR	Mali	Afrotropic
Hall et al. (2003)	Tracheophyta	SR	U.S.A.	Nearctic

Hanley (2011)	Arthropoda	TA & SR	U.K.	Palearctic
Helden and Leather (2004)	Arthropoda	TA & SR	U.K.	Palearctic
Herrmann, Pearse and Baty (2012)	Arthropoda	SR	U.S.A.	Nearctic
Hornung et al. (2007)	Arthropoda	TA & SR	Hungary	Palearctic
Horsák (2009)	Mollusca	SR	Czech Republic	Palearctic
Ishitani, Kotze and Niemelä (2003)	Arthropoda	TA & SR	Japan	Palearctic
Johnson, Gómez and Pinedo-Vasquez (2008)	Arthropoda	TA & SR	Peru	Neotropic
Jonsell (2012)	Arthropoda	TA & SR	Sweden	Palearctic
Kappes, Katzschner and Nowak (2012)	Mollusca	SR	Germany	Palearctic
Knapp (2008)	Arthropoda; Mollusca; Chordata; Ascomycota; Bryophyta; Tracheophyta	SR	Germany	Palearctic
Koh and Sodhi (2004)	Arthropoda	SR	Singapore	Indo-Malay
Krügel and dos Anjos (2000)	Chordata	SR	Brazil	Neotropic
Lorenzetti and Battisti (2007)	Chordata; Tracheophyta	SR	Italy	Palearctic
Magura, Horváth and Tóthmérész (2010)	Arthropoda	TA & SR	Hungary	Palearctic
Mahan and O'Connell (2005)	Chordata	SR	U.S.A.	Nearctic
McFrederick and LeBuhn (2006)	Arthropoda	TA & SR	U.S.A.	Nearctic
Naithani and Bhatt (2012)	Chordata	TA & SR	India	Indo-Malay
Natuhara and Imai (1999)	Chordata	SR	Japan	Palearctic
Noreika and Kotze (2012)	Arthropoda	TA & SR	Finland	Palearctic
Norfolk, Eichhorn and Gilbert (2013)	Tracheophyta	TA & SR	Egypt	Palearctic
Oliver et al. (2011)	Chordata	SR	U.S.A.	Nearctic
Parra-H and Nates-Parra (2006)	Arthropoda	TA & SR	Columbia	Neotropic
Porter, Bulluck and Blair (2005)	Chordata	SR	U.S.A.	Nearctic
Rader et al. (2014)	Arthropoda	TA & SR	New Zealand	Australasia
Rickman and Connor (2003)	Arthropoda	SR	U.S.A.	Nearctic
Robles, Carmarán and Lopez (2011)	Basidiomycota	SR	Argentina	Neotropic
Rubio (2012)	Arthropoda	SR	Argentina	Neotropic
Sanford, Manley and Murphy (2009)	Arthropoda	SR	U.S.A.	Nearctic
Siebert (2011)	Tracheophyta	TA & SR	South Africa	Afrotropic
Soh, Sodhi and Lim (2006)	Chordata	TA & SR	Malaysia	Indo-Malay
Soule et al. (1998)	Chordata	SR	U.S.A.	Nearctic
Stiles and Scheiner (2010)	Tracheophyta	SR	U.S.A.	Nearctic
Su, Zhang and Qiu (2011)	Arthropoda	TA & SR	China	Palearctic
Suarez, Bolger and Case (1998)	Arthropoda	SR	U.S.A.	Nearctic
Suarez-Rubio and Thomlinson (2009)	Chordata	TA & SR	Puerto Rico	Neotropic
Threlfall, Law and Banks (2012)	Chordata	TA & SR	Australia	Australasia
Tonietto et al. (2011)	Arthropoda	TA & SR	U.S.A.	Nearctic
Torre, Bros and Santos (2014)	Mollusca	TA & SR	Spain	Palearctic
van Heezik, Smyth and Mathieu (2008)	Chordata	TA & SR	New Zealand	Australasia
Verboven, Brys and Hermy (2012)	Arthropoda	TA & SR	Belgium	Palearctic
Virgilio et al. (2011)	Arthropoda	TA & SR	Democratic Republic of the Congo	Afrotropic
Waite et al. (2013)	Chordata	TA & SR	New Zealand	Australasia
Waite et al. (2012)	Arthropoda	TA & SR	New Zealand	Australasia
Walker et al. (2006)	Ascomycota	SR	Russia	Palearctic

Watts and Lariviere (2004)	Arthropoda	SR	New Zealand	Australasia
Weller and Ganzhorn (2004)	Arthropoda	TA & SR	Germany	Palearctic
Winfree, Griswold and Kremen (2007)	Arthropoda	TA & SR	U.S.A.	Nearctic

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Table A.2 Groupings of OSM data into land cover classes. Reference 1 represents Bates et al. (2011); 2 Beninde, Veith and Hochkirch (2015); 3 Aronson et al. (2014); 4 Sushinsky et al. (2013); and 5 Fischer et al. (2016).

OSM Categories	**Land Cover Class**	**Ref**
'agricultural', 'allotments', 'community_food_g', 'farm', 'farm_auxiliary', 'farmland', 'farmyard', 'greenhouse', 'greenhouse_horti', 'orchard', 'paddock', 'plant_nursery', 'vineyard'	Agriculture	1
'basin', ‘canal’, 'fountain', ‘lake’, ‘pond’, 'reservoir', ‘river’, 'riverbank', 'salt_pond', ‘stream’, 'water', ‘water basin’, ‘waterfall’, 'well', ‘wetland’	Blue Infrastructure	2
'canopy', 'forest', 'tree_row', 'wood', 'woodland'	Forest	3
A large group of all OSM categories excluding those listed in the rest of this table. A selection of the more common categories are listed here for example: ‘industrial’, ‘retail’, ‘residential’, ‘public_building’, ‘hospital’, ‘garage’, ‘road’, and ‘railway’.	Impervious	
'Athletic_field_h', ‘beach’, 'biergarten', 'brownfield', ‘camp_site’, 'cemetery', 'churchyard', 'city_green', 'common', ‘dog_park’, ‘exercise_point’, ‘fell’, ‘field’, 'flowerbed', 'garden', 'garden_or_rember', ‘golf_course’, 'grass', 'grassland', 'greenfield', ‘heath’, 'marsh', 'meadow', 'park', 'pitch', 'recreation_ground', ‘ridge’, 'sand', 'scrub', 'scrubs', 'village_green'	Grassland	3, 4, 5

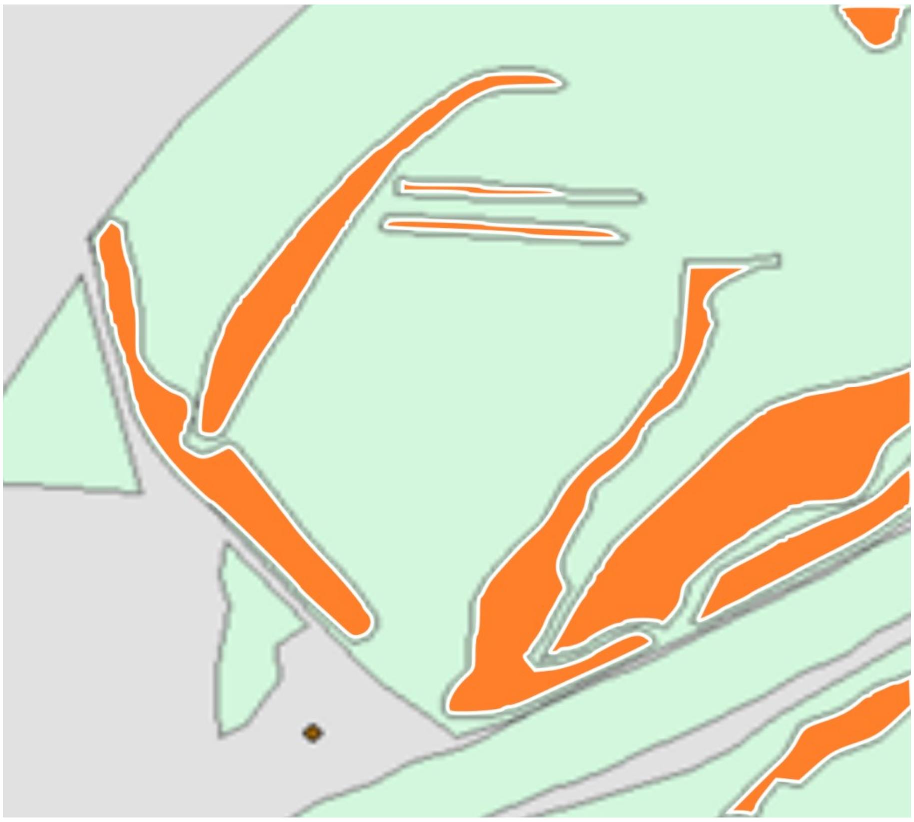

Figure A.1 Example of overlapping spatial data in OpenStreetMap. User 1 draws an urban grassland habitat with area 1000m^2 (green) while user 2 draws the forested areas of the park on top with combined area of 250m^2 (orange). If the area of urban GI is extracted using this data without resolving these overlaps an inflated value of 1250m^2 would be given for an area that is only 1000m^2. To resolve this issue, the grassland polygon is clipped by the forest polygons so that the extracted values are 750m^2 of grassland and 250m^2 of forest.

Table A.3 Averaged mixed-effects models describing land cover covariates of species total abundance and richness. AGRI represents agriculture, BI represents blue infrastructure, FGI represents forested green infrastructure, GRS represents grassland and IMP represents impervious. First and second order polynomials are represented as poly()1 and poly()2, respectively. The amount (m^2) of each land cover type within a 1 km radius of sites is fitted as main fixed effects, as interaction terms with impervious land cover, and with unique study identifier as a random effect. Models represent best (ΔAICc < 2) models from full candidate sets (Table A.4 for full models). Values represent regression slope (standard error, t-value), relative importance of covariate across full candidate model set, and – represents covariates <50% of importance which were omitted.

Covariates	***Total Abundance***	***Species Richness***
Intercept	4.22 (0.36, 11.68)	2.33 (0.11, 20.88)
poly(AGRI,2)1	-1.18 (2.33, -0.51), 1	1.50 (1.28, 1.17), 1
poly(AGRI,2)2	-2.22 (1.46, -1.53), 1	-1.91 (0.89, 2.16), 1
poly(BI,2)1	-0.55 (1.60, -0.35), 1	-1.35 (0.86, 1.57), 1
poly(BI,2)2	-1.15 (1.25, -0.92), 1	0.54 (0.76, 0.71), 1
poly(FGI,2)1	-3.07 (1.91, -1.61), 1	1.43 (1.04, 1.38), 1
poly(FGI,2)2	-2.17 (1.61, -1.35), 1	1.18 (1.04, 1.14), 1
poly(IMP,2)1	-8.27 (2.17, -3.82), 1	-6.03 (1.13, 5.35), 1
poly(IMP,2)2	-1.31 (1.60, -0.81), 1	-2.40 (1.03, 2.33), 1
poly(NFGI,2)1	-4.04 (1.61, -2.51), 1	-2.30 (0.91, 2.52), 1
poly(NFGI,2)2	-2.58 (1.62, -1.60), 1	-0.07 (0.89, 0.08), 1
poly(AGRI,2)1:poly(IMP,2)1	-141.76 (71.41, -1.99), 1	-186.88 (58.14, 3.21), 1
poly(AGRI,2)2:poly(IMP,2)1	-79.63 (50.92, -1.56), 1	-199.06 (45.01, 4.42), 1
poly(AGRI,2)1:poly(IMP,2)2	-116.06 (52.54, -2.21), 1	-94.35 (51.43, 1.83), 1
poly(AGRI,2)2:poly(IMP,2)2	31.54 (39.90, 0.79), 1	31.90 (44.05, 0.72), 1
poly(BI,2)1:poly(IMP,2)1	67.10 (45.70, 1.47), 1	23.53 (37.01, 0.64), 0.56
poly(BI,2)2:poly(IMP,2)1	26.32 (39.46, 0.67), 1	23.78 (34.27, 0.69), 0.56
poly(BI,2)1:poly(IMP,2)2	-68.89 (40.43, -1.70), 1	30.48 (40.10, 0.76), 0.56
poly(BI,2)2:poly(IMP,2)2	-74.12 (37.84, -1.96), 1	-39.13 (44.47, 0.88), 0.56
poly(FGI,2)1:poly(IMP,2)1	-180.31 (57.43, -3.14), 1	-
poly(FGI,2)2:poly(IMP,2)1	-117.31 (50.47, -2.32), 1	-
poly(FGI,2)1:poly(IMP,2)2	-61.81 (45.39, -1.36), 1	-
poly(FGI,2)2:poly(IMP,2)2	-40.75 (42.48, -0.96), 1	-
poly(IMP,2)1:poly(NFGI,2)1	-31.08 (55.67, -0.56), 1	-34.77 (48.60, 0.72), 1
poly(IMP,2)2:poly(NFGI,2)1	-59.01 (51.74, -1.14), 1	-96.39 (44.22, 2.18), 1
poly(IMP,2)1:poly(NFGI,2)2	37.55 (56.04, 0.67), 1	-76.36 (47.34, 1.61), 1
poly(IMP,2)2:poly(NFGI,2)2	-35.86 (52.58, -0.68), 1	-120.86 (44.10, 2.74), 1

