CityNet - Deep Learning Tools for Urban Ecoacoustic Assessment

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SUMMARY

1. Cities support unique and valuable ecological communities, but understanding urban wildlife is limited due to the difficulties of assessing biodiversity. Ecoacoustic surveying is a useful way of assessing habitats, where biotic sound measured from audio recordings is used as a proxy for biodiversity. However, existing algorithms for measuring biotic sound have been shown to be biased by non-biotic sounds in recordings, typical of urban environments.
2. We develop CityNet, a deep learning system using convolutional neural networks (CNNs), to measure audible biotic (CityBioNet) and anthropogenic (CityAnthroNet) acoustic activity in cities. The CNNs were trained on a large dataset of annotated audio recordings collected across Greater London, UK. Using a held-out test dataset, we compare the precision and recall of CityBioNet and CityAnthroNet separately to the best available alternative algorithms: four acoustic indices (AIs): Acoustic Complexity Index, Acoustic Diversity Index, Bioacoustic Index, and Normalised Difference Soundscape Index, and a state-of-the-art bird call detection CNN (bulbul). We also compare the effect of non-biotic sounds on the predictions of CityBioNet and bulbul. Finally we apply CityNet to describe acoustic patterns of the urban soundscape in two sites along an urbanisation gradient.
3. CityBioNet was the best performing algorithm for measuring biotic activity in terms of precision and recall, followed by bulbul, while the AIs performed worst. CityAnthroNet outperformed the Normalised Difference Soundscape Index, but by a smaller margin than CityBioNet achieved against the competing algorithms. The CityBioNet predictions were impacted by mechanical sounds, whereas air traffic and wind sounds influenced the bulbul predictions. Across an urbanisation gradient, we

show that CityNet produced realistic daily patterns of biotic and anthropogenic acoustic activity from real-world urban audio data.

4. Using CityNet, it is possible to automatically measure biotic and anthropogenic acoustic activity in cities from audio recordings. If embedded within an autonomous sensing system, CityNet could produce environmental data for cites at large-scales and facilitate investigation of the impacts of anthropogenic activities on wildlife. The algorithms, code and pre-trained models are made freely available in combination with two expert-annotated urban audio datasets to facilitate automated environmental surveillance in cities.

Keywords: Acoustic Indices, Anthropogenic, Biodiversity Assessment, Convolutional Neural Networks, Deep Learning, Ecoacoustics, London, Machine Learning, Soundscapes, Urban Ecology.

INTRODUCTION

Over half of the world's human population now live in cities (UN-DESA 2016) and urban biodiversity can provide people with a multitude of health and well-being benefits including improved physical and psychological health (Natural England 2016; Crouse *et al.* 2017). 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 (Farinha-Marques *et al.* 2011). 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 (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). 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 (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 and anthropogenic 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), 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 (ML) 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 annotated audio datasets of soniferous species, a ML model can be trained to recognise biotic sounds based on multiple acoustic characteristics, or features, and to associate these features with taxonomic classifications, and can then assign a probabilistic classification to sounds within recordings. AIs only use a limited number of acoustic features in their calculations, 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). Additionally, the relationship between the features and the algorithm outputs are chosen by a human, rather than learned automatically from an annotated dataset. In contrast, ML algorithms can utilise many more features in their calculations, and the relationship between inputs and outputs is determined automatically based on the annotated training data provided. Convolutional Neural Networks, CNNs (or Deep learning) (LeCun, Bengio & Hinton 2015) can even choose, based on the annotations in the training dataset, the features that best discriminate different classes in datasets without being specified a priori, and can take advantage of large quantities of training data where their ability to outperform human defined algorithms increases as more labelled data become available.

Species-specific ML 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, these algorithms are focussed on a small number of species limiting their usefulness for broad classification tasks across communities. More recently, algorithms that detect whole taxonomic groups are being developed, for example bird sounds in audio recordings from the UK and the Chernobyl Exclusion Zone

(Grill & Schlüter 2017), but these algorithms remain untested on noisy audio data from urban environments. There are currently no algorithms that produce whole community measures of biotic sound that are known to be suitable for use in acoustically complex urban environments.

