

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

1 CityNet - Deep Learning Tools for Urban Ecoacoustic Assessment

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24 SUMMARY

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

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

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

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

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60 INTRODUCTION

61 Over half of the world’s human population now live in cities (UN-DESA 2016) and urban
62 biodiversity can provide people with a multitude of health and well-being benefits including
63 improved physical and psychological health (Natural England 2016; Crouse *et al.* 2017).
64 Cities can support high biodiversity including native endemic species (Aronson *et al.* 2014),
65 and act as refuges for biodiversity that can no longer persist in intensely managed agricultural
66 landscapes surrounding cities (Hall *et al.* 2016). However, our understanding of urban
67 biodiversity remains limited (Faeth, Bang & Saari 2011; Beninde, Veith & Hochkirch 2015).
68 One reason for this is the difficulties associated with biodiversity assessment, such as gaining
69 repeated access to survey sites and the resource intensity of traditional methods (Farinha-
70 Marques *et al.* 2011). This inhibits our ability to conduct the large-scale assessment that is
71 necessary for understanding urban ecosystems.

72 Ecoacoustic surveying has emerged as a useful method of large-scale quantification of
73 ecological communities and their habitats (Sueur & Farina 2015). Passive acoustic recording
74 equipment facilitates the collection of audio data over long time periods and large spatial
75 scales with fewer resources than traditional survey methods (Digby *et al.* 2013). A number of
76 automated methods have been developed to measure biotic sound in the large volumes of
77 acoustic data that are typically produced by ecoacoustic surveying (Sueur & Farina 2015).
78 For example, Acoustic Indices (AIs) use the spectral and temporal characteristics of acoustic
79 energy in sound recordings to produce whole community measures of biotic and
80 anthropogenic sound (Sueur *et al.* 2014). However, several commonly used AIs have been
81 shown to be biased by non-biotic sounds (Towsey *et al.* 2014; Fuller *et al.* 2015; Gasc *et al.*
82 2015a), and are not suitable for use in the urban environment without the prior removal of
83 certain non-biotic sounds from recordings (Fairbrass *et al.* 2017).

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84 Machine learning (ML) is being increasingly applied to biodiversity assessment and
85 monitoring because it facilitates the detection and classification of ecoacoustic signals in
86 audio data (Acevedo *et al.* 2009; Walters *et al.* 2012; Stowell & Plumbley 2014). Using
87 annotated audio datasets of soniferous species, a ML model can be trained to recognise biotic
88 sounds based on multiple acoustic characteristics, or features, and to associate these features
89 with taxonomic classifications, and can then assign a probabilistic classification to sounds
90 within recordings. AIs only use a limited number of acoustic features in their calculations,
91 such as spectral entropy within defined frequency bands (Boelman *et al.* 2007; Villanueva-
92 Rivera *et al.* 2011; Kasten *et al.* 2012) or entropy changes over time (Pieretti, Farina & Morri
93 2011). Additionally, the relationship between the features and the algorithm outputs are
94 chosen by a human, rather than learned automatically from an annotated dataset. In contrast,
95 ML algorithms can utilise many more features in their calculations, and the relationship
96 between inputs and outputs is determined automatically based on the annotated training data
97 provided. Convolutional Neural Networks, CNNs (or Deep learning) (LeCun, Bengio &
98 Hinton 2015) can even choose, based on the annotations in the training dataset, the features
99 that best discriminate different classes in datasets without being specified a priori, and can
100 take advantage of large quantities of training data where their ability to outperform human
101 defined algorithms increases as more labelled data become available.

102 Species-specific ML algorithms have been developed to automatically identify the sounds
103 emitted by a range of soniferous organisms including birds (Stowell & Plumbley 2014), bats
104 (Walters *et al.* 2012; Zamora-Gutierrez *et al.* 2016), amphibians (Acevedo *et al.* 2009) and
105 invertebrates (Chesmore & Ohya 2004). However, these algorithms are focussed on a small
106 number of species limiting their usefulness for broad classification tasks across communities.
107 More recently, algorithms that detect whole taxonomic groups are being developed, for
108 example bird sounds in audio recordings from the UK and the Chernobyl Exclusion Zone

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

113 Here, we develop the CityNet acoustic analysis system, which uses two CNNs for measuring
114 audible (0-12 kHz) biotic (CityBioNet) and anthropogenic (CityAnthroNet) acoustic activity
115 in audio recordings from urban environments. We use this frequency range as it contains the
116 majority of sounds emitted by audible soniferous species in the urban environment (Fairbrass
117 *et al.* 2017). The CNNs were trained using CitySounds2017, an expert-annotated dataset of
118 urban sounds collected across Greater London, UK that we develop here. We compared the
119 performance of CityNet using a held-out dataset by comparing the algorithms' precision and
120 recall to four commonly used AIs: Acoustic Complexity Index (ACI) (Pieretti, Farina &
121 Morri 2011), Acoustic Diversity Index (ADI) (Villanueva-Rivera *et al.* 2011), Bioacoustic
122 Index (BI) (Boelman *et al.* 2007), Normalised Difference Soundscape Index (NDSI) (Kasten
123 *et al.* 2012), and to bulbul, a state-of-the-art algorithm for detecting bird sounds in order to
124 summarise avian acoustic activity (Grill & Schlüter 2017). As the main focus of the study
125 was the development of algorithms for ecoacoustic assessment of biodiversity in cities, we
126 conducted further analysis on the two best performing algorithms for measuring biotic sound,
127 CityBioNet and bulbul, by investigating the effect of non-biotic sounds on the accuracy of the
128 algorithms. Finally, we applied CityNet to investigate daily patterns of biotic and
129 anthropogenic sound in the urban soundscape.

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130 MATERIALS AND METHODS

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

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

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

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

145 (4) *Apply different normalisation strategies*: There are many different methods for pre-
146 processing spectrograms before they are used in ML; for example whitening (Lee *et al.* 2009)
147 and subtraction of mean values along each frequency bin (Aide *et al.* 2013). CNNs are able to
148 accept inputs with multiple channels of data, for example the red, green and blue channels of
149 a colour image. We exploited the multiple input channel capability of our CNN by providing
150 as input four spectrograms each pre-processed using a different normalisation strategy (see
151 Supplementary Methods), which gave considerable improvements to network accuracy above
152 any single normalisation scheme in isolation. After applying different normalisation
153 strategies, the input to the network consisted of a 32 x 21 x 4 tensor.

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154 (5) *Apply CNN classifier*: As described above, classification was performed with a CNN,
155 whose parameters were learnt from training data. The CNN comprised a series of layers, each
156 of which modified its input data with parameterised mathematical operations which were
157 optimised to improve classification performance during training (see Supplementary Methods
158 for details). The final layer produced the prediction of presence or absence of biotic or
159 anthropogenic sound.