Table A.4 Top mixed-effects models with ΔAICc < 2 describing the covariates of total abundance and species richness. AGRI represents agriculture, BI represents blue infrastructure, FGI represents forested green infrastructure, GRS represents grassland and IMP represents impervious. Details for the models are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Mixed-Effects Models	**k**	**log(L)**	**AICc**	**ΔAICc**	**AICc weight**
Total abundance					
poly(AGRI,2) + poly(BI,2) + poly(FGI,2) + poly(GRS,2) + poly(IMP,2) + poly(IMP,2):poly(AGRI,2) + poly(IMP,2):poly(BI,2) + poly(IMP,2):poly(FGI,2) + poly(IMP,2):poly(GRS,2)	29	-1381.65	2823.06	0	1
Species richness					
Poly(AGRI, 2) + poly(BI, 2) + poly(BI, 2) + poly(IMP, 2) + poly(GRS, 2) + poly(AGRI, 2):poly(IMP, 2) + poly(BI, 2):poly(IMP, 2) + poly(FGI, 2):poly(IMP, 2) + poly(IMP, 2):poly(GRS, 2)	30	-8428.38	16917.45	0	0.32
Poly(AGRI, 2) + poly(BI, 2) + poly(BI, 2) + poly(IMP, 2) + poly(GRS, 2) + poly(AGRI, 2):poly(IMP, 2) + poly(IM P, 2):poly(GRS, 2)	22	-8436.68	16917.73	0.28	0.27
Poly(AGRI, 2) + poly(BI, 2) + poly(BI, 2) + poly(IMP, 2) + poly(GRS, 2) + poly(AGRI, 2):poly(IMP, 2) + poly(BI, 2):poly(IMP, 2) + poly(IMP, 2):poly(GRS, 2)	26	-8432.72	16917.96	0.51	0.24
Poly(AGRI, 2) + poly(BI, 2) + poly(BI, 2) + poly(IMP, 2) + poly(GRS, 2) + poly(AGRI, 2):poly(IMP, 2) + poly(FG I, 2):poly(IMP, 2) + poly(IMP, 2):poly(GRS, 2)	26	-8433.11	16918.74	1.29	0.17

Appendix B Biases of acoustic indices measuring biodiversity in urban areas

Ecological Indicators 83 (2017) 169–177

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Biases of acoustic indices measuring biodiversity in urban areas

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ARTICLE INFO

Keywords:
Anthropogenic
Ecoacoustics
Green infrastructure
Mixed-effects model
Soundscapes
Urban

ABSTRACT

Urban green infrastructure, GI (e.g., parks, gardens, green roofs) are potentially important biodiversity habitats, however their full ecological capacity is poorly understood, in part due to the difficulties of monitoring urban wildlife populations. Ecoacoustic surveying is a useful way of monitoring habitats, where acoustic indices (AIs) are used to measure biodiversity by summarising the activity or diversity of biotic sounds. However, the biases introduced to AIs in acoustically complex urban habitats dominated by anthropogenic noise are not well understood. Here we measure the level of activity and diversity of the low (0–12 kHz, $_l$) and high (12–96 kHz, $_h$) frequency biotic, anthropogenic, and geophonic components of 2452 h of acoustic recordings from 15 sites across Greater London, UK from June to October 2013 based on acoustic and visual analysis of recordings. We used mixed-effects models to compare these measures to those from four commonly used AIs: Acoustic Complexity Index (ACI), Acoustic Diversity Index (ADI), Bioacoustic Index (BI), and Normalised Difference Soundscape Index (NDSI). We found that three AIs (ACI_l, BI_l, $NDSI_l$) were significantly positively correlated with our measures of $biotic_l$ activity and diversity. However, all three were also correlated with $anthropogenic_l$ activity, and BI_l and $NDSI_l$ were correlated with $anthropogenic_l$ diversity. All low frequency AIs were correlated with the presence of $geophonic_l$ sound. Regarding the high frequency recordings, only one AI (ACI_h) was positively correlated with measured $biotic_h$ activity, but was also positively correlated with $anthropogenic_h$ activity, and no index was correlated with $biotic_h$ diversity. The AIs tested here are therefore not suitable for monitoring biodiversity acoustically in anthropogenically dominated habitats without the prior removal of biasing sounds from recordings. However, with further methodological research to overcome some of the limitations identified here, ecoacoustics has enormous potential to facilitate urban biodiversity and ecosystem monitoring at the scales necessary to manage cities in the future.

1. Introduction

With over half of the world's human population now living in urban areas (UN-DESA 2016), the global challenge is to design sustainable and liveable cities (Elmqvist et al., 2013). A large body of evidence now exists for the multiple human benefits of biodiversity in urban areas through the provision of ecosystem services such as air filtration, pest regulation, storm water management and food provision (Gómez-Baggethun et al., 2013). In urban environments, the local provision of these services can reduce human reliance on external ecosystems and can be highly valuable both economically and socially (Gómez-Baggethun and Barton, 2013). There is also an increasing amount of research showing that cities can support high biodiversity, including native endemic species (Aronson et al., 2014).

Urban green infrastructure (GI), the natural and semi-natural features and green spaces in cities (European Commission 2012), provides opportunities for biodiversity and ecosystems (Sadler et al., 2011; Murphy et al., 2013). GI features and spaces vary widely and include, but are not limited to, parks, gardens, biodiverse roofs and walls, street trees, and sustainable urban drainage systems (Cvejić et al., 2015). Some cities have turned to increasing GI as a means of improving urban environmental quality, while being cheaper than traditional engineered solutions to urban environmental problems (e.g. Seattle's GI flood management strategy, Stenning 2008). However, the suitability of this

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http://dx.doi.org/10.1016/j.ecolind.2017.07.064
Received 13 February 2017; Received in revised form 14 July 2017; Accepted 31 July 2017
Available online 08 August 2017

wide variety of urban GI to support biodiversity and ecosystems is often not well quantified (Pataki et al., 2011; European Commission, 2012).

To understand how sustainable and liveable cities can be designed it is crucial to understand how biodiversity responds to different types of urban GI. Greater efforts must be put into monitoring the biodiversity and ecosystems supported by urban GI (Kremer et al., 2016) so that urban planning decisions can be informed by a strong evidence base. The use of ecoacoustics as a method of quantifying ecological communities and their habitats has received increasing attention (Towsey et al., 2014a; Merchant et al., 2015; Sueur and Farina 2015). Due to recent advances in passive acoustic recording technology, large volumes of acoustic data can be collected with relative ease (Blumstein et al., 2011; Towsey et al., 2014a). However, the extraction of meaningful information from these large datasets is very challenging. Species-specific acoustic monitoring efforts have focussed on the development of classification algorithms to automatically identify the sounds emitted by organisms (Walters et al., 2012; Aide et al., 2013; Stowell and Plumbley, 2014) but they are limited to a small number of species and do not provide information on the wider environment. Acoustic indices (AIs) are novel methods that attempt to overcome these challenges of quantifying the biotic and anthropogenic sounds (Sueur et al., 2014) in the large volumes of data generated by ecoacoustic monitoring.

Although AIs may provide a useful method to measure biodiversity, their sources of bias in acoustically complex urban habitats dominated by anthropogenic noise is not well understood. Verification of the measures of biotic sound captured by AIs has tended to focus on less disturbed environments than cities, with the exception of Joo et al. (2011) where a positive relationship was reported between avian diversity and AI values along an urban-rural gradient. A range of sounds have been found to bias AIs including road traffic (Fuller et al., 2015), human speech (Pieretti et al., 2011), rain and wind (Depraetere et al., 2012; Towsey et al., 2014b). However, formal testing of the bias caused by non-biotic sounds has tended to group non-biotic sounds as 'background noise' rather than examine the effect of individual sound sources (Towsey et al., 2014b; Gasc et al., 2015), and the response of AIs to the full spectrum of sounds typical of the urban environment remains to be tested. Additionally, the application of AIs has been limited to the audible (20 Hz–20 kHz) spectrum, and testing has tended to focus on the bird ecoacoustic community using data from ornithological surveys (Boelman et al., 2007; Pieretti et al., 2011) or from identifications of bird vocalisations within recordings (Farina et al., 2011; Depraetere et al., 2012; Kasten et al., 2012). However there are a number of taxonomic groups common in cities, including bats and invertebrates, which use the ultrasonic spectrum (> 20 kHz). Limiting the application of AIs to the lower frequency spectrum excludes entire taxonomic groups.

Here, we evaluate four AIs on their ability to measure biotic sound captured using low (0–12 kHz, $_l$) and high (12–96 kHz, $_h$) frequency sound recordings from 15 sites across Greater London, UK and investigate which non-biotic sounds are responsible for any bias in the AIs. The AIs tested include: Acoustic Complexity Index (ACI) (Pieretti et al., 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera et al., 2011), Bioacoustic Index (BI) (Boelman et al., 2007), and Normalised Difference Soundscape Index (NDSI) (Kasten et al., 2012). Of the multitude of AIs that exist (Sueur et al., 2014), we test these four as they are designed to be robust to anthropogenic noise based on assumptions regarding the characteristics of biotic and anthropogenic sound (Fig. 1). Commonly used indices that have already been shown to be sensitive to 'background noise' were not tested here (Sueur et al., 2014; Gasc et al., 2015). There have been varying definitions of the different sounds that constitute a soundscape. Following Pijanowski et al. (2011), we define biotic as sounds generated by non-human biotic organisms, anthropogenic as sounds associated with human activities, and geophonic as non-biological ambient sounds e.g. wind and rain. We compare the activity and diversity of the biotic and non-biotic (anthropogenic and geophonic) components of our recordings to those values obtained by AIs.

2. Materials and methods

2.1. Data collection

In order to maximise the variability in urban sounds with which to test the performance of the AIs, we selected 15 recording sites in habitats within and around Greater London, UK ranging from 995 to 14248 m^2 (Fig. 2, Table S1), and used a sampling protocol to capture the seasonal variability in the soundscape. In this analysis, we did not aim to test the effect of different habitats or environmental conditions on the performance of the AIs. GI selection was limited to churches and churchyards as they are spatially evenly distributed due to their legal protection in the UK (Disused Burial Grounds Act, 1884). They also represent a wide range of urban environments that are similar to other types of urban GI due to the heterogeneity of management regimes. For example, some undergoing intensive maintenance similar to urban parks, others have large areas often left alone making them more similar to urban protected areas, and some sites that are managed by congregations are often characterised by ornamental planting making them quite similar to domestic gardens. Sites were classified using Google Earth (Google Earth, 2012) into three size categories (including the building footprint): (i) small (< 0.5 ha); (ii) medium (0.5-1.5 ha); and (iii) large (> 1.5 ha); and three urban intensity categories based on the predominant land cover surrounding sites within a 500 m radius: (i) high (typically contiguous multi-storey buildings); (ii) medium (typically detached and semi-detached housing); and (iii) low (typically fields and/or woodland) (Fig. 2, Table S1).

Acoustic recordings were collected for 7 consecutive days at each site to capture the daily variability in activity across a week. In order to maximise the variability in the biotic sounds recorded, surveys were conducted between June and October 2013 which sampled both the avian breeding season (March-July) (Cramp 1994), and the peak in activity and diversity of a range of other taxonomic groups including bats (Kunz and Fenton, 2003) and invertebrates (Chinery 1993; Tolman and Lewington 2009). Surveys were conducted in the summer when ecological activity is highest in the UK, rather than in winter when the variability of the soundscape is more limited to just anthropogenic and geophonic sounds. At each location, a Song Meter SM2+ and a SM2BAT+ digital audio field recorder (Wildlife Acoustics, Inc., Concord, Massachusetts, USA) were deployed, recording sound within the low (0–12 kHz, $_l$) and high (12–96 kHz, $_h$) frequency ranges. The AIs tested were developed using a range of upper spectral thresholds, i.e. 8 kHz for BI (Boelmann et al., 2008) and NDSI (Kasten et al., 2012), and 11–12 kHz for ADI (Villanueva-Rivera and Pijanowski, 2014) and ACI (Pierretti et al., 2011). For consistency, we tested all AIs using an upper threshold of 12 kHz. We acknowledge that this would have included frequencies above the thresholds of the BI and NDSI, but this is unlikely to affect our results as few sounds occur between 8 and 12 kHz (Fig. 3). Each recorder was equipped with a single omnidirectional microphone (frequency response: −35 ± 4 dB) oriented horizontally at a height of 1 m. Files were saved in *.wav* format. SM2+ recordings were made in manageable chunks of 29 min of every half hour leading to a total of 146,160 min of recording (9744 min for each of the 15 sites). SM2BAT+ recordings were made using an internal trigger for > 12 kHz sounds and set to continue recording until no trigger was detected for a 2.0 s period, leading to a total of 474 min of high frequency recording (median 8.8, [5.4 and 24.8 the lower and upper 95% CI observations respectively] minutes per site).