Here, we develop the CityNet acoustic analysis system, which uses two CNNs for measuring audible (0-12 kHz) biotic (CityBioNet) and anthropogenic (CityAnthroNet) acoustic activity in audio recordings from urban environments. We use this frequency range as it contains the majority of sounds emitted by audible soniferous species in the urban environment (Fairbrass *et al.* 2017). The CNNs were trained using CitySounds2017, an expert-annotated dataset of urban sounds collected across Greater London, UK that we develop here. We compared the performance of CityNet using a held-out dataset by comparing the algorithms' precision and recall 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). As the main focus of the study was the development of algorithms for ecoacoustic assessment of biodiversity in cities, we 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, we applied CityNet to investigate daily patterns of biotic and anthropogenic sound in the urban soundscape.

MATERIALS AND METHODS

We developed two CNN models, CityBioNet and CityAnthroNet within the CityNet system to generate measures of biotic and anthropogenic sound, respectively. The CityNet pipeline (Figure 1) consisted of 7 main steps as follows:

(1) *Record audio*: Audible 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 ML; 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. We exploited the multiple input channel capability of our CNN by providing as input four spectrograms each pre-processed using a different normalisation strategy (see Supplementary Methods), which 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 learnt from training data. The CNN comprised a series of layers, each of which modified its input data with parameterised mathematical operations which were optimised to improve classification performance during training (see Supplementary Methods for details). The final layer produced the prediction of presence or absence of biotic or anthropogenic sound.

(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 ML 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 ML and librosa v.0.4.2 (McFee *et al.* 2015) for audio processing.

Acoustic Dataset

We 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 2, Table S1). At each location, a Song Meter SM2+ digital audio field sensor (Wildlife Acoustics, Inc., Concord, Massachusetts, USA) was deployed, recording sound between 0 and 12 kHz at a 24 kHz sample rate. The sensor was equipped with a single

omnidirectional microphone (frequency response: -35±4 dB) oriented horizontally at a height of 1m. Files were saved in *.wav* format onto a SD card. Audio was recorded 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). This constituted the CitySounds2017 dataset.

Acoustic Training Dataset

To create our training dataset (CitySounds2017$_{train}$) we randomly selected twenty five 1-minute recordings from 70% of the study sites (44 sites, 1100 recordings). A.F. 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). Spectrograms were annotated by localising 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 S1), 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.* (2011), where 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.

Acoustic Testing Dataset and Evaluation

To evaluate the performance of the CityNet algorithms, we created a testing dataset (CitySounds2017$_{test}$) by strategically selecting 40 recordings from CitySounds2017 from the

remaining 30% of sites (19 sites) that contained a range of both biotic and anthropogenic acoustic activity. CitySounds2017$_{test}$ was sampled from different recording sites to CitySounds2017$_{train}$ to demonstrate that the CityNet algorithms generalise to sounds recorded at new site locations (Figure 2, Table S1). To optimise the quality of the annotations in CitySounds2017$_{test}$, we selected five human labellers to separately annotate the sounds within the audio recordings (using the same methods as above) to create a single annotated test dataset. Conflicts were resolved using a majority rule, and in cases where there was no majority, we used our own judgement on the most suitable classification. Our CitySounds2017 annotated training and testing datasets are available at https://figshare.com/s/adab62c0591afaeafedd.

Using the CitySounds2017$_{test}$ dataset, we separately assessed the performance of the two CityNet algorithms, CityBioNet and CityAnthroNet, using two measures: precision and recall. The CityBioNet and CityAnthroNet algorithms give 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 were computed for the average precision under all the threshold values 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).

Competing Algorithms

We also compared the precision and recall of the CityNet algorithms 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, we 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. 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 we 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. 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.

The precision and recall of CityBioNet was also compared to bulbul (Grill & Schlüter 2017), an algorithm for detecting bird 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, it 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 CitySounds2017$_{test}$, using the pre-trained model provided by the authors together with their code.

Impact of Non-Biotic Sounds

We conducted additional analysis on the non-biotic sounds that affect the predictions of CityBioNet and bulbul, as these were found to be the best performing algorithms for measuring biotic sound. To do this, we 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. We then used a Chi-squared test to identify significant differences in the proportion of seconds in which the presence/absence of biotic sound at threshold 0.5 was correctly predicted in the full and subset datasets by each algorithm, 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).