160 (6) *Make prediction for each moment in time*: At test time, steps (3)-(5) were repeated every
161 1 second throughout the audio file, to give a measure of biotic or anthropogenic activity
162 throughout time. Predictions for each chunk of audio were made independently.

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

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

170 Acoustic Dataset

171 We selected 63 green infrastructure (GI) sites in and around Greater London, UK to collect
172 audio data to train and test the CityNet algorithms. These sites represent a range of GI in and
173 around Greater London in terms of GI type, size and urban intensity. Each site was sampled
174 for 7 consecutive days systematically across the months of May to October between 2013 and
175 2015 (Figure 2, Table S1). At each location, a Song Meter SM2+ digital audio field sensor
176 (Wildlife Acoustics, Inc., Concord, Massachusetts, USA) was deployed, recording sound
177 between 0 and 12 kHz at a 24 kHz sample rate. The sensor was equipped with a single

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178 omnidirectional microphone (frequency response: -35 ± 4 dB) oriented horizontally at a height
179 of 1m. Files were saved in *.wav* format onto a SD card. Audio was recorded in
180 computationally manageable chunks of 29 minutes of every 30 mins (23.2 hours of recording
181 per day), which were divided into 1-minute audio files using Slice Audio File Splitter (NCH
182 Software Inc. 2014), leading to a total of 613,872 discrete minutes of audio recording (9,744
183 minutes for each of the 63 sites). This constituted the CitySounds2017 dataset.

184 Acoustic Training Dataset

185 To create our training dataset (*CitySounds2017_{train}*) we randomly selected twenty five 1-
186 minute recordings from 70% of the study sites (44 sites, 1100 recordings). A.F. manually
187 annotated the spectrograms of each recording, computed as the log magnitude of a discrete
188 Fourier transform (non-overlapping Hamming window size=720 samples=10 ms), using
189 AudioTagger (available at <https://github.com/groakat/AudioTagger>). Spectrograms were
190 annotated by localising the time and frequency bands of discrete sounds by drawing bounding
191 boxes as tightly as visually possible within spectrograms displayed on a Dell UltraSharp
192 61cm LED monitor. Types of sound, such as “invertebrate”, “rain”, and “road traffic”, were
193 identified by looking for typical patterns in spectrograms (Figure S1), and by listening to the
194 audio samples represented in the annotated parts of the spectrogram. Categories of sounds
195 were then grouped into biotic, anthropogenic and geophonic classes following Pijanowski *et*
196 *al.* (2011), where we define biotic as sounds generated by non-human biotic organisms,
197 anthropogenic as sounds associated with human activities, and geophonic as non-biological
198 ambient sounds e.g. wind and rain.

199 Acoustic Testing Dataset and Evaluation

200 To evaluate the performance of the CityNet algorithms, we created a testing dataset
201 (*CitySounds2017_{test}*) by strategically selecting 40 recordings from CitySounds2017 from the

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202 remaining 30% of sites (19 sites) that contained a range of both biotic and anthropogenic
203 acoustic activity. CitySounds2017_{test} was sampled from different recording sites to
204 CitySounds2017_{train} to demonstrate that the CityNet algorithms generalise to sounds recorded
205 at new site locations (Figure 2, Table S1). To optimise the quality of the annotations in
206 CitySounds2017_{test}, we selected five human labellers to separately annotate the sounds within
207 the audio recordings (using the same methods as above) to create a single annotated test
208 dataset. Conflicts were resolved using a majority rule, and in cases where there was no
209 majority, we used our own judgement on the most suitable classification. Our
210 CitySounds2017 annotated training and testing datasets are available at
211 <https://figshare.com/s/adab62c0591afaeafedd>.

212 Using the CitySounds2017_{test} dataset, we separately assessed the performance of the two
213 CityNet algorithms, CityBioNet and CityAnthroNet, using two measures: precision and
214 recall. The CityBioNet and CityAnthroNet algorithms give a probabilistic estimate of the
215 level of biotic or anthropogenic acoustic activity for each 1-second audio chunk as a number
216 between 0 and 1. Different thresholds could be used to convert these probabilities into sound
217 category assignments (e.g. ‘sound present’ or ‘sound absent’). At each threshold, a value of
218 precision and recall was computed, where precision was the fraction of 1-second chunks
219 correctly identified as containing the sound according to the annotations in
220 CitySounds2017_{test}, and recall was the fraction of 1-second chunks labelled as containing the
221 sound which was retrieved by the algorithm under that threshold. As the threshold was swept
222 between 0 and 1, the resulting values of precision and recall were plotted as a precision-recall
223 curve. Summary statistics were computed for the average precision under all the threshold
224 values and the recall when the threshold chosen gave a precision of 0.95. Using a threshold of
225 0.5 on the predictions, confusion matrices were calculated showing how each moment of time
226 was classified relative to the annotations. These analyses were conducted in Python v.2.7.12

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227 (Python Software Foundation 2016) using Scikit-learn v.0.18.1 (Pedregosa *et al.* 2011) and
228 Matplotlib v.1.5.1 (Hunter 2007).

229 Competing Algorithms

230 We also compared the precision and recall of the CityNet algorithms to acoustic measures
231 produced by four AIs: Acoustic Complexity Index (ACI) (Pieretti, Farina & Morri 2011),
232 Acoustic Diversity Index (ADI) (Villanueva-Rivera *et al.* 2011), Bioacoustic Index (BI)
233 (Boelman *et al.* 2007), and Normalised Difference Soundscape Index (NDSI) (Kasten *et al.*
234 2012). The NDSI generates a measure of anthropogenic disturbance according to the formula

$$235 \quad NDSI = \frac{NDSI_{bio} - NDSI_{anthro}}{NDSI_{bio} + NDSI_{anthro}} \quad \text{Equation 1}$$

236 where $NDSI_{bio}$ and $NDSI_{anthro}$ are the total biotic and anthropogenic acoustic activity in each
237 recording, respectively. Rather than compare CityNet to the NDSI, we compared the biotic
238 ($NDSI_{bio}$) and anthropogenic ($NDSI_{anthro}$) elements of the NDSI to the measures produced by
239 CityBioNet and CityAnthroNet, respectively, as these were more comparable. As the AIs are
240 all designed to give a summary of acoustic activity for an entire file, they were analysed on
241 the CitySounds2017_{test} dataset by treating each 1-second chunk of audio as a separate sound
242 file to enable direct comparisons to CityNet. The AI measures do not have a natural threshold
243 for classification into biotic/non-biotic sound, meaning we could not calculate confusion
244 matrices. However, a threshold between their lowest value and their highest value was used
245 in combination with the range of precision and recall values to form precision-recall curves.
246 All AIs were calculated in R v.3.4.1 (R Core Team 2017) using the ‘seewave’ v.1.7.6 (Sueur,
247 Aubin & Simonis 2008) and ‘soundecology’ v.1.2 (Villanueva-Rivera & Pijanowski 2014)
248 packages.

