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Biases of acoustic indices measuring biodiversity in urban areas

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A B S T R A C T

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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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

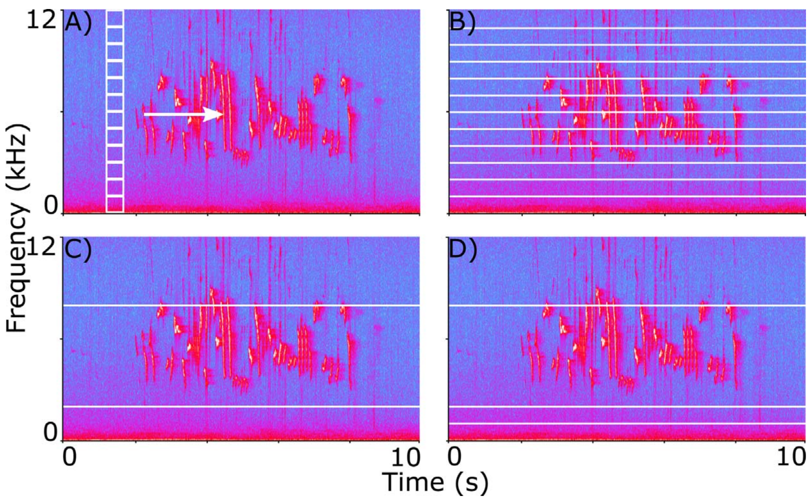

Fig. 1. Calculation of four Acoustic Indices (AIs) on example ecoacoustic data. Data is represented in spectrograms (FFT non-overlapping Hamming window size = 1024) where blue to yellow corresponds to increasing sound amplitude (dB). Spectrograms represent calculations of (A) Acoustic Complexity Index (ACI_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 S2 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 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.)

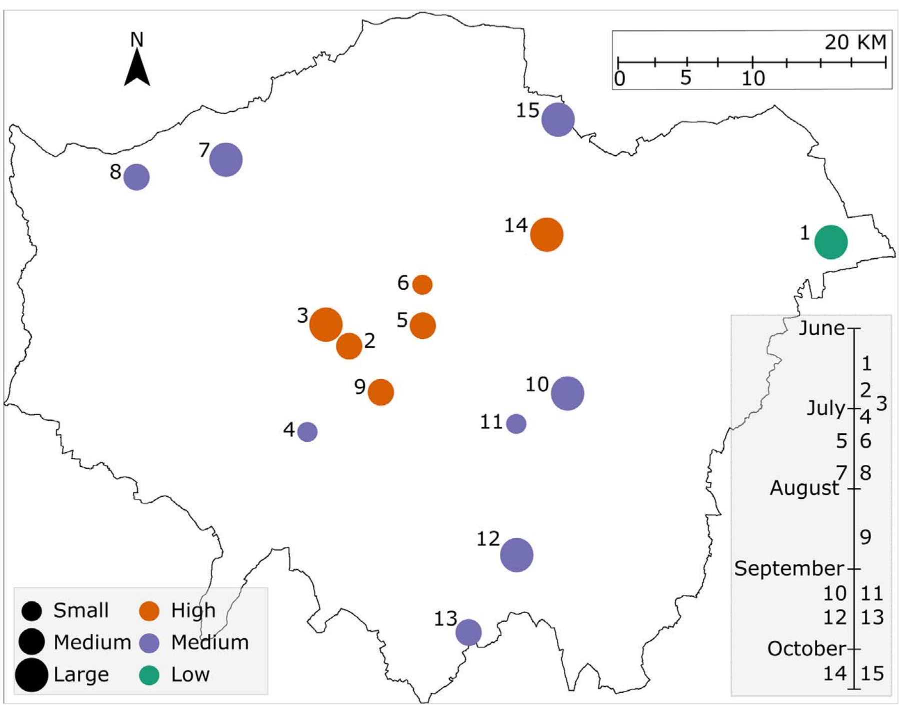

Fig. 2. Locations and characteristics of 15 survey sites across Greater London, UK. Dots and numbers indicate sites. Relative site size indicated by dot size, urban intensity indicated by dot colour (red: high, blue: medium, green: low). Location of numbers along date scale indicates date of survey at 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