Ecological Application

We used CityNet to generate daily average patterns of biotic and anthropogenic acoustic activity for two study sites across an urbanisation gradient (sites E29RR and IG62XL with high and low urbanisation respectively, Table S1). To control for the date of recording; both sites were surveyed between May and June 2015. 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 using a 0.5 probability threshold. 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.

RESULTS

Acoustic Performance

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 (Table 1, Figure 3). In comparison 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). CityBioNet also outperformed bulbul which had an average precision of 0.872 and recall at 0.95 of 0.398 (Table 1). In comparison to CityAnthroNet, the $NDSI_{anthro}$ had a lower average precision (0.975) and lower recall at 0.95 precision (0.815). 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%, for CityBioNet and bulbul respectively) (Figure 4). 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).

296 Impacts of Non-Biotic Sounds

297 CityBioNet was strongly (Cramer's V effect size >0.5) negatively affected by mechanical
298 sound (the presence/absence of biotic sound was correctly predicted in 28.60% less of the
299 data when mechanical sounds were also present) (Table 2). Bulbul was moderately (Cramer's
300 V effect size 0.1-0.5) negatively affected by the sound of air traffic and wind (the
301 presence/absence of biotic sound was correctly predicted in 5.34% and 6.93% less of the data
302 when air traffic and wind sounds were also present in recordings, respectively).

303 Ecological Application

304 CityNet produced realistic patterns of biotic and anthropogenic acoustic activity in the urban
305 soundscape at two study sites of low and high urban intensity (Figure 2B and C). At both
306 sites, biotic acoustic activity peaked just after sunrise and declined rapidly after sunset. A
307 second peak of biotic acoustic activity was recorded at sunset at the low urban intensity site
308 but not at the high urban intensity site. At both sites anthropogenic acoustic activity rose
309 sharply after sunrise, remained constant throughout the day and declined after sunset.

310 DISCUSSION

311 Both CityBioNet and CityAnthroNet outperformed the competing algorithms on the
312 CitySound2017$_{test}$ dataset. CityBioNet performed better than bulbul on noisy recordings from
313 the urban environment; it was robust to more non-biotic sounds, including road traffic, air
314 traffic and rain. Being robust to the sound of road traffic supports the suitability of
315 CityBioNet for use in cities, as the urban soundscape is dominated by the sound of road
316 traffic (Fairbrass *et al.* 2017) which has been shown to bias several of the AIs tested here
317 (Fuller *et al.* 2015; Fairbrass *et al.* 2017). The sound of rain has also been shown to bias
318 several AIs (Depraetere *et al.* 2012; Gasc *et al.* 2015b; Fairbrass *et al.* 2017) and the
319 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 (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 or from audio data. Others 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 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 requires more sophisticated algorithms than the measurement of anthropogenic sound. Possibly anthropogenic sounds are 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), facilitating the use of human defined algorithms such as NDSI$_{anthro}$. Whereas, because biotic sounds occur in a frequency

345 space shared with anthropogenic and geophonic sounds (Fairbrass *et al.* 2017), algorithms
346 such as AIs which only use a small number of features to discriminate sounds are not
347 sufficient for use in cities. Therefore, ML algorithms which are able to utilise larger numbers
348 of features to discriminate sounds, such as the CNNs implemented in the CityNet system, are
349 better able to detect biotic sounds in recordings that also contain non-biotic sounds. A recent
350 unsupervised method developed by Lin, Fang and Tsao (2017) to separate biological sounds
351 from long recordings could be used as a pre-processing step to further improve CityNet's
352 performance.

353 Low cost acoustic sensors and algorithms for the automatic measurement of biotic sound in
354 audio data is facilitating the assessment and monitoring of biodiversity at large temporal and
355 spatial scales (Sueur & Farina 2015), but to date this technology has only been deployed in
356 non-urban environments (e.g. Aide *et al.* 2013). In cities, the availability of mains power and
357 Wifi connections is supporting the development of the urban Internet of Things (IoT) using
358 sensors integrated into existing infrastructure to monitor environmental factors including air
359 pollution, noise levels, and energy use (Zanella *et al.* 2014). The CityNet system could be
360 integrated into an IoT sensing network to facilitate large-scale urban environmental
361 assessment. Large-scale deployment of algorithms such as CityNet requires low power usage
362 and fast running times. One way to help to achieve this aim would be to combine the two
363 networks (CityBioNet and CityAnthroNet) into one CNN which predicts both biotic and
364 anthropogenic acoustic activity simultaneously.