Each 29-min low frequency recording was divided into 1-min audio files using Slice Audio File Splitter (NCH Software Inc. 2014) and each high frequency recording was reduced to 2-s audio files using Sound eXchange (Bagwell, 2014). In order to maximise the variability of sounds with which to test the AIs, twenty-five 1-min low frequency and

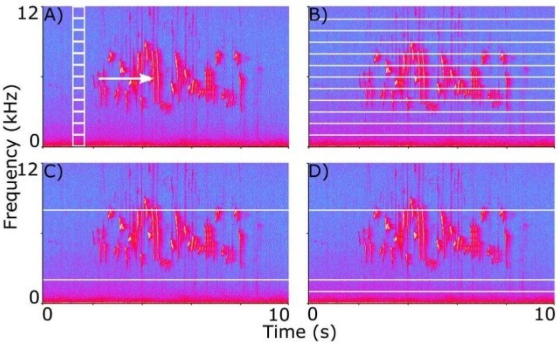

Fig. 1. Calculation of four Acoustic Indices (AIs) on example ecoacoustic data. Data is represented in spectrograms (FFT non-overlapping Hamming window size = 1024) where blue to yellow corresponds to increasing sound amplitude (dB). Spectrograms represent calculations of (A) Acoustic Complexity Index (ACI_f), (B) Acoustic Diversity Index (ADI_f), (C) Bioacoustic Index (BI_f), and (D) Normalised Difference Soundscape Index ($NDSI_f$). Frequency or temporal bins are indicated in white (see Table S2 for specifications). ACI_f sums the absolute difference in signal power within frequency bins over time using a sliding window and defined temporal steps (indicated by arrow). ADI_f is calculated as the Shannon's diversity index for each recording based on the signal power occupancy of each 1 kHz frequency band. BI_f calculates the signal power within 2–8 kHz frequency band of recordings. $NDSI_f$ calculates the ratio of signal power in the frequency bands between 1 and 2 kHz and 2–8 kHz to measure the level of anthropogenic disturbance on the landscape. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

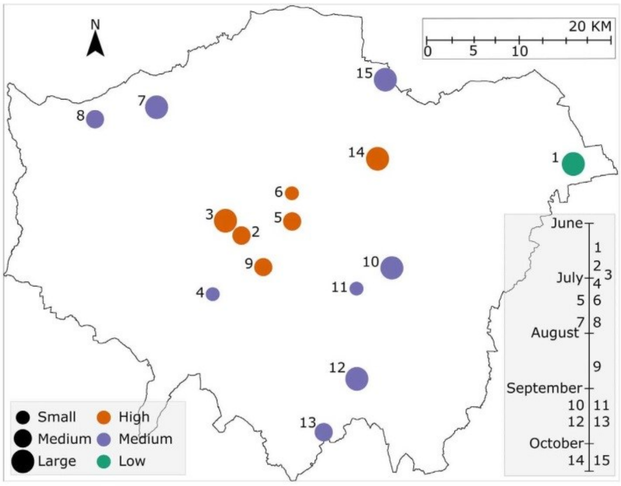

Fig. 2. Locations and characteristics of 15 survey sites across Greater London, UK. Dots and numbers indicate sites. Relative site size indicated by dot size, urban intensity indicated by dot colour (red: high, blue: medium, green: low). Location of numbers along date scale indicates date of survey at each site. Boundary data from the UK Census (http://www.ons.gov.uk/, accessed 04/11/2014).

25 2-s high frequency recordings were randomly selected from each site resulting in a dataset of 375 min of low frequency and 12.5 min of high frequency audio recordings. We used a random sample rather than focussing on times of peak biotic activity, because anthropogenic sound tends to be lower at these times of day (i.e. dawn and dusk), which would have reduced the variability of anthropogenic sounds with which to test the AIs. A wide range of sampling protocols has been used in ecoacoustic studies to date. For example, Pieretti and Farina (2013) used 4 1-min samples from 8 recording sites to investigate the effect of traffic noise on the relationship between the ACI and avian singing dynamics, while Towsey et al. (2014b) used 60-min per day for 5 days from a single site to test the relationship between AIs and avian species richness. Our sampling protocol is similar to that used by Fuller et al. (2015) who also investigated the performance of a suite of AIs in an anthropogenically-disturbed environment.

2.2. Acoustic analysis

To compare the measures of biotic and non-biotic (anthropogenic and geophonic) components of our recordings to those values obtained by AIs, we generated three measures of acoustic data for each audio recording: acoustic activity (number of spectrogram pixels occupied by sound), acoustic diversity (number of unique sound types), and disturbance (ratio between biotic and anthropogenic acoustic activity). To generate these measures, we manually annotated spectrograms of each recording, computed as the log magnitude of a discrete Fourier transform (non-overlapping Hamming window size = 720 samples = 10 ms), using a bespoke software programme AudioTagger (available: https://github.com/groakat/AudioTagger). We then localised the time and frequency bands of discrete sounds by drawing bounding boxes as tightly as visually possible within spectrograms displayed on a Dell UltraSharp 61 cm LED monitor with a Nvidia Quadro K600 graphics card. Types of sound, such as "invertebrate", "rain", and "road traffic", were identified by A.F. by looking for typical patterns in spectrograms (Fig. 3), and by listening to the audio samples represented in the annotated parts of the spectrogram. An urban transport expert provided support in the identification of the complex sounds produced by transport infrastructure. Electrical buzzes and

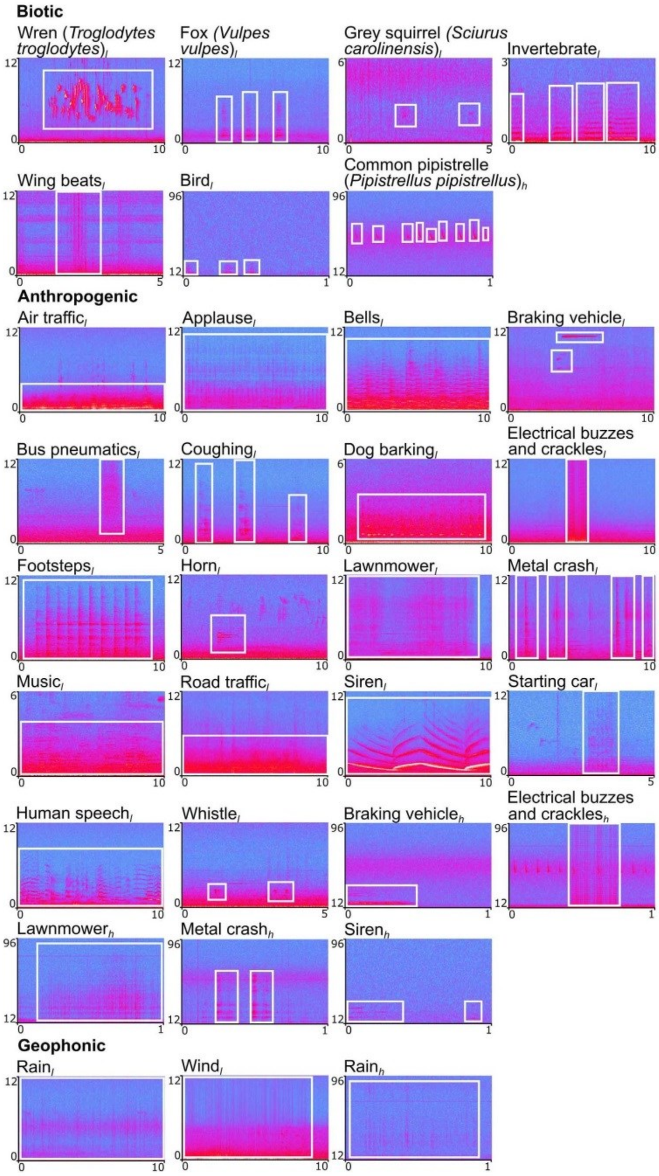

Fig. 3. Examples of all sound types present in recordings. Bird and bat sounds were identified further to species with one example of each given here. Unidentified sounds not shown due to wide range of sound types within this group. Data is represented in spectrograms (FFT non-overlapping Hamming window size = 1024) where blue to yellow corresponds to sound amplitude (dB). Frequency (kHz) and time (s) are represented on the y- and x-axes, respectively. Spectrograms represent biotic (sounds generated by non-human biotic organisms), anthropogenic (sounds associated with human activities including human speech) and geophonic sounds, where $_l$ and $_h$ denote low (< 12 kHz) and high (> 12 kHz) frequency sound, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

crackles from the recording devices were classified as anthropogenic sound, and this electrical self-noise will vary depending on the recording devices used.

2.2.1. Acoustic activity

Acoustic activity within recordings was measured by the number of spectrogram pixels contained by the bounding boxes. This measurement was conducted by AudioTagger based on the x and y-coordinates of the corners of the bounding boxes. Sound types (n = 68) (Fig. 3) were grouped into four broad sound classes: (a) biotic (sounds generated by non-human biotic organisms, e.g. blue tit, common pipistrelle, n = 47 types); (b) anthropogenic (sounds associated with human activities including human speech, n = 18); (c) geophonic (rain and wind, n = 2); and (d) unidentifiable sounds (n = 1). The activity of each sound class within recordings was calculated as the sum of activity (number of spectrogram pixels contained by the bounding boxes) of all sound types within each class.

2.2.2. Acoustic diversity

Acoustic diversity was measured by the number of unique sound types associated with the relevant sound class identified in each recording. For biotic diversity, sound types correspond directly to species scientific names. Where species identification was not possible, e.g. in the case of invertebrate sounds and harmonics of bird vocalisations in the high frequency recordings, these sounds were identified to one of two taxonomic groups: unidentified birds (3.2% of biotic sounds recorded) or unidentified invertebrates (0.3%). Low frequency biotic$_l$ sounds were identified and verified by two independent ecological experts; high frequency biotic$_h$ sounds were identified to species-level using Sonobat v.3.1.6p (Szewczak, 2010) and iBatsID (Walters et al., 2012) which uses ensembles of artificial neural networks to probabilistically classify European bat calls. To minimise error, taxonomic classifications were manually validated using a classification probability threshold of > 70%. Anthropogenic and geophonic diversity were calculated as the number of sound types associated with the anthropogenic and geophonic sound classes within each recording. Unidentified sound diversity was treated as a presence/absence as we did not differentiate between different types of unidentifiable sounds.

2.2.3. Disturbance

The NDSI$_l$ quantifies disturbance based on the ratio of biotic to anthropogenic sound in recordings (Kasten et al., 2012, Fig. 1D). To test the NDSI$_l$ with its intended measure we calculated our own measure of disturbance (γ) using our observed activity measures as follows:

$$\gamma = \frac{\beta - \alpha}{\beta + \alpha}$$

where β and α are the total biotic and anthropogenic acoustic activity in each recording, respectively. Observed geophonic and unidentified acoustic activity were used as additional measures of disturbance.

2.2.4. Acoustic indices

Four AIs (ACI$_l$, ADI$_l$, BI$_l$ and NDSI$_l$) were calculated for each low frequency recording and two AIs for each high frequency recording (ACI$_h$ and ADI$_h$) in R v.3.1.2 (R Core Team 2014) using the 'soundecology' package v.1.1.1 (Villanueva-Rivera and Pijanowski, 2014) (Fig. 1, Table S2). We did not test the BI and NDSI with high frequency data as this would require changing their biotic and anthropogenic frequency thresholds. Such adaptation would require investigation of the spectral characteristics of high frequency biotic and anthropogenic sounds which is beyond the scope of this study.