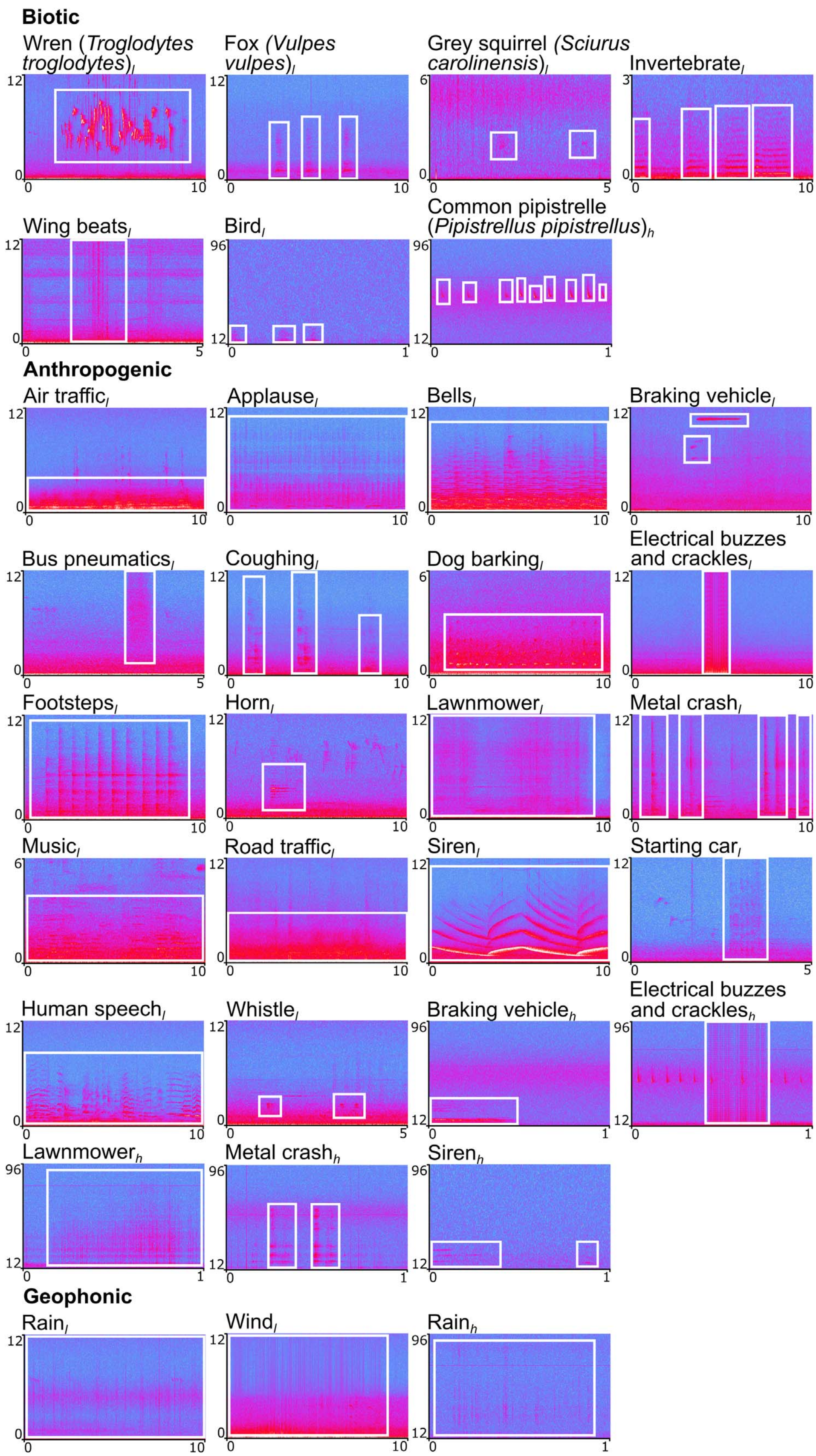

Fig. 3. Examples of all sound types present in recordings. Bird and bat sounds were identified further to species with one example of each given here. Unidentified sounds not shown due to wide range of sound types within this group. Data is represented in spectrograms (FFT non-overlapping Hamming window 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).

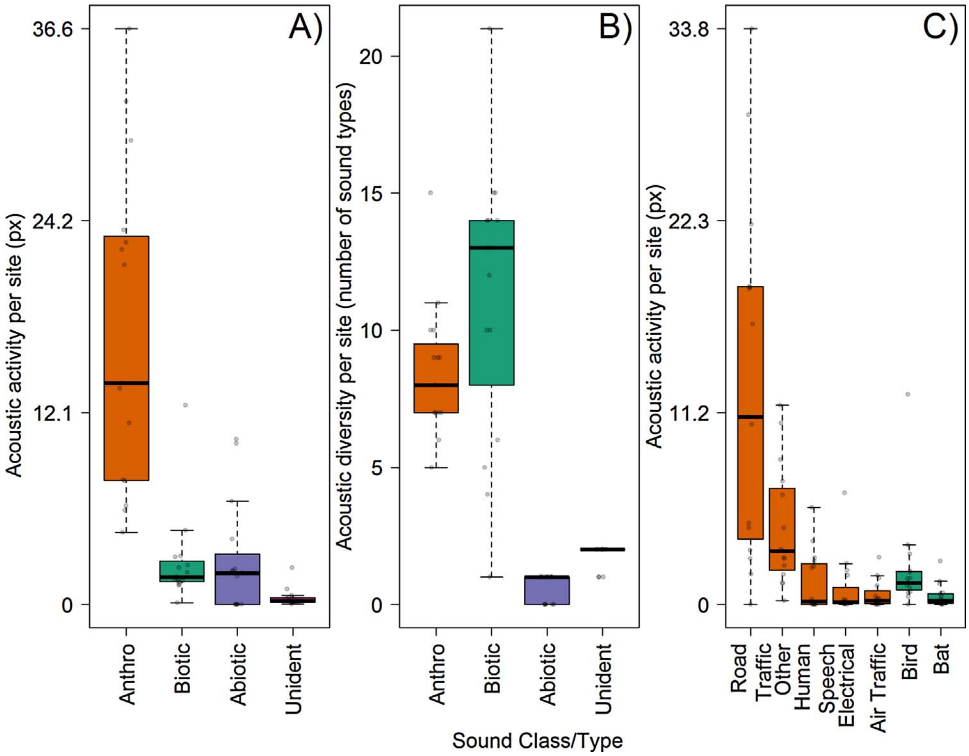

Fig. 4. Average sound activity and diversity per site (n = 15) in Greater London for A) and B) each sound class, and C) the most common anthropogenic and biotic sound types. Acoustic activity reported as number of pixels (px, total = 75858750) occupied by each sound class/type in the spectrograms of 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.

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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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