365 An expansion of CityNet to ultrasonic frequencies would increase the generality of the tool as
366 it could be used to monitor species in cities that emit sounds at frequencies higher than 12
367 kHz such as bats and some invertebrates. Bats are frequently used as ecological indicators
368 because they are sensitive to environmental changes (Walters *et al.* 2013). Acoustic methods
369 are commonly used to monitor bat populations using passive ultrasonic recorders meaning bat

researchers and conservationists are faced with the challenge of extracting 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.

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. Our data collection was restricted to a single week at each study site, which limits our ability to assess the ability of CityNet system to detect environmental changes. Future work should focus on the collection of longitudinal acoustic data to assess the sensitivity of the algorithms to detect environmental changes. Our use of human labellers would have introduced subjectivity and bias into our dataset. 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. These datasets do not fully represent the characteristics of urban soundscapes 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 CityNet measures both anthropogenic and biotic sounds. Finally, each file in these datasets has a sound present, while urban soundscapes contain many periods of silence or geophonic sounds, two

important states which are not present in UrbanSounds and UrbanSounds8k. Due to these factors, these datasets are unsuitable for the purpose of this research project, although recent work has overcome a few of these shortcoming using synthesised soundscape data (Salamon *et al.* 2017). 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.

Conclusions

The CityNet system for measuring biotic and anthropogenic acoustic activity in noisy urban audio data outperformed the state-of-the-art algorithms for measuring biotic and anthropogenic sound in entire audio recordings. Integrated into an IoT network 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 biodiversity assessment. We make our system available open source in combination with two expertly annotated urban soundscape datasets to facilitate future research development in this field.

AUTHOR CONTRIBUTION STATEMENT

AF, MF, HT and KJ conceived ideas and designed methodology; AF collected the data; AF and MF analysed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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420 DATA ACCESSIBILITY

421 All recordings and annotations in the CitySounds2017 dataset and all Python code underlying
422 the CityNet algorithms are available on Figshare
423 (https://figshare.com/s/adab62c0591afaeafedd).

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601

602 TABLES

603 **Table 1.** Average precision and recall results for CityNet and competing algorithms for each
604 1-second audio chunk in the CitySounds2017$_{test}$ dataset. Recall results are presented at 0.95
605 precision. Higher values are better for both metrics. The highest values in each section are
606 shown in bold. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI
607 Bioacoustic Index, and NDSI$_{bio}$ and NDSI$_{anthro}$ biotic and anthropogenic Normalised
608 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