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249 The precision and recall of CityBioNet was also compared to bulbul (Grill & Schlüter 2017),
250 an algorithm for detecting bird sounds in entire audio recordings in order to summarise avian
251 acoustic activity which was the winning entry in the 2016-7 Bird Audio Detection challenge
252 (Stowell *et al.* 2016). Like CityNet, bulbul is a CNN-based classifier which uses
253 spectrograms as input. However, it does not use the same normalisation strategies as CityNet,
254 and it was not trained on data from noisy, urban environments. Bulbul was applied to each
255 second of audio data in CitySounds2017_{test}, using the pre-trained model provided by the
256 authors together with their code.

257 Impact of Non-Biotic Sounds

258 We conducted additional analysis on the non-biotic sounds that affect the predictions of
259 CityBioNet and bulbul, as these were found to be the best performing algorithms for
260 measuring biotic sound. To do this, we created subsets of the CitySounds2017_{test} dataset
261 comprising all the seconds that contained a range of non-biotic sounds, e.g. a road traffic data
262 subset containing all of the seconds in CitySounds2017_{test} where the sound of road traffic was
263 present. We then used a Chi-squared test to identify significant differences in the proportion
264 of seconds in which the presence/absence of biotic sound at threshold 0.5 was correctly
265 predicted in the full and subset datasets by each algorithm, and the Cramer's V statistic was
266 used to assess the effect size of differences (Cohen 1992). These analyses were conducted in
267 R v.3.4.1 (R Core Team 2017).

268 Ecological Application

269 We used CityNet to generate daily average patterns of biotic and anthropogenic acoustic
270 activity for two study sites across an urbanisation gradient (sites E29RR and IG62XL with
271 high and low urbanisation respectively, Table S1). To control for the date of recording; both
272 sites were surveyed between May and June 2015. CityNet was run over the entire 7 days of

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273 recordings from each site to predict the presence/absence of biotic and anthropogenic sound
274 for every 1-second audio chunk using a 0.5 probability threshold. Measures of biotic and
275 anthropogenic activity were created for each half hour window between midnight and
276 midnight by averaging the predicted number of seconds containing biotic or anthropogenic
277 sound within that window over the entire week.

278 RESULTS

279 Acoustic Performance

280 CityBioNet had an average precision of 0.934 and recall of 0.710 at 0.95 precision, while
281 CityAnthroNet had an average precision of 0.977 and recall of 0.858 at 0.95 precision (Table
282 1, Figure 3). In comparison the ACI, ADI, BI and $NDSI_{bio}$ had a lower average precision
283 (0.663, 0.439, 0.516, and 0.503, respectively) and lower recall at 0.95 (all less than 0.01).
284 CityBioNet also outperformed bulbul which had an average precision of 0.872 and recall at
285 0.95 of 0.398 (Table 1). In comparison to CityAnthroNet, the $NDSI_{anthro}$ had a lower average
286 precision (0.975) and lower recall at 0.95 precision (0.815). When biotic sound was present in
287 recordings, CityBioNet correctly predicted the presence of biotic sound (True Positives) in a
288 greater proportion of audio data than bulbul (33.2% in comparison with 18.5%, for
289 CityBioNet and bulbul respectively) (Figure 4). However, CityBioNet failed to correctly
290 predict the presence of biotic sound (False Negatives) in 1.7% of recordings in comparison
291 with 1.0% incorrect predictions by bulbul. When biotic sound was absent from recordings,
292 CityBioNet correctly predicted the absence of biotic sound (True Negatives) in 51.6% of the
293 audio data in comparison with 52.6% for bulbul, and CityBioNet failed to correctly predict
294 the absence of biotic sound (False Positives) in 13.5% of audio data in comparison with
295 20.0% incorrect predictions by bulbul (Figure 4).

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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

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320 of ecoacoustics. The urban biotic soundscape is dominated by the sounds emitted by birds
321 (Fairbrass *et al.* 2017), and the good performance of bulbul, an algorithm for measuring
322 exclusively bird sounds, on the CitySounds2017_{test} dataset, confirms this. Birds are used as
323 indicator species in existing urban biodiversity monitoring schemes (Kohsaka *et al.* 2013)
324 using data collected from traditional forms of biodiversity survey. The algorithms developed
325 here could be used to support such existing schemes by making it easier to collect data on
326 these indicator taxa.

327 CityNet is the only method currently available for measuring both biotic and anthropogenic
328 acoustic activity using a single system in noisy audio data from urban environments. There is
329 increasing evidence that anthropogenic noise affects wildlife in a variety of ways including
330 altering communication behaviour (Gil & Brumm 2014) and habitat use (Deichmann *et al.*
331 2017). However, these investigations are limited in scale by the use of resource intensive
332 methods of measuring biotic and anthropogenic sound in the environment or from audio data.
333 Others rely on AIs (Pieretti & Farina 2013) which have been shown to be unreliable in
334 acoustically disturbed environments (Fairbrass *et al.* 2017). CityNet could facilitate the
335 investigation of the impacts of anthropogenic activities on wildlife populations at scales not
336 currently possible with traditional acoustic analysis methods.

337 CityBioNet clearly outperformed all the AIs tested, but the difference in performance
338 between CityAnthroNet and the competing algorithm for measuring anthropogenic acoustic
339 activity ($NDSI_{anthro}$) was much less marked. These results suggest that the measurement of
340 biotic sound in noisy audio data from urban environments requires more sophisticated
341 algorithms than the measurement of anthropogenic sound. Possibly anthropogenic sounds are
342 more easily separable from other sounds in frequency space, a theory which is the basis of a
343 number of AIs (Boelman *et al.* 2007; Kasten *et al.* 2012), facilitating the use of human
344 defined algorithms such as $NDSI_{anthro}$. Whereas, because biotic sounds occur in a frequency

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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

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370 researchers and conservationists are faced with the challenge of extracting meaningful
371 information from large volumes of audio data. The development of automated methods for
372 measuring bat calls in ultrasonic data has focused to date on the identification of bat species
373 calls and many algorithms are proprietary (e.g., Szewczak 2010; Wildlife Acoustics 2017).
374 The development of an open-source algorithm that produces community-level measures of
375 bats would be a valuable addition to the toolbox of bat researchers and conservationists.