2.3. Statistical analysis

To investigate the measures of biotic sound captured by the AIs and which non-biotic sounds are responsible for any bias, we fit generalised linear (GLMER) or linear (LMER) mixed-effects models in R using the 'lme4' v.1.1-7 (Bates et al., 2014) and 'glmmADMB' v.0.8.0 (Skaug et al., 2011) packages. To examine the measures of biotic sound captured by the AIs, models were fit with AIs as response variables, acoustic measures from acoustic and visual analysis of recordings as fixed effects, and site as a random effect. To investigate which non-biotic sounds were responsible for any bias, we fit the same models as above but with anthropogenic sound type as fixed effects. All variables were standardised prior to analysis to make them comparable as the measures of acoustic activity and diversity varied greatly across sound classes/types (Schielzeth 2010). We used GLMERs to fit ADI$_l$ and ACI$_h$ data with a Gaussian error structure and we applied a log link function and a Lambert-W transformation (Goerg 2011) to the ACI$_l$ data to normalise its heavy-tailed distribution. Due to the bounded nature of the NDSI$_l$ (-1 to 1), the data was transformed according to the formula (NDSI$_l$ + 1)/2 and fit with a beta error structure (Cribari-Neto and Zeileis 2009). All other data were normally distributed and were fit with LMERs. Full models were checked for assumption violation of mixed-effect models of correlation of fixed-effects, collinearity, homoscedasticity, residual normality and influence of outliers using linear regression and residual plots. In all multivariate analyses, the relative importance of predictor variables was computed as the sum of the Akaike weights (based on the Akaike information criterion, AIC) for the variables included in the averaged models (Burnham and Anderson 2002). Parameter estimates were averaged across models with ΔAIC < 4, and the corrected AIC was used to select and rank the most parsimonious models using the 'MuMIn' package v.1.12.1 (Bartoń 2012).

3. Results

3.1. Urban soundscape composition

Most sites were dominated by both low and high frequency anthropogenic activity. Anthropogenic sound in our dataset was composed of a large variety of sound types, predominantly road traffic sounds, followed by human voices, electrical buzzes and crackles from the recorders and the environment, and air traffic (56.5%, 5.7%, 4.0% and 2.6% of total activity, respectively) (Fig. 4). Biotic sound was mainly associated with birds and bats (9.3% and 2.3% of total activity, respectively). Other less common biotic sounds were produced by invertebrates, foxes (*Vulpes vulpes*) and grey squirrels (*Sciurus carolinensis*).

3.2. Acoustic activity

Three AIs (ACI$_l$, BI$_l$, and NDSI$_l$) were significantly positively correlated with biotic$_l$ activity (Table 1, Table S3), but two AIs (ACI$_l$, BI$_l$) were also correlated positively with anthropogenic$_l$ activity. NDSI$_l$ was significantly negatively correlated with anthropogenic$_l$ activity. All except one AI (BI$_l$) was correlated positively with geophonic$_l$ activity. In the high frequency recordings, ACI$_h$ was significantly positively correlated with both biotic$_h$ and anthropogenic$_h$ activity, while being unbiased by geophonic$_h$ activity. ADI$_h$ was not correlated with either biotic$_h$ or anthropogenic$_h$ activity, and was positively correlated with geophonic$_h$ activity.

3.3. Acoustic diversity

Three AIs (ACI$_l$, BI$_l$, and NDSI$_l$) were significantly positively correlated with biotic$_l$ diversity (Table 1, Table S4). However, BI$_l$ was positively correlated with anthropogenic$_l$ diversity, while ADI$_l$ and NDSI$_l$ were negatively correlated. All AIs were significantly positively correlated with the diversity of geophonic$_l$ sound. ACI$_h$ was not correlated with any of the acoustic diversity covariates, while ADI$_h$ was negatively correlated with both biotic$_h$ and anthropogenic$_h$ diversity and positively with the diversity of geophonic$_h$ sound.

3.4. Disturbance

NDSI$_l$ was significantly positively correlated with both anthropogenic$_l$ (γ) disturbance, and geophonic$_l$ activity (Table 1, Table S5).

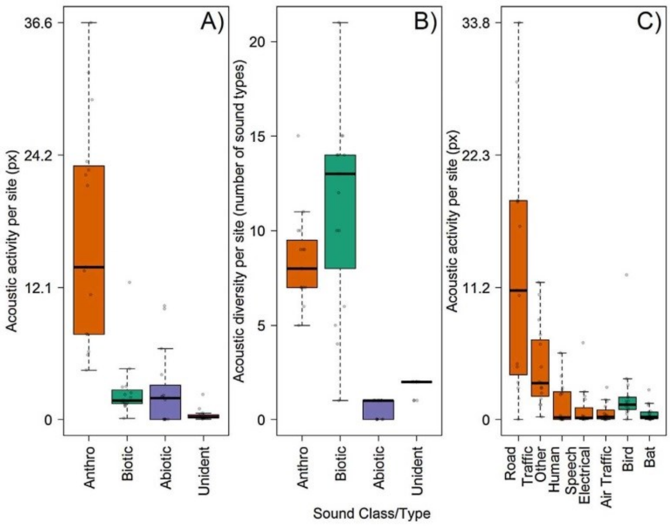

Fig. 4. Average sound activity and diversity per site (n = 15) in Greater London for A) and B) each sound class, and C) the most common anthropogenic and biotic sound types. Acoustic activity reported as number of pixels (px, total = 75858750) occupied by each sound class/type in the spectrograms of the 25 l-min low and 25 2-s high frequency recordings per site, where the x-axis is scaled to 10^6. Acoustic diversity reported as the number of sound types, where species are treated as unique sound types in the case of birds and bats, within each sound class. The bar indicates the median, the box indicates the inequality range, the whiskers indicate the range, and the points indicate the site data. 'Anthro' indicates anthropogenic sounds and 'Unident' indicated unidentifed sounds.

3.5. Acoustic sound bias

All AIs were significantly correlated with the presence of one or more anthropogenic sounds in recordings (Table 2, Table S6). Human speech was correlated with all four low frequency indices: positively with ACI_l and BI_l and negatively with the ADI_l and $NDSI_l$. Braking vehicles, road traffic and electrical sounds were negatively correlated with the ACI_l, ADI_l and $NDSI_l$. ACI_h was significantly positively correlated with electrical and braking vehicle sounds, and ADI_h was negatively correlated with the sound of braking vehicles.

4. Discussion

This is the first examination of the performance of a suite of AIs in the urban environment. Our acoustic data indicates that the urban environment is dominated by a much wider range of anthropogenic sounds than has been dealt with by research into AIs to date. Our results reveal that in terms of both biotic activity and diversity, this subset of published AIs either do not measure biotic sound or are biased by non-biotic sound in recordings. In only a few cases, could the AIs be used reliably to measure biotic sound in the urban environment during

Table 1

Averaged mixed-effects models describing acoustic covariates of four Acoustic Indices (AIs), for sound class activity, diversity, and disturbance. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where $_l$ and $_h$ denotes low and high frequency versions, respectively. Models represent best (ΔAICc < 4) models from full candidate sets (Tables S3-5 for full models). Bold type indicates 95% significant covariates. Values represent regression slope (standard error, Z-value), relative importance of covariate across full candidate model set, and − represents covariates < 50% of importance which were omitted.

	Acoustic Indices					
	Low frequency				*High frequency*	
Covariates	ACI_l	ADI_l	BI_l	$NDSI_l$	ACI_h	ADI_h
Activity						
Intercept	1801.70 (1.76, 1022.5)	0.20 (0.09, 2.3)	9.91 (1.29, 7.7)	−0.45 (0.17, 3.86)	−0.03 (0.01, 5.1)	2.15 (0.25, 8.6)
Biotic	**8.91 (0.78, 11.4), 1**	–	**2.11 (0.36, 5.9), 1**	**0.30 (0.04, 6.9), 1**	**0.04 (0.01, 15.2), 1**	–
Anthropogenic	**2.68 (1.25, 2.1), 0.69**	−0.09 (0.05, 1.7), 0.61	**3.52 (0.59, 5.9), 1**	**−0.23 (0.07, 3.1), 1**	**0.02 (0.01, 4.3), 1**	–
Geophonic	**7.18 (0.68, 10.5), 1**	**0.08 (0.01, 5.1), 1**	–	**0.19 (0.04, 5.2), 1**	–	**0.07 (0.04, 1.7), 0.63**
Unidentified	–	**−0.29 (0.14, 2.0), 1**	–	–	–	**0.14 (0.04, 3.4), 1**
Diversity						
Intercept	1800.56 (1.90, 945.0)	0.44 (0.08, 5.4)	11.14 (1.70, 6.6)	−0.20 (0.13, 1.5)	−0.01 (0.01, 0.7)	2.35 (0.27, 8.7)
Biotic	**4.16 (0.43, 9.6), 1**	–	**0.95 (0.20, 4.8), 1**	**0.09 (0.02, 4.0), 1**	–	**−0.26 (0.13, 2.1), 0.78**
Anthropogenic	0.96 (0.65, 1.5), 0.51	**−0.13 (0.02, 6.7), 1**	**0.71 (0.30, 2.3), 0.93**	**−0.20 (0.04, 5.6), 1**	–	**−0.23 (0.12, 2.1), 0.74**
Geophonic	**26.25 (2.59, 10.1), 1**	**0.21 (0.05, 3.8), 1**	**2.45 (1.16, 2.1), 0.79**	**0.46 (0.13, 3.5), 1**	–	–
Unidentified	3.29 (1.87, 1.8), 0.62	−0.24 (0.06, 3.9), 1	–	–	–	**0.38 (0.19, 2.0), 0.77**
Disturbance						
Intercept				0.02 (0.11, 0.1)		
Disturbance				**0.73 (0.07, 10.0), 1**		
Geophonic				**0.14 (0.04, 3.8), 1**		
Unidentified				–		

Table 2
Averaged mixed-effects models describing acoustic covariates of four Acoustic Indices (AIs), for the presence of anthropogenic sound types. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where $_l$ and $_h$ denotes low and high frequency versions, respectively. Models represent best (ΔAICc < 4) models from full candidate sets (Table S6 for full models). Bold type indicates 95% significant covariates. Values represent regression slope (standard error, Z-value), relative importance of covariate across full candidate model set, and − represents covariates < 50% of importance which were omitted.

	Acoustic Indices			
	Low frequency			
Covariates	ACI_l	ADI_l	BI_l	$NDSI_l$
Intercept	1814.02 (3.06, 591.5)	0.50 (0.09, 5.8)	10.32 (1.65, 7.9)	0.07 (0.14, 0.5)
Air Traffic	–	**−0.20 (0.06, 3.2), 1**	–	**−0.42 (0.11, 3.7), 1**
Beep	–	–	–	–
Braking vehicle	−3.23 (2.14, 1.5), 0.52	**−0.15 (0.07, 2.1), 0.84**	–	**−0.17 (0.10, 1.7), 0.61**
Electrical	**−5.19 (2.03, 2.5), 0.92**	**−0.25 (0.05, 4.9), 1**	–	**−0.17 (0.09, 1.8), 0.66**
Road traffic	**−7.03 (2.32, 3.0), 1**	**−0.21 (0.05, 4.4), 1**	–	**−0.48 (0.11, 4.5), 1**
Human Speech	**10.85 (2.24, 4.8), 1**	**−0.20 (0.06, 3.2), 1**	**3.19 (0.89, 3.6), 1**	**−0.31 (0.11, 2.9), 1**
		High frequency		
	ACI_h	ADI_h		
Intercept	−0.01 (0.01, 0.4)	2.27 (0.22, 10.2)		
Braking vehicle	**−0.03 (0.01, 2.3), 0.90**	**−0.76 (0.19, 1.0), 1**		
Electrical	**0.04 (0.01, 2.4), 0.93**	–		
Metal	–	–		

appropriate weather conditions: the ACI_l could be used to measure low frequency $biotic_l$ diversity while the $NDSI_l$ could be used to measure the ratio of $biotic_l$ to $anthropogenic_l$ activity as a proxy for disturbance.

If AIs are to be used in the urban environment, they must be improved to be robust to the high diversity of anthropogenic sounds in this environment. Our recordings were dominated by road traffic sound and also contained a large number of other anthropogenic sounds. The BI_l was biased by the fewest anthropogenic sound types being affected only by human speech. However, we found several anthropogenic sounds bias the other AIs tested here, this is in concordance with previous studies (Pieretti and Farina 2013; Towsey et al., 2014b; Fuller et al., 2015). Common methods for dealing with these sounds prior to analysis using AIs include the use of filters to remove low frequency sound from recordings (Sueur et al., 2008; Towsey et al., 2014b; Pieretti et al., 2015) and the manual identification and removal of recordings containing biasing sounds (Gasc et al., 2013; Rodriguez et al., 2014). The former method is not suitable for the urban environment as many of the anthropogenic sounds recorded here occupy the same frequencies as biotic sound (Fig. 3). The latter is impractical when considering the large volumes of data typically generated by ecoacoustic monitoring (Towsey et al., 2014a). Our challenge is to find better ways of reducing the bias caused by these sounds. Automated methods for identifying multiple sound types, such as the machine-learning techniques used for species identification (Walters et al., 2012; Stowell and Plumbley, 2014), could be used to identify and remove biasing sounds prior to the application of AIs. For example, if the BI_l was used in combination with a detection algorithm for human speech it could be a suitable AI for use in the urban environment. The identification of sounds from within the large datasets typical of ecoacoustics is a valuable area of future research.