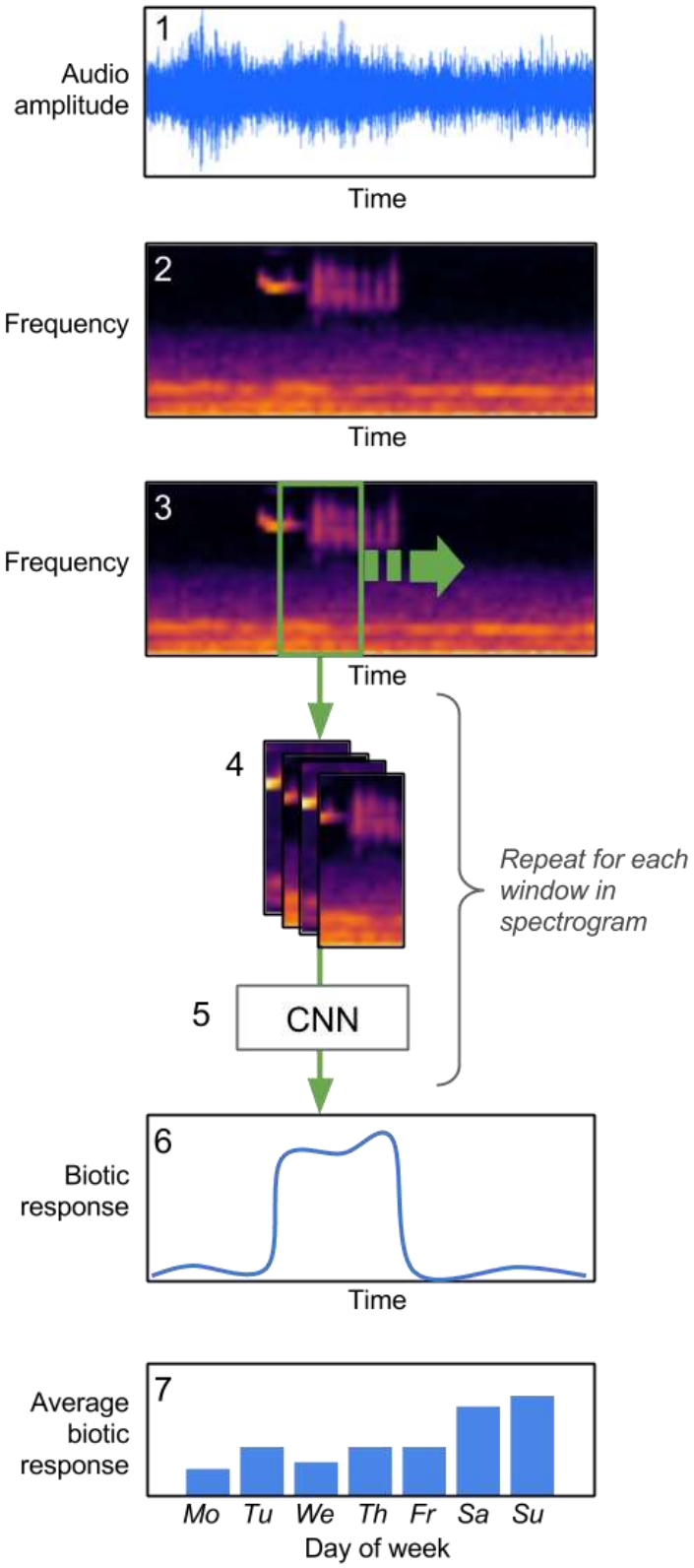
609

610 **Table 2.** Impact of non-biotic sounds on the CityBioNet and bulbul predictions. Values
611 represent differences in the proportion of 1-second audio chunks in the full CitySound2017$_{test}$
612 dataset (40 minutes) and the subset datasets (size in time indicated in left-hand column) in
613 which the presence/absence of biotic sound was correctly predicted by both algorithms, (chi-
614 squared test statistic for difference in proportions of successes in each dataset, and Cramer's
615 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)**