376 Retraining CityNet with labelled audio data from other cities would make it possible to use
377 the system to monitor urban biotic and anthropogenic acoustic activity more widely.

378 However, as London is a large and heterogeneous city, CityNet has been trained using a
379 dataset containing sounds that characterise a wide range of urban environments. Our data
380 collection was restricted to a single week at each study site, which limits our ability to assess
381 the ability of CityNet system to detect environmental changes. Future work should focus on
382 the collection of longitudinal acoustic data to assess the sensitivity of the algorithms to detect
383 environmental changes. Our use of human labellers would have introduced subjectivity and
384 bias into our dataset. The task of annotating large audio datasets from acoustically complex
385 urban environments is highly resource intensive, a problem which has been recently tackled
386 with citizen scientists to create the UrbanSounds and UrbanSound8k datasets using audio
387 data from New York city, USA (Salamon, Jacoby & Bello 2014). These comprise short
388 snippets of 10 different urban sounds such as jackhammers, engines idling and gunshots.

389 These datasets do not fully represent the characteristics of urban soundscapes for three
390 reasons. Firstly, they assume only one class of sound is present at each time, while in fact
391 multiple sound types can be present at one time (consider a bird singing while an aeroplane
392 flies overhead). Secondly, they only include anthropogenic sounds, while CityNet measures
393 both anthropogenic and biotic sounds. Finally, each file in these datasets has a sound present,
394 while urban soundscapes contain many periods of silence or geophonic sounds, two

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395 important states which are not present in UrbanSounds and UrbanSounds8k. Due to these
396 factors, these datasets are unsuitable for the purpose of this research project, although recent
397 work has overcome a few of these shortcomings using synthesised soundscape data (Salamon
398 *et al.* 2017). This highlights the need for an internationally coordinated effort to create a
399 consistently labelled audio dataset from cities to support the development of automated urban
400 environmental assessment systems with international application.

401 Conclusions

402 The CityNet system for measuring biotic and anthropogenic acoustic activity in noisy urban
403 audio data outperformed the state-of-the-art algorithms for measuring biotic and
404 anthropogenic sound in entire audio recordings. Integrated into an IoT network for recording
405 and analysing audio data in cities it could facilitate urban environmental assessment at greater
406 scales than has been possible to date using traditional methods of biodiversity assessment.
407 We make our system available open source in combination with two expertly annotated urban
408 soundscape datasets to facilitate future research development in this field.

409 AUTHOR CONTRIBUTION STATEMENT

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

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419 H.T., and EPSRC grant (EP/K015664/1) to K.E.J, G.B. and M.F.

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>).

424 REFERENCES

425 Acevedo, M.A., Corrada-Bravo, C.J., Corrada-Bravo, H., Villanueva-Rivera, L.J. & Aide,
426 T.M. (2009) Automated classification of bird and amphibian calls using machine
427 learning: A comparison of methods. *Ecological Informatics*, **4**, 206-214.

428 Aide, T.M., Corrada-Bravo, C., Campos-Cerqueira, M., Milan, C., Vega, G. & Alvarez, R.
429 (2013) Real-time bioacoustics monitoring and automated species identification. **1**,
430 e103. Available: [http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3719130/pdf/peerj-](http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3719130/pdf/peerj-01-103.pdf)
431 [01-103.pdf](http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3719130/pdf/peerj-01-103.pdf) Accessed: 19/12/2016

432 Aronson, M.F.J., La Sorte, F.A., Nilon, C.H., Katti, M., Goddard, M.A., Lepczyk, C.A.,
433 Warren, P.S., Williams, N.S.G., Cilliers, S., Clarkson, B., Dobbs, C., Dolan, R.,
434 Hedblom, M., Klotz, S., Kooijmans, J.L., Kühn, I., MacGregor-Fors, I., McDonnell,
435 M., Mörtberg, U., Pyšek, P., Siebert, S., Sushinsky, J., Werner, P. & Winter, M.
436 (2014) A global analysis of the impacts of urbanization on bird and plant diversity
437 reveals key anthropogenic drivers. **281**, 20133330. Available:
438 <http://rsos.royalsocietypublishing.org/content/281/1780/20133330.abstract> Accessed:
439 02/12/2016

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 440 Beninde, J., Veith, M. & Hochkirch, A. (2015) Biodiversity in cities needs space: a meta-
441 analysis of factors determining intra-urban biodiversity variation. *Ecology Letters*, **18**,
442 581–592.
- 443 Boelman, N.T., Asner, G.P., Hart, P.J. & Martin, R.E. (2007) Multi-trophic invasion
444 resistance in Hawaii: Bioacoustics, field surveys, and airborne remote sensing.
445 *Ecological Applications*, **17**, 2137-2144.
- 446 Chesmore, E. & Ohya, E. (2004) Automated identification of field-recorded songs of four
447 British grasshoppers using bioacoustic signal recognition. *Bulletin of Entomological*
448 *Research*, **94**, 319-330.
- 449 Cohen, J. (1992) Statistical power analysis. *Current directions in psychological science*, **1**,
450 98-101.
- 451 Crouse, D.L., Pinault, L., Balram, A., Hystad, P., Peters, P.A., Chen, H., van Donkelaar, A.,
452 Martin, R.V., Ménard, R., Robichaud, A. & Villeneuve, P.J. (2017) Urban greenness
453 and mortality in Canada's largest cities: a national cohort study. *The Lancet Planetary*
454 *Health*, **1**, e289-e297.
- 455 Deichmann, J.L., Hernández-Serna, A., Delgado C, J.A., Campos-Cerqueira, M. & Aide,
456 T.M. (2017) Soundscape analysis and acoustic monitoring document impacts of
457 natural gas exploration on biodiversity in a tropical forest. *Ecological Indicators*, **74**,
458 39-48.
- 459 Depraetere, M., Pavoine, S., Jiguet, F., Gasc, A., Duvail, S. & Sueur, J. (2012) Monitoring
460 animal diversity using acoustic indices: implementation in a temperate woodland.
461 *Ecological Indicators*, **13**, 46-54.
- 462 Dieleman, S., Schlüter, J., Raffel, C., Olson, E., Sønnderby, S.K., Nouri, D., Maturana, D.,
463 Thoma, M., Battenberg, E., Kelly, J., De Fauw, J., Heilman, M., de Almeida, D.M.,
464 McFee, B., Weideman, H., Takács, G., de Rivaz, P., Crall, J., Sanders, G., Rasul, K.,