It is difficult to interpret the negative bias caused by road traffic in our dataset as the actual amount of biotic sound in the environment might be depressed due to an effect of traffic noise on species. For example, signal-generating organisms have been shown to respond to traffic noise in multiple ways, including changing the amplitude (Pieretti and Farina, 2013) and pitch (Lampe et al., 2012) of acoustic signals, to altering habitat use (McClure et al., 2013), and foraging behaviour (Schaub et al., 2008). Simulation techniques such as those employed by Gasc et al. (2015) that control the amount of biotic sound in recordings while manipulating traffic noise may help to clarify whether the bias of traffic sound is a methodological shortcoming of AIs or a product of the ecological effects of traffic noise on biodiversity.

Geophonic sounds have been shown to bias AIs (Towsey et al., 2014b; Gasc et al., 2015) and our results reveal that this rule holds in the urban environment. However, the heterogeneity of the urban environment (Grimm et al., 2008) may greatly influence the strength of this relationship across a city. For example, a green roof located on top of a ten-storey building is more exposed to wind and rain events than an urban park sheltered by buildings and mature trees. Therefore, the suitability of using AIs in the urban environment may be highly site specific. Commonly used methods for reducing the bias of geophonic sounds are similar to those used for anthropogenic sounds including low frequency filters (Sueur et al., 2008; Pieretti et al., 2015) and manual identification and exclusion of recordings (Boelman et al., 2007; Gasc et al., 2013; Rodriguez et al., 2014). However the same issues that limit the use of these methods for anthropogenic sounds also apply for geophonic sounds: spectral overlap with biotic sounds and large volumes of recordings. Methods must be developed that are robust to the characteristic broad frequency ranges and modulations of geophonic sound.

In this study we did not test the effect of environmental factors on the performance of the AIs, but such research is required to understand what can be inferred about urban habitats from AIs. Research in non-urban habitats has revealed that environmental factors do impact the performance of AIs, for example in temperate woodlands the correlation between biodiversity and AIs weakens with increasing anthropogenic disturbance (Depraetere et al., 2012). However, the fundamental relationship between the acoustic and physical environments requires further investigation. In spite of suggestions about how biodiversity may relate to spectral diversity (Krause and Farina, 2016), it remains unclear what can be inferred about the physical environment from the soundscape. In addition, species have highly variable acoustic detection probabilities (Wiley and Richards, 1978), and it is not clear what can be inferred about communities from measures that are derived solely from the species which emit sound at sufficient volume (dB) to be detected by acoustic sensors. Until these relationships are better understood, ecoacoustic monitoring should be used whilst understanding the limitations of the approach.

Our study could be improved by including more than one type of urban land use. Using church and churchyard green space will have limited the sounds recorded to those of the biotic communities and physical environments associated with these areas (Irvine et al., 2009). However, our use of sites that represent a range of sizes and levels of urban intensity spread widely across the city would have maximised the range of potential soundscapes recorded on this type of GI. Our data collection was also limited to a single city in a single country. Cities may be characterised by unique acoustic profiles (Aiello et al., 2016) due to factors such as industries present, modes of public transport and spatial configurations of the built environment which impact the propagation of sound through the city (Piercy et al., 1977). Conducting our study in a large and heterogeneous city such as London meant we were able to record soundscapes that characterise a wide range of urban environments. Due to the lack of automated tools for sound detection and identification, we were unable to test the AIs on our entire dataset as manual acoustic data processing is highly time-consuming. Our use of 25 low and high frequency recordings per site was based on practicality and is similar to previous work on AIs from disturbed environments (Fuller et al., 2015). Sites were not sampled systematically across the survey period in terms of urban intensity and size due to site access restrictions, which resulted in a slight bias towards sampling low urban intensity sites in spring, and no sampling over winter periods. However, because we were testing the performance of AIs by maximising variation in soundscapes recorded, rather than comparing the AIs across sites, we do not believe that our sampling design would have had an impact on the overall conclusions of the study. For example, we found all AIs to be biased by non-biotic sound despite sampling during the times when biotic sound would have been at its highest, therefore this finding would have remained consistent if we had also sampled during times such as winter when biotic sound is lower and non-biotic sound dominates the urban environment. Our recordings were randomly selected within sampling weeks between the months of June-October so we were unable to investigate the effect of seasonality or daily variation on the acoustic components investigated. Due to power and storage constraints, our use of the SM2BAT+ trigger to record high frequency sounds means that we were unable to test the AIs on silent high frequency recordings. Finally our use of humans to detect, classify and measure sounds in our recordings, would have introduced error and bias into our data (Kershenbaum et al., 2014). For example, using bounding boxes for detecting sounds presumes that the extent of the sound can be accurately quantified, and the activity of sounds that did not completely fill the shape of the box may have been inflated. Development of machine-learnt algorithms for the detection and classification of urban sounds in audio recordings (Salamon and Bello 2015) could reduce the subjectivity of using humans to identify and annotate sounds in the future.

4.1. Application

There is growing recognition from government, industry and the environmental sector that urban GI is not currently monitored sufficiently to fulfil one of its key roles of supporting urban biodiversity and ecosystems (UK-GBC, 2009; European Commission, 2012; UK Parliament, 2013). It is being increasingly recognised that there is a positive link between human well-being and biodiversity in the urban environment (HM Government, 2010; UNEP-WCMC, 2010; Dale et al., 2011), and government, industry and the environmental sector are hungry for new methods to make urban biodiversity monitoring easier and more reliable. If AIs are to be used, biasing sounds must be removed from recordings, prior to the calculation of AIs, such as has been done in marine environments to remove anthropogenic seismic exploration signals from recordings prior to the calculation of AIs (Parks et al., 2014). With this pre-processing the AIs could be used to measure a range of biotic factors in urban areas: activity could be monitored using the ACI_l, BI_l, $NDSI_l$, and ACI_h, while diversity of organisms could be monitored using the ACI_l, BI_l, $NDSI_l$ and ADI_h. The $NDSI_l$ which was designed to measure disturbance (Kasten et al., 2012) could be used to monitor long-term trends in human disturbance at individual sites. However, we do not recommend the use of AIs on recordings without the prior removal of biasing sounds. The use of automated methods such as machine-learnt algorithms to detect and identify biasing sounds could make this pre-processing feasible with large ecoacoustic datasets. The effect of this pre-processing on AI measures must be tested before AIs can be used in the urban environment. As the global human footprint increases (UN-DESA, 2015), ecoacoustic scientists and practitioners need to be increasingly aware of the range of anthropogenic sounds that human activity generates such as those identified here, and take steps to reduce their effect on ecoacoustic measures of biodiversity.

5. Conclusions

Ecoacoustics presents a promising tool to facilitate urban biodiversity monitoring by making it possible to collect and process the volumes of data required to monitor cities at large spatial and temporal scales. By testing the application of existing AIs to measure biotic sound in this highly complex and anthropogenically disturbed environment, we show that there is potential in this field but much area for improvement. With the development of better methods for measuring urban biotic sound that are robust to the quantity and diversity of non-biotic sounds in this environment, ecoacoustics could lead the way in smart nature monitoring of our future cities.

6. Data accesibility

All acoustic data created by AudioTagger and all R code is available at https://doi.org/10.6084/m9.figshare.c.3361488.v1.

Acknowledgements

We thank the Diocese of London for supporting the study by providing access to study sites, Andy Lester and Thomas Matthews for conducting the low frequency biotic sound identification, Jiemin Xie for acoustic processing support, and Lisa Hundt and the Bat Conservation Trust for help and support. We were financially supported by a BHP Billiton Sustainable Resources for Sustainable Cities Catalyst Grant and by the Engineering and Physical Sciences Research Council (EPSRC) though a doctoral training grant (EP/G037698/1) to H.T., and EPSRC grant (EP/K015664/1) to K.E.J.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2017.07.064.

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Table B.1 Details of survey sites and dates across Greater London, UK. Size categories defined as: (i) small (<0.5 ha); (ii) medium (0.5-1.5 ha); and (iii) large (>1.5 ha). Urban intensity categories defined based on the predominant land cover surrounding sites within a 500m radius: (i) high (contiguous multi-storey buildings); (ii) medium (detached and semi-detached housing); and (iii) low (fields and/or woodland). DD denotes decimal degrees.

Site Number	Site Code	Survey Start Date	Survey End Date	Latitude (DD)	Longitude (DD)	Size	Urban Intensity
1	RM14 3YB	11/06/2013	19/06/2013	51.55121	0.266853	Large	Low
2	W8 4LA	21/06/2013	28/06/2013	51.50223	-0.19147	Medium	High
3	NW1	24/06/2013	01/07/2013	51.5105	-0.20574	Large	High
4	SW15 4LA	02/07/2013	07/07/2013	51.44914	-0.23697	Small	Medium
5	WC2H 8LG	08/07/2013	14/07/2013	51.51521	-0.12823	Medium	High
6	W11 2NN	08/07/2013	16/07/2013	51.53452	-0.12957	Small	High
7	HA8 6RB	23/07/2013	30/07/2013	51.60862	-0.2899	Large	Medium
8	HA5 3AA	23/07/2013	30/07/2013	51.59478	-0.37885	Medium	Medium
9	SW11 2PN	16/08/2013	23/08/2013	51.47057	-0.16973	Medium	High
10	SE3	06/09/2013	13/09/2013	51.46261	0.001164	Large	Medium
11	SE23	06/09/2013	13/09/2013	51.45047	-0.05146	Small	Medium
12	CR0 5EF	15/09/2013	22/09/2013	51.37199	-0.05031	Large	Medium
13	CR8	15/09/2013	22/09/2013	51.3305	-0.09394	Medium	Medium
14	E10 5JP	06/10/2013	13/10/2013	51.56386	-0.01604	Large	High
15	E4 7EN	06/10/2013	13/10/2013	51.63101	0.001266	Large	Medium

Table B.2 Summary of acoustic parameters used to calculate Acoustic Indices (AIs). ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where l and h denotes low and high frequency versions, respectively. Reference 1 represents Pieretti, Farina and Morri (2011); 2 Villanueva-Rivera et al. (2011); 3 Boelman et al. (2007); and 4 Kasten et al. (2012). Anthropogenic and biotic sound bins are indicated by 'Anthro' and 'Bio' respectively. J denotes the temporal step in seconds. dB denotes decibels. Shannon denotes the Shannon's diversity index.

Acoustic Index	Spectrogram FFT window size (ms)	Bin min frequency (kHz)	Bin max frequency (kHz)	AI specific parameters	Ref
ACI_l	512	-	12	J = 5	1
ACI_h	512	12	96	J = 1	1
ADI_l	512	-	12	dB threshold = -50, frequency step = 1kHz, Shannon = True	2
ADI_h	512	12	96	dB threshold = -15, frequency step = 1kHz, Shannon = True	2
BI_l	512	2	8	-	3
$NDSI_l$	512	Anthro = 1; Bio = 2	Anthro = 2; Bio = 8	-	4

Table B.3 All mixed-effects models with ΔAICc < 4 describing the covariates of four Acoustic Indices (AI) for acoustic activity. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where l and h denotes low and high frequency versions, respectively. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Acoustic Indices Mixed-Effects Models	**k**	**log(L)**	**AICc**	**ΔAICc**	**AICc weight**
Low frequency					
ACI_l					
Anthropogenic + Biotic + Geophonic	6	-1481.46	2975.15	0	0.37
Anthropogenic + Biotic + Geophonic + Unknown	7	-1480.55	2975.41	0.26	0.32
Biotic + Geophonic + Unknown	6	-1482.25	2976.72	1.57	0.17
Biotic + Geophonic	5	-1483.39	2976.95	1.81	0.15
ADI_l					
Anthropogenic + Biotic + Geophonic + Unknown	7	-271.84	557.98	0	0.31
Anthropogenic + Geophonic + Unknown	6	-272.89	558.01	0.03	0.31
Geophonic + Unknown	5	-274.33	558.82	0.84	0.20
Biotic + Geophonic + Unknown	6	-273.41	559.04	1.06	0.18
BI_l					
Anthropogenic + Biotic	5	-1185.96	2382.09	0	0.39
Anthropogenic + Biotic + Geophonic	6	-1185.05	2382.34	0.25	0.34
Anthropogenic + Biotic + Unknown	6	-1185.94	2384.10	2.01	0.14
Anthropogenic + Biotic + Geophonic + Unknown	7	-1185.02	2384.35	2.26	0.13
$NDSI_l$					
Anthropogenic + Biotic + Geophonic	6	197.72	--383.22	0	0.74
Anthropogenic + Biotic + Geophonic + Unknown	7	197.74	-381.17	2.04	0.26
High frequency					
ACI_h					
Anthropogenic + Biotic	5	606.90	-1203.64	0	0.49
Anthropogenic + Biotic + Unknown	6	607.19	-1202.15	1.49	0.23
Anthropogenic + Biotic + Geophonic	6	606.95	-1201.68	1.96	0.18
Anthropogenic + Biotic + Geophonic + Unknown	7	607.27	-1200.23	3.41	0.09
ADI_h					
Geophonic + Unknown	5	-440.28	890.73	0	0.30
Unidentified	4	-441.72	891.54	0.81	0.20
Biotic + Geophonic + Unknown	6	-440.04	892.30	1.57	0.14
Anthropogenic + Geophonic + Unknown	6	-440.15	892.54	1.81	0.12
Biotic + Unknown	5	-441.50	893.17	2.44	0.09
Anthropogenic + Unknown	5	-441.61	893.38	2.65	0.08
Anthropogenic + Biotic + Geophonic + Unknown	7	-439.84	893.98	3.25	0.06