616

617 FIGURES

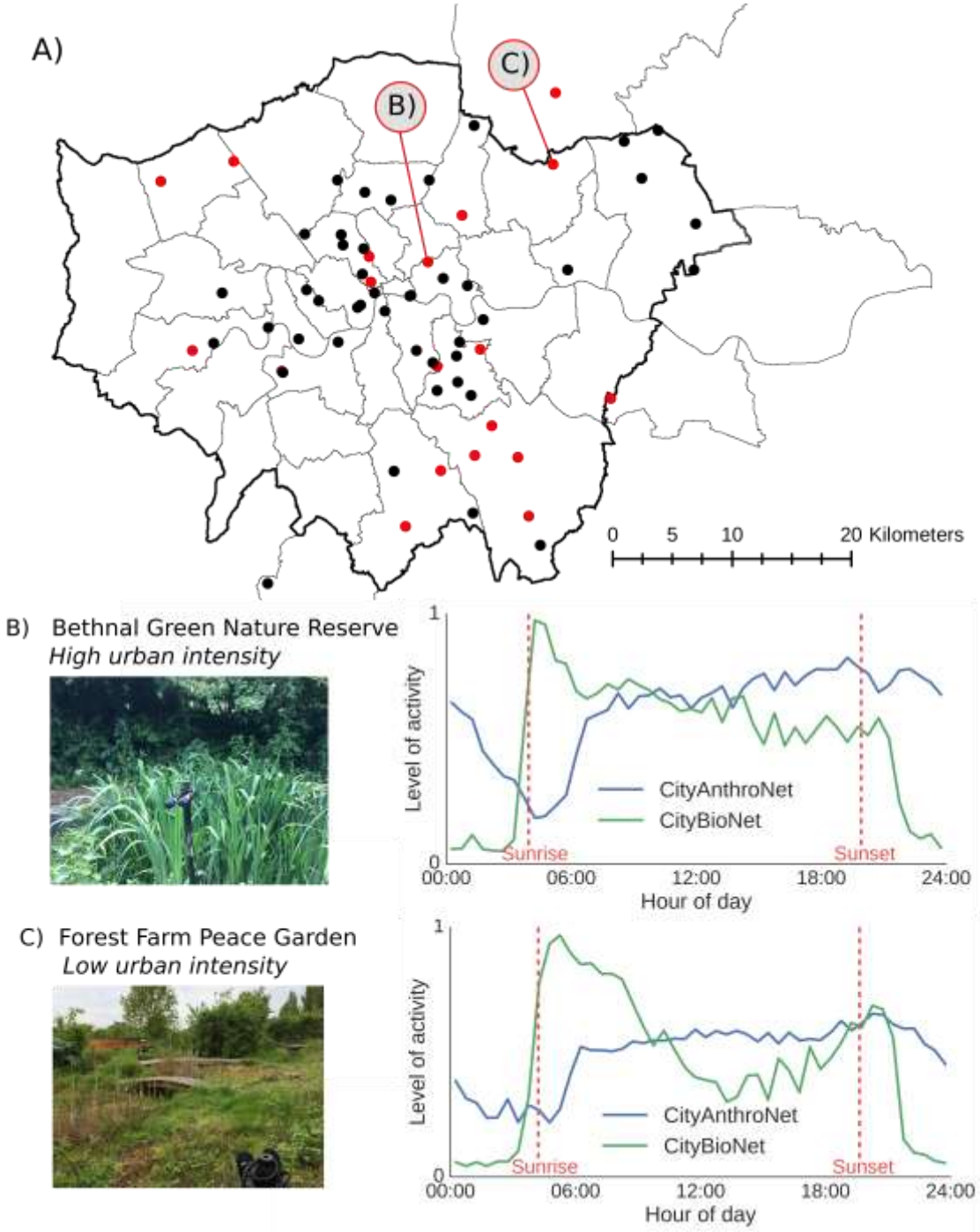


618

619 **Figure 1.** The CityNet analysis pipeline for measuring biotic and anthropogenic acoustic

620 activity. Raw audio (1), recorded in the field, is converted to a spectrogram representation

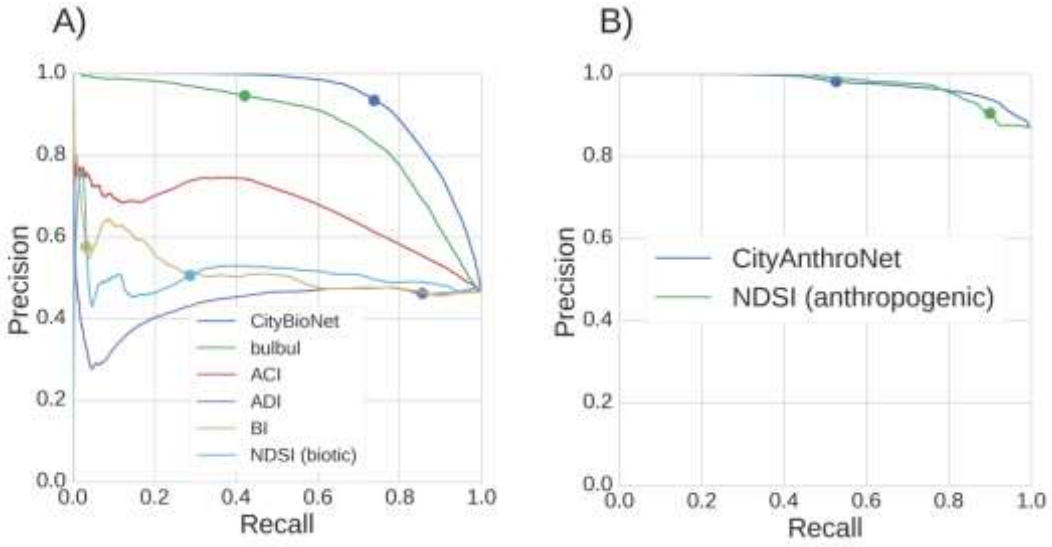
(2). A sliding window is run across the time dimension, and a window of the spectrogram extracted at each step (3). This spectrogram window is pre-processed with four different normalisation strategies, and the results concatenated. This stack of spectrograms is passed through a CNN (5), which was trained 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). Finally, these per-time-step measures can be aggregated to give summaries over time or space (7).