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 465 Liu, C., French, G. & Degraeve, J. (2015) *Lasagne*. Available:
466 <http://dx.doi.org/10.5281/zenodo.27878> Accessed: 19/09/2017
- 467 Digby, A., Towsey, M., Bell, B.D. & Teal, P.D. (2013) A practical comparison of manual
468 and autonomous methods for acoustic monitoring. *Methods in Ecology and Evolution*,
469 **4**, 675-683.
- 470 Faeth, S.H., Bang, C. & Saari, S. (2011) Urban biodiversity: patterns and mechanisms. *Year*
471 *in Ecology and Conservation Biology*, **1223**, 69-81.
- 472 Fairbrass, A.J., Rennett, P., Williams, C., Titheridge, H. & Jones, K.E. (2017) Biases of
473 acoustic indices measuring biodiversity in urban areas. *Ecological Indicators*, **83**,
474 169-177.
- 475 Farinha-Marques, P., Lameiras, J., Fernandes, C., Silva, S. & Guilherme, F. (2011) Urban
476 biodiversity: a review of current concepts and contributions to multidisciplinary
477 approaches. *Innovation: The European Journal of Social Science Research*, **24**, 247-
478 271.
- 479 Fuller, S., Axel, A.C., Tucker, D. & Gage, S.H. (2015) Connecting soundscape to landscape:
480 Which acoustic index best describes landscape configuration? *Ecological Indicators*,
481 **58**, 207-215.
- 482 Gasc, A., Pavoine, S., Lellouch, L., Grandcolas, P. & Sueur, J. (2015a) Acoustic indices for
483 biodiversity assessments: Analyses of bias based on simulated bird assemblages and
484 recommendations for field surveys. *Biological Conservation*, **191**, 306-312.
- 485 Gasc, A., Pavoine, S., Lellouch, L., Grandcolas, P. & Sueur, J. (2015b) Acoustic indices for
486 biodiversity assessments: Analyses of bias based on simulated bird assemblages and
487 recommendations for field surveys. *Biological Conservation*, **191**, 306-312.

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 488 Gil, D. & Brumm, H. (2014) Acoustic communication in the urban environment: patterns,
489 mechanisms, and potential consequences of avian song adjustments. *Avian urban*
490 *ecology* (eds D. Gil & H. Brumm), pp. 69-83. Oxford University Press, Oxford, UK.
- 491 Grill, T. & Schlüter, J. (2017) Two Convolutional Neural Networks for Bird Detection in
492 Audio Signals. *25th European Signal Processing Conference (EUSIPCO2017)*. Kos,
493 Greece.
- 494 Hall, D.M., Camilo, G.R., Tonietto, R.K., Smith, D.H., Ollerton, J., Ahrné, K., Arduser, M.,
495 Ascher, J.S., Baldock, K.C. & Fowler, R. (2016) The city as a refuge for insect
496 pollinators. *Conservation Biology*, **31**, 24-29.
- 497 Hunter, J.D. (2007) Matplotlib: A 2D graphics environment. *Computing In Science &*
498 *Engineering*, **9**, 90-95.
- 499 Ioffe, S. & Szegedy, C. (2015) Batch normalization: Accelerating deep network training by
500 reducing internal covariate shift. *Proceedings of the 32nd International Conference*
501 *on Machine Learning*, pp. 448-456. Lille, France.
- 502 Kasten, E.P., Gage, S.H., Fox, J. & Joo, W. (2012) The remote environmental assessment
503 laboratory's acoustic library: An archive for studying soundscape ecology. *Ecological*
504 *Informatics*, **12**, 50-67.
- 505 Kingma, D. & Ba, J. (2015) Adam: A Method for Stochastic Optimization. *Proceedings of*
506 *the International Conference on Learning Representations 2015*. San Deigo, USA.
- 507 Kohsaka, R., Pereira, H.M., Elmqvist, T., Chan, L., Moreno-Peñaranda, R., Morimoto, Y.,
508 Inoue, T., Iwata, M., Nishi, M. & da Luz Mathias, M. (2013) Indicators for
509 management of urban biodiversity and ecosystem services: city biodiversity index.
510 *Urbanization, biodiversity and ecosystem services: challenges and opportunities* (eds
511 T. Elmqvist, M. Fragkias, J. Goodness, B. Güneralp, P.J. Marcotullio, R.I. McDonald,

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 512 S. Parnell, M. Schewenius, M. Sendstad, K.C. Seto & C. Wilkinson), pp. 699-718.
513 Springer, Netherlands.
- 514 LeCun, Y., Bengio, Y. & Hinton, G. (2015) Deep learning. *Nature*, **521**, 436-444.
- 515 Lee, H., Pham, P., Largman, Y. & Ng, A.Y. (2009) Unsupervised feature learning for audio
516 classification using convolutional deep belief networks. *Proceedings of the 22nd*
517 *International Conference on Neural Information Processing Systems*, pp. 1096-1104.
518 Istanbul, Turkey.
- 519 Lin, T.-H., Fang, S.-H. & Tsao, Y. (2017) Improving biodiversity assessment via
520 unsupervised separation of biological sounds from long-duration recordings. **7**.
521 Available: <https://www.nature.com/articles/s41598-017-04790-7> Accessed:
522 19/09/2017
- 523 Maas, A.L., Hannun, A.Y. & Ng, A.Y. (2013) Rectifier nonlinearities improve neural
524 network acoustic models. *Proceedings of the 30th International Conference on*
525 *Machine Learning*. Atlanta, USA.
- 526 McFee, B., Raffel, C., Liang, D., Ellis, D.P., McVicar, M., Battenberg, E. & Nieto, O. (2015)
527 librosa: Audio and music signal analysis in python. *Proceedings of the 14th python in*
528 *science conference*, pp. 18-25. Austin, Texas.
- 529 Natural England (2016) Links between natural environments and mental health: evidence
530 briefing. Available: <http://publications.naturalengland.org.uk> Accessed: 24/11/2017
- 531 Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M.,
532 Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D.,
533 Brucher, M. & Perrot, M.D., E. (2011) Scikit-learn: Machine Learning in Python.
534 *Journal of machine learning research*, **12**, 2825-2830.