Table B.4 All mixed-effects models with ΔAICc < 4 describing the covariates of four Acoustic Indices (AI) for acoustic diversity. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where l and h denotes low and high frequency versions, respectively. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Acoustic Indices Mixed-Effects Models	k	log(L)	AICc	ΔAICc	AICc weight
Low frequency					
ACI$_l$					
Biotic + Geophonic + Unidentified	6	-1495.78	3003.79	0	0.31
Anthropogenic + Biotic + Geophonic + Unidentified	7	-1494.77	3003.84	0.04	0.31
Anthropogenic + Biotic + Geophonic	6	-1496.23	3004.69	0.9	0.2
Biotic + Geophonic	5	-1497.4	3004.95	1.16	0.18
ADI$_l$					
Anthropogenic + Geophonic + Unidentified	6	-243.63	499.5	0	0.66
Anthropogenic + Biotic + Geophonic + Unidentified	7	-243.27	500.84	1.34	0.34
BI$_l$					
Anthropogenic + Biotic + Geophonic	6	-1200.81	2413.85	0	0.49
Anthropogenic + Biotic + Geophonic + Unidentified	7	-1200.5	2415.3	1.45	0.24
Anthropogenic + Biotic	5	-1203.2	2416.56	2.71	0.13
Anthropogenic + Biotic + Unidentified	6	-1202.61	2417.46	3.61	0.08
Biotic + Geophonic	5	-1203.76	2417.68	3.83	0.07
NDSI$_l$					
Anthropogenic + Biotic + Geophonic	6	187.61	-362.99	0	0.62
Anthropogenic + Biotic + Geophonic + Unidentified	7	188.14	-361.97	1.01	0.38
High frequency					
ACI$_h$					
Biotic	4	525.63	-1043.14	0	0.18
Null	3	524.44	-1042.82	0.33	0.16
Biotic + Geophonic	5	526.00	-1041.84	1.30	0.10
Geophonic	4	524.93	-1041.75	1.39	0.09
Anthropogenic	4	524.87	-1041.63	1.51	0.09
Anthropogenic + Biotic	5	525.66	-1041.15	1.99	0.07
Biotic + Unidentified	5	525.63	-1041.10	2.04	0.07
Unidentified	4	524.48	-1040.84	2.30	0.06
Anthropogenic + Geophonic	5	525.38	-1040.59	2.55	0.05
Anthropogenic + Biotic + Geophonic	6	526.05	-1039.87	3.27	0.04
Geophonic + Unidentified	5	524.99	-1039.81	3.33	0.03
Biotic + Geophonic + Unidentified	6	526.00	-1039.78	3.37	0.03
Anthropogenic + Unidentified	5	524.91	-1039.66	3.48	0.03
ADI$_h$					
Anthropogenic + Biotic + Unidentified	6	-440.51	893.24	0	0.25
Anthropogenic + Biotic + Geophonic + Unidentified	7	-439.81	893.92	0.69	0.18
Anthropogenic + Biotic	5	-442.07	894.30	1.06	0.15
Anthropogenic + Biotic + Geophonic	6	-441.60	895.44	2.20	0.08
Biotic + Unidentified	5	-442.82	895.81	2.57	0.07
Geophonic + Unidentified	5	-442.85	895.85	2.61	0.07
Unidentified	4	-443.93	895.97	2.73	0.06
Biotic + Geophonic + Unidentified	6	-441.92	896.06	2.82	0.06
Anthropogenic + Geophonic + Unidentified	6	-442.19	896.61	3.37	0.05
Anthropogenic + Unidentified	5	-443.23	896.63	3.39	0.05

Table B.5 All mixed-effects models with ΔAICc < 4 describing the covariates of Normalised Difference Soundscape Index (NDSI) for acoustic disturbance, where l denotes low frequency version. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

NDSI$_l$ Mixed-Effects Models	**k**	**log(L)**	**AICc**	**ΔAICc**	**AICc weight**
Biotic:Anthropogenic Ratio + Geophonic	5	214.41	-418.67	0	0.73
Biotic:Anthropogenic Ratio + Geophonic + Unidentified	6	214.43	-416.63	2.04	0.27

Table B.6 All mixed-effects models with ΔAICc < 4 describing the covariates of four Acoustic Indices (AI) for the presence of anthropogenic sound type. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI Bioacoustic Index, and NDSI Normalised Difference Soundscape Index, where $_l$ and $_h$ denotes low and high frequency versions, respectively. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Acoustic Indices Mixed-Effects Models	**k**	**log(L)**	**AICc**	**ΔAICc**	**AICc weight**
Low frequency					
ACI$_l$					
Braking + Electrical + Road traffic + Human speech	7	-1548.43	3111.16	0	0.21
Electrical + Road traffic + Human speech	6	-1549.50	3111.22	0.06	0.21
Beep + Braking + Electrical + Road traffic + Human speech	8	-1547.81	3112.01	0.85	0.14
Beep + Electrical + Road traffic + Human speech	7	-1549.01	3112.33	1.17	0.12
Air traffic + Braking + Electrical + Road traffic + Human speech	8	-1548.42	3113.24	2.08	0.08
Air traffic + Electrical + Road traffic + Human speech	7	-1549.49	3113.30	2.13	0.07
Air traffic + Beep + Braking + Electrical + Road traffic + Human speech	9	-1547.81	3114.11	2.95	0.05
Air traffic + Beep + Electrical + Road traffic + Human speech	8	-1549.01	3114.42	3.26	0.04
Braking + Road traffic + Human speech	6	-1551.14	3114.51	3.35	0.04
Road traffic + Human speech	5	-1552.29	3114.74	3.58	0.04
ADI$_l$					
Air traffic + Braking + Electrical + Road traffic + Human speech	8	-250.79	517.98	0	0.61
Air traffic + Beep + Braking + Electrical + Road traffic + Human speech	9	-250.70	519.90	1.92	0.23
Air traffic + Electrical + Road traffic + Human speech	7	-253.18	520.66	2.68	0.16
BI$_l$					
Human speech	4	-1209.95	2428.00	0	0.15
Electrical + Human speech	5	-1209.10	2428.36	0.36	0.12
Air traffic + Human speech	5	-1209.43	2429.03	1.03	0.09
Air traffic + Electrical + Human speech	6	-1208.56	2429.35	1.35	0.08
Beep + Human speech	5	-1209.85	2429.86	1.86	0.06
Road traffic + Human speech	5	-1209.87	2429.90	1.90	0.06
Braking + Human speech	5	-1209.95	2430.06	2.05	0.05
Beep + Electrical + Human speech	6	-1208.98	2430.19	2.19	0.05
Electrical + Road traffic + Human speech	6	-1209.08	2430.38	2.38	0.05

Braking + Electrical + Human speech	6	-1209.10	2430.43	2.43	0.04
Air traffic + Beep + Human speech	6	-1209.35	2430.93	2.93	0.03
Air traffic + Road traffic + Human speech	6	-1209.37	2430.98	2.97	0.03
Air traffic + Braking +Human speech	6	-1209.43	2341.09	3.09	0.03
Air traffic + Beep + Electrical + Human speech	7	-1208.46	2431.23	3.32	0.03
Air traffic + Electrical + Road traffic + Human speech	7	-1208.55	2431.40	3.40	0.03
Air traffic + Braking + Electrical + Human speech	7	-1208.56	2431.43	3.43	0.03
Beep + Road traffic + Human speech	6	-1209.77	2431.77	3.77	0.02
Beep + Braking + Human speech	6	-1209.85	2431.92	3.92	0.02
Braking + Road traffic + Human speech	6	-1209.87	2431.96	3.96	0.02
NDSI$_l$					
Air traffic + Braking + Electrical + Road traffic + Human speech	8	181.62	-346.84	0	0.23
Air traffic + Beep + Braking + Electrical + Road traffic + Human speech	9	182.31	-346.14	0.70	0.16
Air traffic + Electrical + Road traffic + Human speech	7	180.22	-346.13	0.71	0.16
Air traffic + Braking + Road traffic + Human speech	7	179.96	-345.62	1.22	0.13
Air traffic + Beep + Electrical + Road traffic + Human speech	8	180.75	-345.10	1.74	0.10
Air traffic + Road traffic + Human speech	6	178.53	-344.82	2.02	0.09
Air traffic + Beep + Braking + Road traffic + Human speech	8	180.58	-344.76	2.08	0.08
Air traffic + Beep + Road traffic + Human speech	7	178.97	-343.63	3.21	0.05
High frequency					
ACI$_h$					
Braking + Electrical	5	529.40	-1048.64	0	0.44
Braking + Electrical + Metal	6	530.31	-1048.39	0.26	0.39
Electrical	4	526.87	-1045.62	3.02	0.10
Braking	4	526.46	-1044.82	3.83	0.07
ADI$_h$					
Braking	4	-439.45	887.01	0	0.53
Braking + Metal	5	-439.36	888.87	1.86	0.21
Braking + Electrical	5	-439.45	889.06	2.04	0.19
Braking + Electrical + Metal	6	-439.35	890.93	3.91	0.07

Appendix C

Supplementary Methods C.1

Normalisation Methods

The four normalisation methods used are as follows:

1. The entire spectrogram S was subtracted from each row in W_S. This helped to act as a noise-reducing normalisation strategy
2. Each row of W_S was whitened to have zero mean and unit variance.
3. Each value in W_S was whitened to have zero mean and unit variance.
4. Each value in W_S was divided by the maximum value in W_S.

Prediction Process

Both CityBioNet and CityAnthroNet have a convolutional layer with 32 filters, followed by a max pooling layer, then another 32-filter convolutional layer and finally two dense layers (with 128 units) before a binary class output - see Figure 4.1 for an overview of the network architecture. For nonlinearities very leaky rectifiers were used (Maas, Hannun & Ng 2013), and Dropout (Srivastava et al. 2014) was used to help to regularise the network and batch normalisation (Ioffe & Szegedy 2015) to increase the speed of convergence during training. The network was trained for 30 epochs using the Adam (Kingma & Ba 2015) update scheme with a learning rate of 0.0005. An ensemble of five such networks was trained using the same architecture and training data, but with different random initialisations. The final predictions are made by averaging together the predictions of each member in the ensemble.

Table C.1 Details of acoustic recording sites across Greater London, UK. Sites separated into two groups illustrating whether recordings from sites were included in the CitySounds2017$_{train}$ or CitySounds2017$_{test}$ datasets. Urban intensity categories defined based on the predominant land cover surrounding sites within a 500m radius: (i) high (contiguous multi-storey buildings); (ii) medium (detached and semi-detached housing); and (iii) low (fields and/or woodland). DD denotes decimal degrees. In terms of site type, C denotes church or churchyard, CG denoted community garden, GR denotes green roof, GW denotes green wall, and NR denotes nature reserve.