628

629 **Figure 2.** Location of study sites and average daily acoustic patterns at two sites along an
630 urbanisation gradient. Points in (A) represent locations used for the training dataset,
631 CitySounds2017$_{train}$ (black) and testing dataset, CitySounds2017$_{test}$ (red). Here CityNet was
632 run across the entire 7 days of recording at two sites of high (B) and low (C) urban intensity
633 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).



638

639 **Figure 3.** Precision-recall curves for CityNet and competing algorithms predicting A) biotic
640 and B) anthropogenic acoustic activity for each 1-second audio chunk in the
641 CitySounds2017$_{test}$ dataset. Dots indicate the precision and recall values at a threshold value
642 of 0.5. ACI represents Acoustic Complexity Index, ADI Acoustic Diversity Index, BI
643 Bioacoustic Index, and NDSI$_{bio}$ and NDSI$_{anthro}$ biotic and anthropogenic Normalised
644 Difference Soundscape Index, respectively.

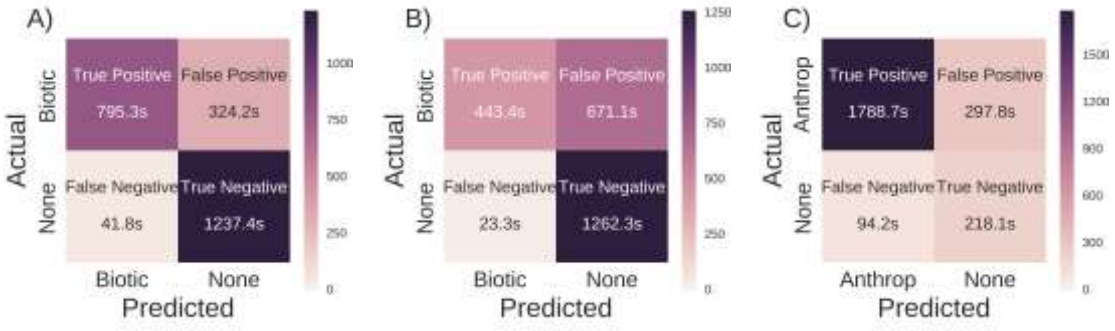


Figure 4. Confusion matrices comparing the predicted acoustic activity of A) CityBioNet, B), bulbul, and C) CityAnthroNet for each 1-second audio chunk in the CitySounds2017$_{test}$ dataset. Numbers in each cell report the number of 1-second audio clips in the CitySounds2017$_{test}$ dataset predicted 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.

SUPPORTING INFORMATION

Section S1: Supplementary Methods

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 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 S1. 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.