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 535 Pieretti, N. & Farina, A. (2013) Application of a recently introduced index for acoustic
536 complexity to an avian soundscape with traffic noise. *The Journal of the Acoustical*
537 *Society of America*, **134**, 891-900.
- 538 Pieretti, N., Farina, A. & Morri, D. (2011) A new methodology to infer the singing activity of
539 an avian community: the Acoustic Complexity Index (ACI). *Ecological Indicators*,
540 **11**, 868-873.
- 541 Pijanowski, B.C., Villanueva-Rivera, L.J., Dumyahn, S.L., Farina, A., Krause, B.L.,
542 Napoletano, B.M., Gage, S.H. & Pieretti, N. (2011) Soundscape ecology: the science
543 of sound in the landscape. *Bioscience*, **61**, 203-216.
- 544 Python Software Foundation (2016) *Python Language Reference*. Available:
545 <http://www.python.org> Accessed: 19/09/2017
- 546 R Core Team (2017) *R: A language and environment for statistical computing*. Available:
547 <http://www.R-project.org>. Accessed: 31/10/2014
- 548 Salamon, J., Jacoby, C. & Bello, J.P. (2014) A dataset and taxonomy for urban sound
549 research. *ACM MM'14*, pp. 1041-1044. Association for Computing Machinery,
550 Orlando, USA.
- 551 Salamon, J., MacConnell, D., Cartwright, M., Li, P. & Bello, J.P. (2017) Scaper: A library for
552 soundscape synthesis and augmentation. *2017 IEEE Workshop on Applications of*
553 *Signal Processing to Audio and Acoustics*. New Paltz, NY.
- 554 Srivastava, N., Hinton, G.E., Krizhevsky, A., Sutskever, I. & Salakhutdinov, R. (2014)
555 Dropout: a simple way to prevent neural networks from overfitting. *Journal of*
556 *machine learning research*, **15**, 1929-1958.
- 557 Stowell, D. & Plumbley, M.D. (2014) Automatic large-scale classification of bird sounds is
558 strongly improved by unsupervised feature learning. **2**, e488. Available:
559 <http://dx.doi.org/10.7717/peerj.488> Accessed: 09/12/2016

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 560 Stowell, D., Wood, M., Stylianou, Y. & Glotin, H. (2016) Bird detection in audio: a survey
561 and a challenge. *2016 IEEE 26th International Workshop on Machine Learning for*
562 *Signal Processing*, pp. 1-6. IEEE, Vietri sul Mare, Italy.
- 563 Sueur, J., Aubin, T. & Simonis, C. (2008) Equipment review: seewave, a free modular tool
564 for sound analysis and synthesis. *Bioacoustics*, **18**, 213-226.
- 565 Sueur, J. & Farina, A. (2015) Ecoacoustics: the Ecological Investigation and Interpretation of
566 Environmental Sound. *Biosemiotics*, **8**, 493–502.
- 567 Sueur, J., Farina, A., Gasc, A., Pieretti, N. & Pavoine, S. (2014) Acoustic Indices for
568 Biodiversity Assessment and Landscape Investigation. *Acta Acustica united with*
569 *Acustica*, **100**, 772-781.
- 570 Szewczak, J.M. (2010) *SonoBat*. Available: www.sonobat.com Accessed: 29/05/2014
- 571 The Theano Development Team, Al-Rfou, R., Alain, G., Almahairi, A., Angermueller, C.,
572 Bahdanau, D., Ballas, N., Bastien, F., Bayer, J. & Belikov, A. (2016) Theano: A
573 Python framework for fast computation of mathematical expressions. Available:
574 <https://arxiv.org/abs/1605.02688> Accessed: 19/09/2017
- 575 Towsey, M., Wimmer, J., Williamson, I. & Roe, P. (2014) The Use of Acoustic Indices to
576 Determine Avian Species Richness in Audio-recordings of the Environment.
577 *Ecological Informatics*, **21**, 110–119.
- 578 UN-DESA (2016) The World's Cities in 2016. Data Booklet. Available:
579 <http://www.un.org/en/development/desa/population/> Accessed: 10/02/2017
- 580 Villanueva-Rivera, L.J. & Pijanowski, B.C. (2014) Package ‘soundecology’. *Soundscape*
581 *ecology*. Available: <http://cran.r-project.org/web/packages/soundecology/index.html>
582 Accessed: 15/04/2015
- 583 Villanueva-Rivera, L.J., Pijanowski, B.C., Doucette, J. & Pekin, B. (2011) A primer of
584 acoustic analysis for landscape ecologists. *Landscape Ecology*, **26**, 1233-1246.

Deep Learning Urban Ecoacoustic Tools – Fairbrass Firman *et al.*

- 585 Walters, C.L., Collen, A., Lucas, T., Mroz, K., Sayer, C.A. & Jones, K.E. (2013) Challenges
586 of Using Bioacoustics to Globally Monitor Bats. *Bat Evolution, Ecology, and*
587 *Conservation*, pp. 479-499. Springer.
- 588 Walters, C.L., Freeman, R., Collen, A., Dietz, C., Brock Fenton, M., Jones, G., Obrist, M.K.,
589 Puechmaille, S.J., Sattler, T., Siemers, B.M., Parsons, S. & Jones, K.E. (2012) A
590 continental-scale tool for acoustic identification of European bats. *Journal of Applied*
591 *Ecology*, **49**, 1064-1074.
- 592 Wildlife Acoustics, I. (2017) *Kaleidoscope Analysis Software*. Available:
593 <https://www.wildlifeacoustics.com/products/kaleidoscope-software-ultrasonic>
594 Accessed: 24/08/2017
- 595 Zamora-Gutierrez, V., Lopez-Gonzalez, C., MacSwiney Gonzalez, M.C., Fenton, B., Jones,
596 G., Kalko, E.K., Puechmaille, S.J., Stathopoulos, V. & Jones, K.E. (2016) Acoustic
597 identification of Mexican bats based on taxonomic and ecological constraints on call
598 design. *Methods in Ecology and Evolution*, **7**, 1082-1091.
- 599 Zanella, A., Bui, N., Castellani, A., Vangelista, L. & Zorzi, M. (2014) Internet of things for
600 smart cities. *IEEE Internet of Things journal*, **1**, 22-32.
- 601

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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
<i>Biotic</i>		
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
<i>Anthropogenic</i>		
CityAnthroNet	0.858	0.977
NDSI _{anthro}	0.815	0.975