Site Code	Site Type	Survey Start Date	Survey End Date	Latitude (DD)	Longitude (DD)	Urban Intensity
CitySounds2017$_{train}$						
RM14 3YB	C	11/06/2013	19/06/2013	51.55121	0.266853	Low
W8 4LA	C	21/06/2013	28/06/2013	51.50223	-0.19147	High
SW15 4LA	C	02/07/2013	07/07/2013	51.44914	-0.23697	Medium
NW1	C	24/06/2013	01/07/2013	51.5105	-0.20574	High
SW11 2PN	C	16/08/2013	23/08/2013	51.47057	-0.16973	High
E4 7EN	C	06/10/2013	13/10/2013	51.63101	0.001266	High
SE1 2RT 7	GR	19/05/2014	27/05/2014	51.30.16N	0.4.53W	High
SE1 2RT 10	GR	19/05/2014	27/05/2014	51.30.16N	0.4.50W	High
SW1W 0QP	GW	30/05/2014	06/06/2014	51.49627	-0.14489	High
SW1E 6BN	GR	30/05/2014	06/06/2014	51.4981	-0.14138	High
SE11 6DN	GR	11/06/2014	20/06/2014	51.49313	-0.11199	High
SE4 1SA	GR	20/06/2014	30/06/2014	51.45817	-0.02751	Medium
WC2N 6RH	GR	01/07/2014	10/07/2014	51.50706	-0.12388	High
CR0 1SG	C	02/07/2014	09/07/2014	51.3722	-0.10604	High
CR0	C	02/07/2014	09/07/2014	51.33934	-0.01266	Medium
RM2 5EL	C	10/07/2014	17/07/2014	51.58773	0.201817	Medium
RM4 1LD	C	10/07/2014	17/07/2014	51.62349	0.223904	Low
SE22 0SD	GR	28/07/2014	04/08/2014	51.45332	-0.05583	Medium
TW7 6BE	C	30/07/2014	06/08/2014	51.4719	-0.31981	Medium
W4 2PH	C	30/07/2014	06/08/2014	51.48308	-0.25326	Medium
SE6	C	19/08/2014	26/08/2014	51.42804	-0.01095	Medium
SE8 4EA	C	19/08/2014	27/08/2014	51.46841	-0.02344	Medium
IG11 0FJ	GR	21/08/2014	01/09/2014	51.52069	0.109187	Medium
W5 5EQ	GR	28/08/2014	05/09/2014	51.50975	-0.30812	Medium
E14 0EY	C	02/09/2014	10/09/2014	51.51072	-0.01192	High
E1 0NR	C	03/09/2014	11/09/2014	51.51676	-0.04122	Medium
SE10 9EY	GR	05/09/2014	12/09/2014	51.4849	0.006003	Medium
N2 9BX	GR	15/09/2014	22/09/2014	51.59274	-0.16569	Medium
SW6 6DU	GR	16/09/2014	23/09/2014	51.47369	-0.21695	Medium
SE6 4PL	CG	24/05/2015	01/06/2015	51.43821	-0.02711	Medium
W1T 4BQ	GR	22/06/2015	30/06/2015	51.52143	-0.13836	High
N4 1ES	NR	23/06/2015	02/07/2015	51.57656	-0.1017	Medium
TN14 7QB	NR	25/06/2015	03/07/2015	51.31364	0.067323	Low
NW3 3RY	NR	14/07/2015	22/07/2015	51.54357	-0.16054	High
N8 8JD	CG	11/07/2015	19/07/2015	51.58333	-0.13292	Medium
KT18 6AP	NR	27/07/2015	05/08/2015	51.29036	-0.26158	Low
NW2 3SH	NR	11/08/2015	18/08/2015	51.55287	-0.20628	Medium
N17	CG	17/08/2015	27/08/2015	51.59105	-0.0549	High
RM4 1PL	C	27/08/2015	04/09/2015	51.61588	0.18189	Medium
SE23 2NZ	NR	16/09/2015	23/09/2015	51.43224	-0.05197	Medium
NW3 2BZ	NR	17/09/2015	25/09/2015	51.55181	-0.16259	Medium
NW1 0TA	NR	15/10/2015	22/10/2015	51.54073	-0.13613	High
SE15 4EE	CG	13/10/2015	20/10/2015	51.46301	-0.07519	Medium
RM15 4HX	NR	20/10/2015	28/10/2015	51.51749	0.261494	Low
CitySounds2017$_{test}$						
W11 2NN	C	08/07/2013	16/07/2013	51.53452	-0.12957	High
WC2H 8LG	C	08/07/2013	14/07/2013	51.51521	-0.12823	High
HA8 6RB	C	23/07/2013	30/07/2013	51.60862	-0.2899	Medium
HA5 3AA	C	23/07/2013	30/07/2013	51.59478	-0.37885	Medium
SE23	C	06/09/2013	13/09/2013	51.45047	-0.05146	Medium
SE3	C	06/09/2013	13/09/2013	51.46261	0.001164	Medium

CR8	C	15/09/2013	22/09/2013	51.3305	-0.09394	Medium
CR0 5EF	C	15/09/2013	22/09/2013	51.37199	-0.05031	Medium
E10 5JP	C	06/10/2013	13/10/2013	51.56386	-0.01604	Medium
SW15 4JY	GR	27/08/2014	03/09/2014	51.45012	-0.23859	Medium
IG6 2XL	CG	08/05/2015	15/05/2015	51.60046	0.095681	Low
E2 9RR	NR	25/05/2015	02/06/2015	51.5295	-0.05875	High
TW7 6ER	C	23/06/2015	30/06/2015	51.46711	-0.3454	Medium
BR2 0EG	C	17/07/2015	26/07/2015	51.4047	0.012974	Medium
BR2 8LB	C	31/07/2015	07/08/2015	51.38029	0.042746	Medium
BR6 7US	C	31/07/2015	07/08/2015	51.33605	0.054201	Low
BR4	C	18/08/2015	25/08/2015	51.38261	-0.00868	Medium
DA5	NR	24/08/2015	01/09/2015	51.42268	0.156502	Medium
CM16 7NP	NR	08/09/2015	15/09/2015	51.65396	0.101227	Low

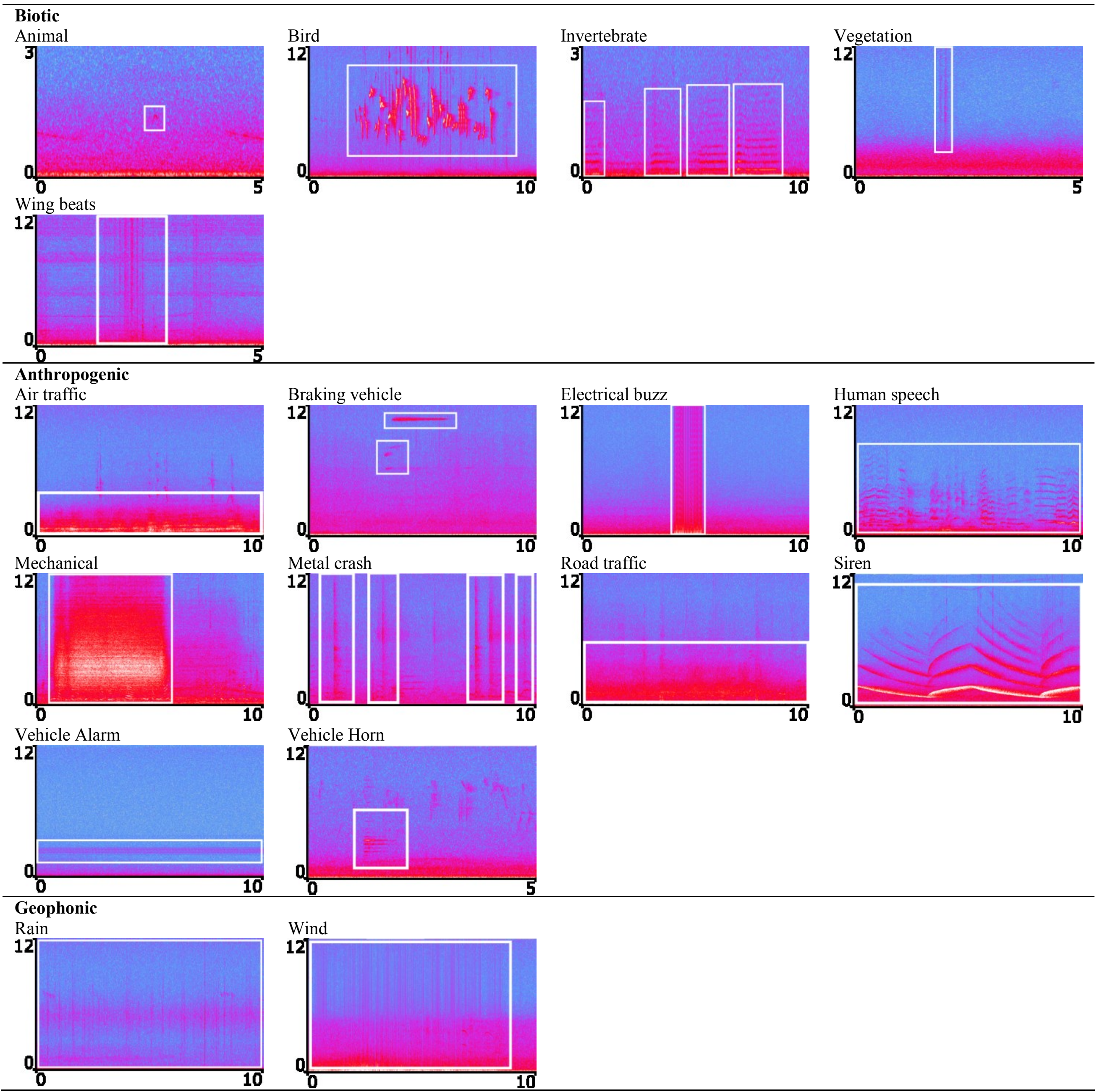

Figure C.1 Examples of all sound types present in CitySounds2017. ‘Animal’ denotes biotic sounds that could not be taxonomically identified. Unidentified sounds not shown due to wide range of sound types within this group. Data is represented in spectrograms (FFT non-overlapping Hamming window size=1024) where blue to yellow corresponds to sound amplitude (dB). Frequency (kHz) and time (s) are represented on the y- and x-axes, respectively. Spectrograms represent biotic (sounds generated by non-human biotic organisms), anthropogenic (sounds associated with human activities including human speech) and geophonic sounds.

Appendix D

Table D.1 Details of acoustic recording sites across Greater London, UK. Urban intensity categories defined based on the predominant land cover surrounding sites within a 500m radius: (i) high (contiguous multi-storey buildings); (ii) medium (detached and semi-detached housing); and (iii) low (fields and/or woodland). DD denotes decimal degrees.

Site Number	Site Code	Latitude (DD)	Longitude (DD)	Survey Start Date	Habitat Complexity	Habitat Diversity	Area (m^2)	Urban Intensity
1	BR20EG	51.4047	0.012974	17/07/2015	3	29	6523	Medium
2	BR28LB	51.38029	0.042746	31/07/2015	3	28	6060	Medium
3	BR4	51.38261	-0.00868	18/08/2015	3	28	2721	Medium
4	BR67US	51.33605	0.054201	31/07/2015	3	27	2008	Low
5	CM167NP	51.65396	0.101227	08/09/2015	3	47	385690	Low
6	CR0	51.33934	-0.01266	02/07/2014	3	31	1996	Medium
7	CR01SG	51.3722	-0.10604	02/07/2014	3	29	6385	High
8	CR05EF	51.37199	-0.05031	15/09/2013	3	92	13612	Medium
9	CR8	51.3305	-0.09394	15/09/2013	3	38	2348	Medium
10	DA5	51.42268	0.156502	24/08/2015	3	24	1211762	Medium
11	E105JP	51.56386	-0.01604	06/10/2013	3	126	8220	Medium
12	E10NR	51.51676	-0.04122	03/09/2014	3	20	20359	Medium
13	E140EY	51.51072	-0.01192	02/09/2014	3	35	11542	High
14	E29RR	51.5295	-0.05875	25/05/2015	4	77	2874	High
15	E47EN	51.63101	0.001266	06/10/2013	3	80	6214	High
16	HA53AA	51.59478	-0.37885	23/07/2013	3	69	1926	Medium
17	HA86RB	51.60862	-0.2899	23/07/2013	3	91	9261	Medium
18	IG110FJ	51.52069	0.109187	21/08/2014	2	25	2949	Medium
19	IG62XL	51.60046	0.095681	08/05/2015	4	72	9227	Low
20	KT186AP	51.29036	-0.26158	27/07/2015	3	88	2721645	Low
21	N17	51.59105	-0.0549	17/08/2015	3	68	31572	High
22	N29BX	51.59274	-0.16569	15/09/2014	1	7	39	Medium
23	N41ES	51.57656	-0.1017	23/06/2015	3	44	9770	Medium
24	N88JD	51.58333	-0.13292	11/07/2015	2	22	6656	Medium
25	NW1	51.5105	-0.20574	08/07/2013	3	88	20728	High
26	NW10TA	51.54073	-0.13613	15/10/2015	2	30	525	High
27	NW23SH	51.55287	-0.20628	11/08/2015	4	66	4377	Medium
28	NW32BZ	51.55181	-0.16259	17/09/2015	4	19	4622	Medium
29	NW33RY	51.54357	-0.16054	14/07/2015	4	64	10774	High
30	RM143YB	51.55232	0.265708	11/06/2013	3	82	4019	Low
31	RM154HX	51.51749	0.261494	20/10/2015	4	31	979887	Low
32	RM25EL	51.58773	0.201817	10/07/2014	3	32	4432	Medium
33	RM41LD	51.62349	0.223904	10/07/2014	3	27	5123	Low
34	RM41PL	51.61588	0.18189	27/08/2015	3	37	6712	Medium
35	SE109EY	51.4849	0.006003	05/09/2014	2	16	8	Medium
36	SE116DN	51.49313	-0.11199	11/06/2014	4	102	111	High
37	SE12RT-1	51.30.16N	0.4.50W	19/05/2014	1	12	154	High

