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Biases of acoustic indices measuring biodiversity in urban areas

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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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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