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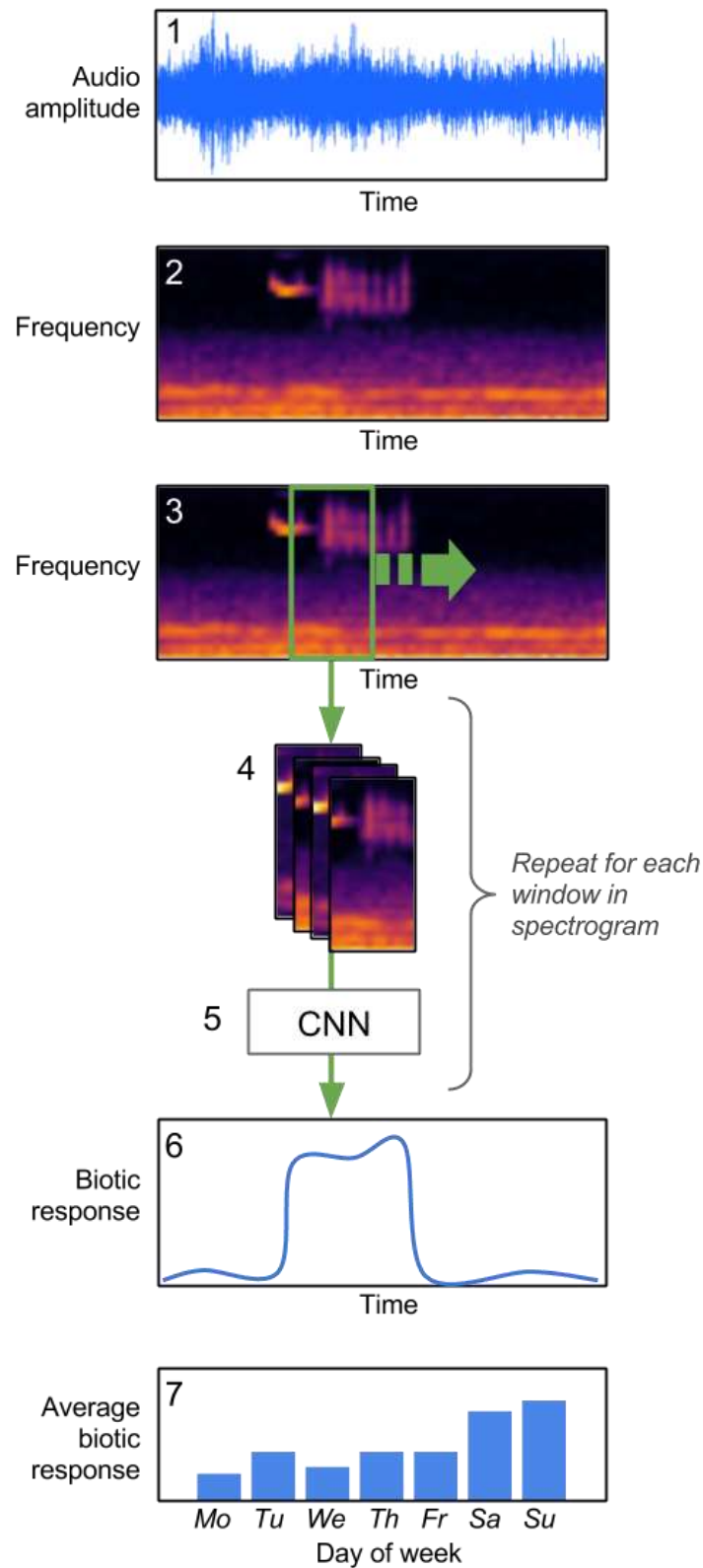
610 **Table 2.** Impact of non-biotic sounds on the CityBioNet and bulbul predictions. Values
 611 represent differences in the proportion of 1-second audio chunks in the full CitySound2017_{test}
 612 dataset (40 minutes) and the subset datasets (size in time indicated in left-hand column) in
 613 which 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
<i>Anthropogenic</i>		
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)*
<i>Geophonic</i>		
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

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617 FIGURES



618

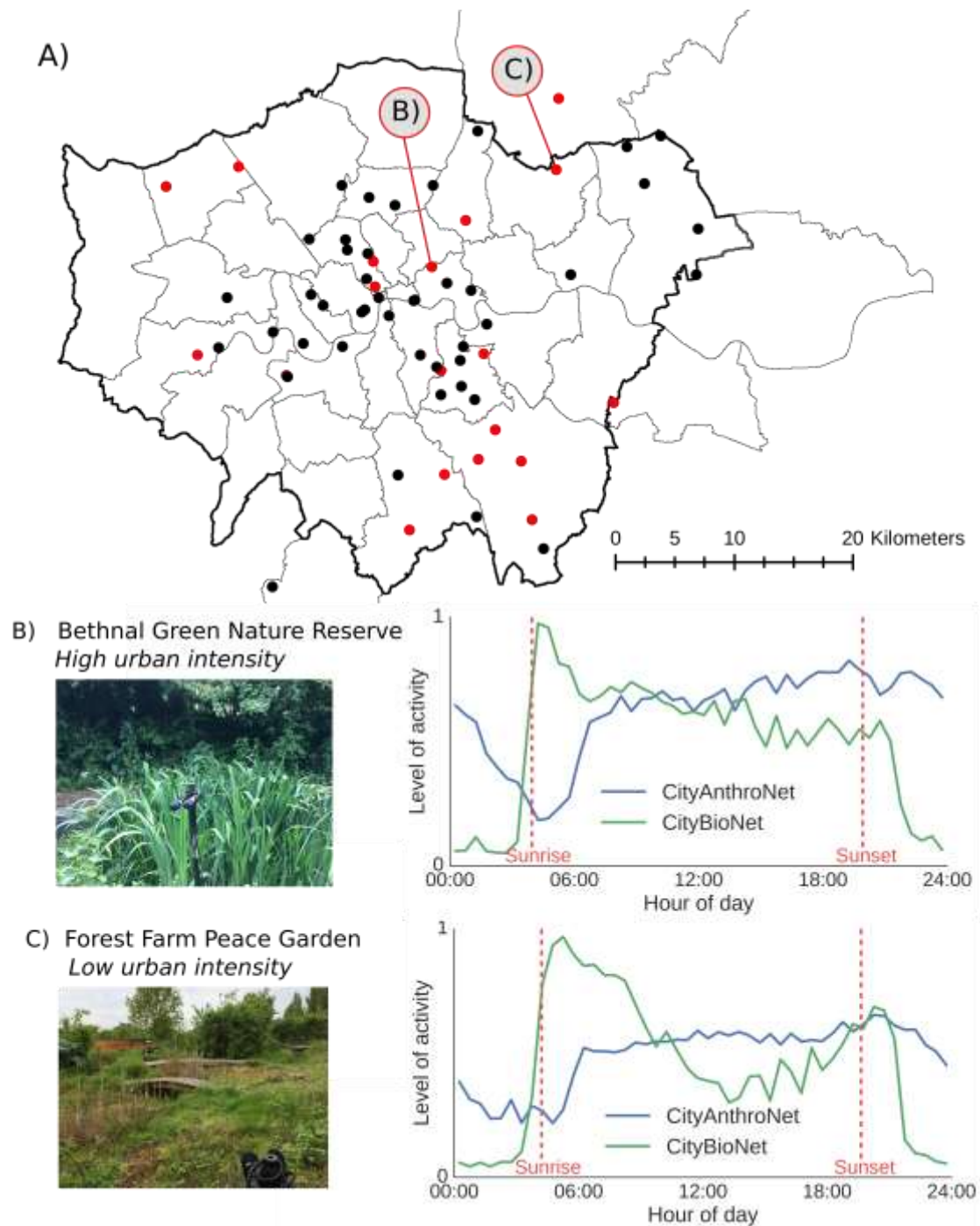
619 **Figure 1.** The CityNet analysis pipeline for measuring biotic and anthropogenic acoustic

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

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621 (2). A sliding window is run across the time dimension, and a window of the spectrogram
622 extracted at each step (3). This spectrogram window is pre-processed with four different
623 normalisation strategies, and the results concatenated. This stack of spectrograms is passed
624 through a CNN (5), which was trained on CitySounds2017_{train}. The CNN gives, at each 1-
625 second time step, a prediction of the presence/absence of biotic or anthropogenic acoustic
626 activity (6). Finally, these per-time-step measures can be aggregated to give summaries over
627 time or space (7).