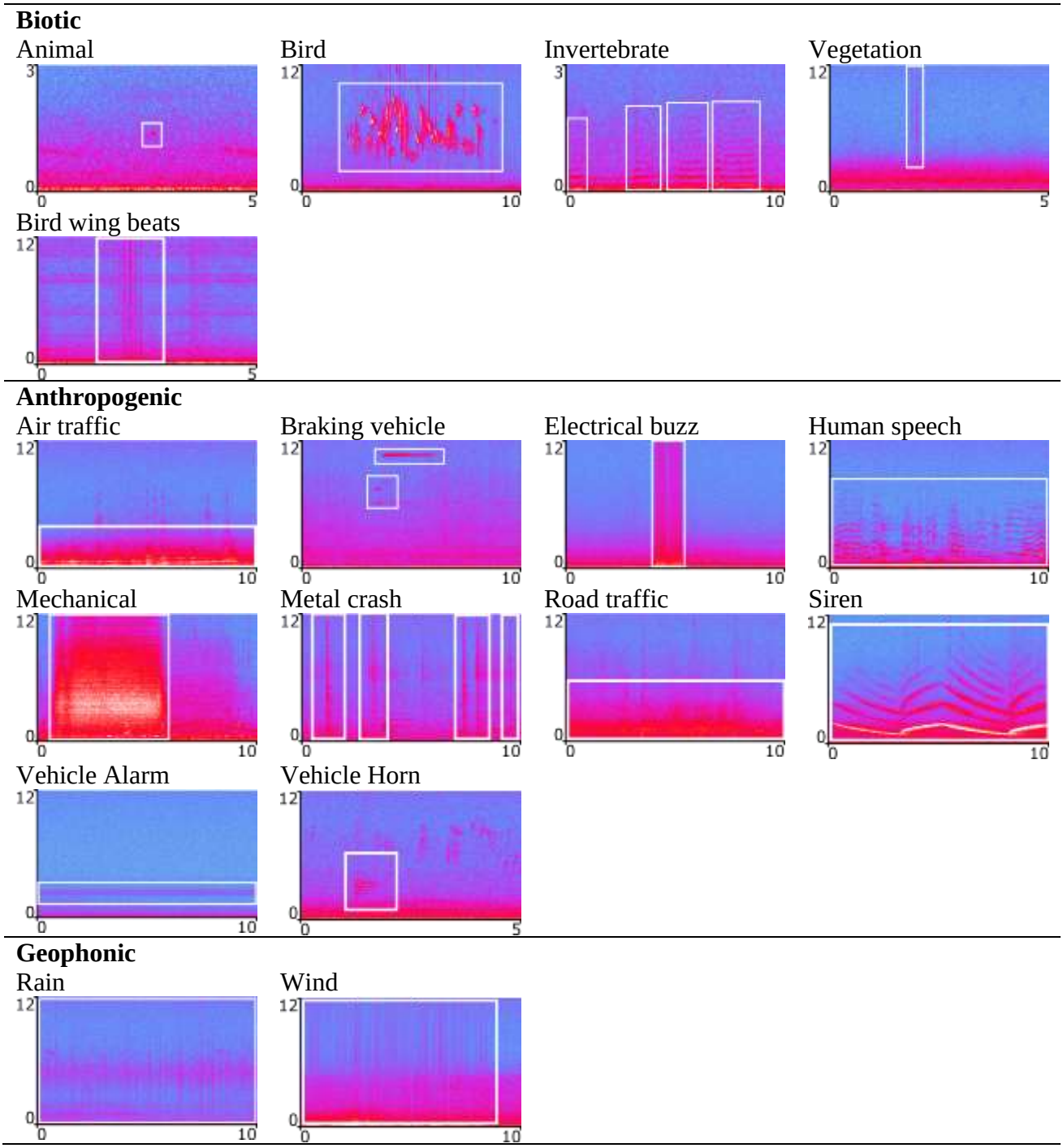
Site Code	Site Type	Survey Start Date	Survey End Date	Latitude (DD)	Longitude (DD)	Urban Intensity
CitySounds2017$_{train}$						
RM14 3YB	C	11/06/2013	19/06/2013	51.55121	0.266853	Low
W8 4LA	C	21/06/2013	28/06/2013	51.50223	-0.19147	High
SW15 4LA	C	02/07/2013	07/07/2013	51.44914	-0.23697	Medium
NW1	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

682



683 **Figure S1.** Examples of all sound types present in CitySounds2017. 'Animal' denotes biotic
684 sounds that could not be taxonomically identified. Unidentified sounds not shown due to
685 wide range of sound types within this group. Data is represented in spectrograms (FFT non-
686 overlapping Hamming window size=1024) where blue to yellow corresponds to sound
687 amplitude (dB). Frequency (kHz) and time (s) are represented on the y- and x-axes,
688 respectively. Spectrograms represent biotic (sounds generated by non-human biotic

689 organisms), anthropogenic (sounds associated with human activities including human speech)
690 and geophonic sounds.

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