38	SE12RT-2	51.30.16N	0.4.53W	19/05/2014	1	8	553	High
39	SE154EE	51.46301	-0.07519	13/10/2015	3	120	2175	Medium
40	SE220SD	51.45332	-0.05583	28/07/2014	1	14	23	Medium
41	SE23	51.45047	-0.05146	06/09/2013	3	67	4150	Medium
42	SE232NZ	51.43224	-0.05197	16/09/2015	4	23	2091	Medium
43	SE3	51.46261	0.001164	06/09/2013	3	57	5950	Medium
44	SE41SA	51.45817	-0.02751	20/06/2014	1	7	281	Medium
45	SE6	51.42804	-0.01095	19/08/2014	3	34	4328	Medium
46	SE64PL	51.43821	-0.02711	24/05/2015	3	50	12512	Medium
47	SE84EA	51.46841	-0.02344	19/08/2014	3	41	3781	Medium
48	SW112PN	51.47057	-0.16973	16/08/2013	3	59	6340	High
49	SW154JY	51.45012	-0.23859	27/08/2014	1	10	12	Medium
50	SW154LA	51.44914	-0.23697	02/07/2013	3	66	1615	Medium
51	SW1E6BN	51.4981	-0.14138	30/05/2014	1	21	439	High
52	SW1W0QP	51.49627	-0.14489	30/05/2014	0	0	350	High
53	SW66DU	51.47369	-0.21695	16/09/2014	1	2	35	Medium
54	TN147QB	51.31364	0.067323	25/06/2015	3	42	272500	Low
55	TW76BE	51.4719	-0.31981	30/07/2014	3	34	8194	Medium
56	TW76ER	51.46711	-0.3454	23/06/2015	3	21	2334	Medium
57	W112NN	51.53452	-0.12957	24/06/2013	3	39	3520	High
58	W1T4BQ	51.52143	-0.13836	22/06/2015	2	20	191	High
59	W42PH	51.48308	-0.25326	30/07/2014	2	22	33455	Medium
60	W55EQ	51.50975	-0.30812	28/08/2014	1	4	227	Medium
61	W84LA	51.50223	-0.19147	21/06/2013	3	54	7297	High
62	WC2H8LG	51.51521	-0.12823	08/07/2013	3	33	4449	High
63	WC2N6RH	51.50706	-0.12388	01/07/2014	1	8	288	High

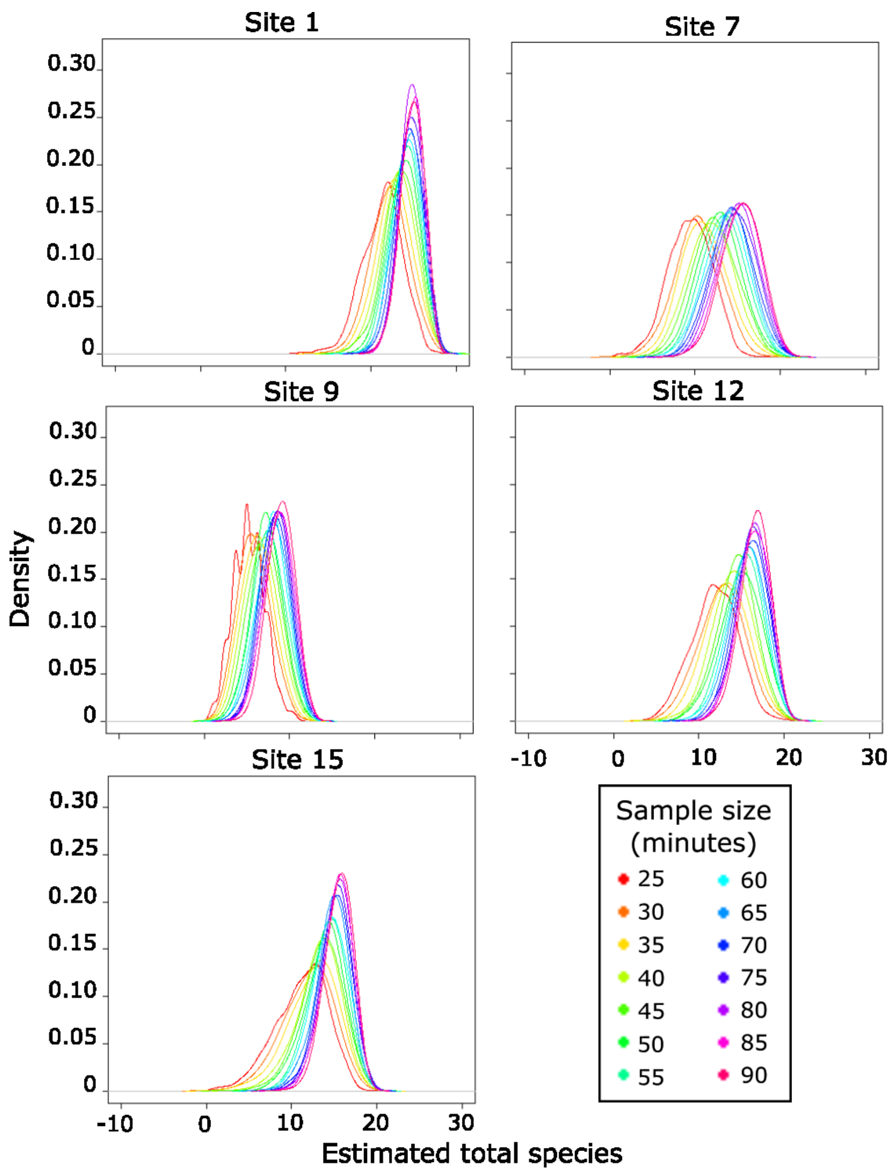

Figure D.1 Sample size analysis plots of estimated species richness from audio data. Species were identified from 90 randomly selected 1-minute recordings from each of six sites (plot of site 61 not shown displayed as zero species were identified at this site). Density plots show the total species richness estimates from 1000 iterations of randomly selected files from fourteen different sample sizes (25 to 90 minutes in 5 minute increments).

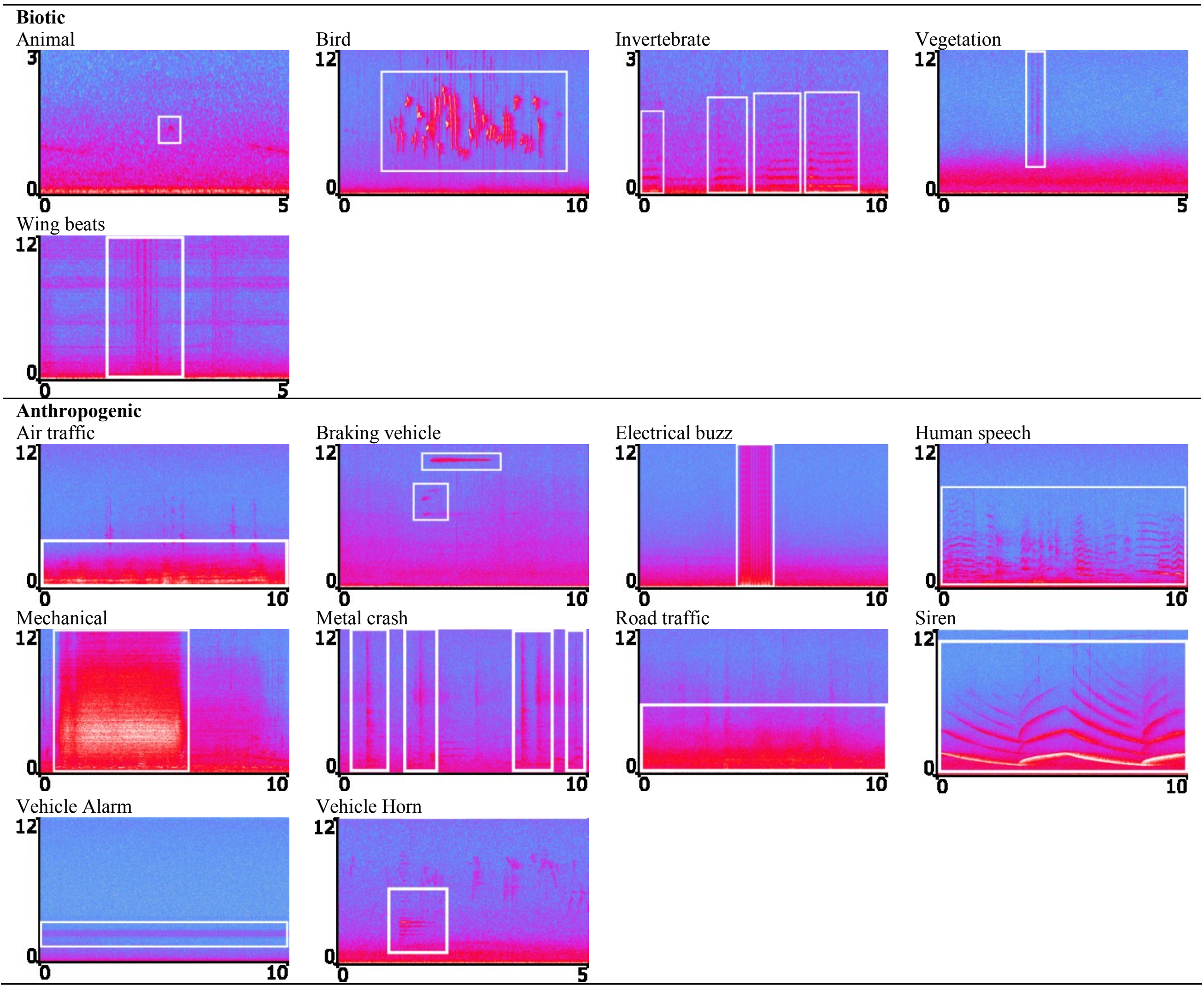

Figure D.2 Examples of all sound types present in recordings. ‘Animal’ denotes biotic sounds that could not be taxonomically identified. Bird sounds were identified further to species with one example given here. Unidentified sounds not shown due to wide range of sound types within this group. Data is represented in spectrograms (FFT non-overlapping Hamming window size=1024) where blue to yellow corresponds to sound amplitude (dB). Frequency (kHz) and time (s) are represented on the y- and x-axes, respectively. Spectrograms represent biotic (sounds generated by non-human biotic organisms) and anthropogenic (sounds associated with human activities including human speech) sounds.

Table D.2 All mixed-effects models with ΔAICc < 2 describing the environmental covariates of biotic and anthropogenic acoustic activity. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Acoustic Activity Mixed-Effects Models	k	log(L)	AICc	ΔAICc	AICc weight
Biotic					
Habitat complexity + Green space 1km	4	55.50	-102.29	0	0.41
Habitat complexity + Green space 1km + Habitat diversity	5	56.26	- 101.44	0.85	0.27
Habitat complexity	3	53.42	-100.43	1.86	0.16
Habitat complexity + Green space 1km + Mean temperature	5	55.71	-110.34	1.95	0.16
Anthropogenic					
Green space 50m + Green space 1km + Habitat diversity	5	31.89	-52.70	0	0.71
Habitat area + Green space 50m + Green space 1km + Habitat diversity	6	32.20	-50.87	1.83	0.29

Table D.3 All mixed-effects models with ΔAICc < 2 describing the environmental covariates of biotic and anthropogenic acoustic diversity. Details for each model are k, the number of parameters in each model; log(L) the log-likelihood; AICc information criterion value; ΔAICc the AICc difference value; and AICc weight, for each model.

Acoustic Diversity Mixed-Effects Models	k	log(L)	AICc	ΔAICc	AICc weight
Biotic					
Habitat area + Green space 1km + Habitat diversity	4	-204.88	418.47	0	0.40
Habitat area + Green space 50m + Green space 1km + Habitat diversity	5	-204.21	419.49	1.02	0.24
Habitat area + Habitat complexity + Green space 1km + Habitat diversity	5	-204.49	420.05	1.58	0.18
Habitat area + Green space 1km + Mean temperature + Habitat diversity	5	-204.56	420.20	1.73	0.17
Anthropogenic					
Habitat area + Habitat diversity	3	-148.68	303.78	0	0.59
Habitat area + Green space 50m + Habitat diversity	4	-147.89	304.48	0.7	0.41