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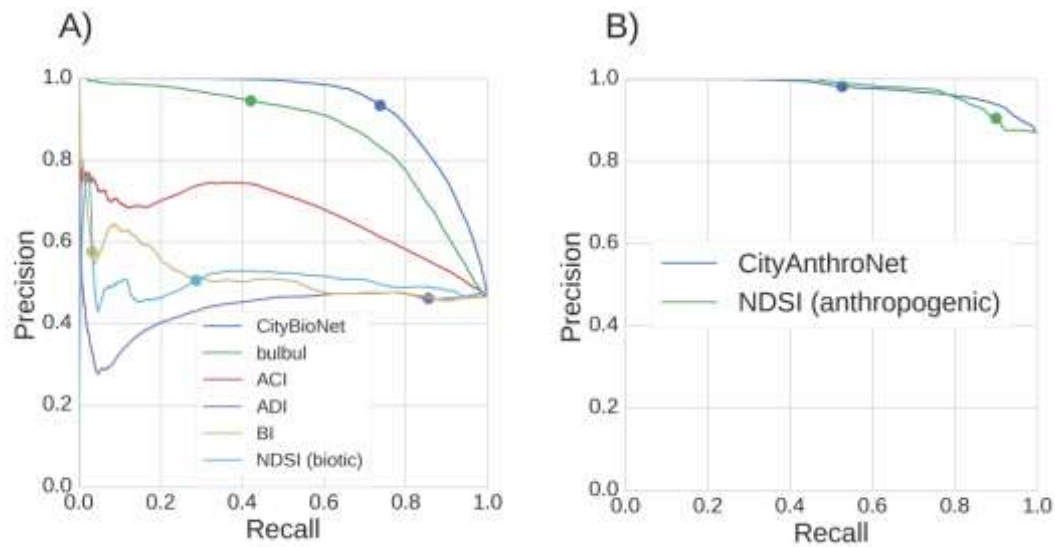
628

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

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634 using a 0.5 probability threshold. The predicted number of seconds containing biotic and
635 anthropogenic sound for each half-hour period was averaged over the week to produce
636 average daily patterns of acoustic activity. Greater London boundary indicated with bold line.
637 Boundary data from the UK Census (<http://www.ons.gov.uk/>, accessed 04/11/2014).

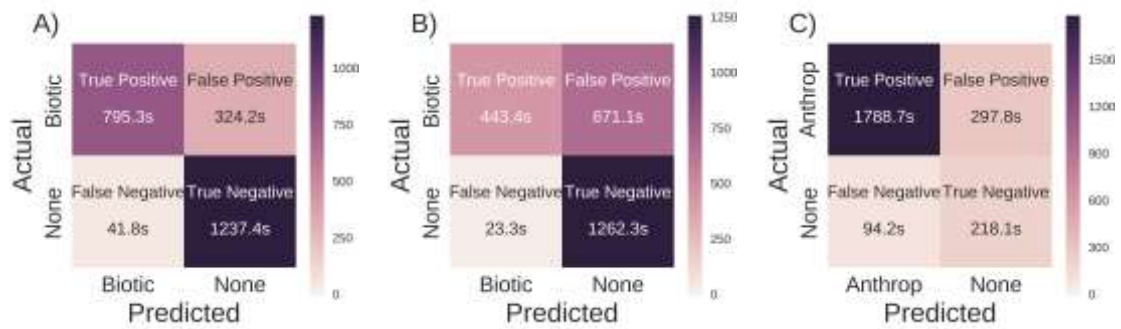
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638

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.

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645

646 **Figure 4.** Confusion matrices comparing the predicted acoustic activity of A) CityBioNet,
647 B), bulbul, and C) CityAnthroNet for each 1-second audio chunk in the CitySounds2017_{test}
648 dataset. Numbers in each cell report the number of 1-second audio clips in the
649 CitySounds2017_{test} dataset predicted either correctly (True Positives and True Negatives) or
650 incorrectly (False Positives and False Negatives) as containing biotic (A and B) or
651 anthropogenic (C) sound. To create the confusion matrices, the probabilistic predictions from
652 the classifiers are converted to binary classifications using a threshold that gives a precision
653 of 0.95.

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654 SUPPORTING INFORMATION

655 Section S1: Supplementary Methods

656 Normalisation Methods

657 The four normalisation methods used are as follows:

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

663 Prediction Process

664 Both CityBioNet and CityAnthroNet have a convolutional layer with 32 filters, followed by a
665 max pooling layer, then another 32-filter convolutional layer and finally two dense layers
666 (with 128 units) before a binary class output - see Figure 1 for an overview of the network
667 architecture. For nonlinearities very leaky rectifiers were used (Maas, Hannun & Ng 2013),
668 and Dropout (Srivastava *et al.* 2014) was used to help to regularise the network and batch
669 normalisation (Ioffe & Szegedy 2015) to increase the speed of convergence during training.
670 The network was trained for 30 epochs using the Adam (Kingma & Ba 2015) update scheme
671 with a learning rate of 0.0005. An ensemble of five such networks was trained using the same
672 architecture and training data, but with different random initialisations. The final predictions
673 are made by averaging together the predictions of each member in the ensemble.

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674 **Table S1.** Details of acoustic recording sites across Greater London, UK. Sites separated into
 675 two groups illustrating whether recordings from sites were included in the
 676 CitySounds2017_{train} or CitySounds2017_{test} datasets. Urban intensity categories defined based
 677 on the predominant land cover surrounding sites within a 500m radius: (i) high (contiguous
 678 multi-storey buildings); (ii) medium (detached and semi-detached housing); and (iii) low
 679 (fields and/or woodland). DD denotes decimal degrees. In terms of site type, C denotes
 680 church or churchyard, CG denoted community garden, GR denotes green roof, GW denotes
 681 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

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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

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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

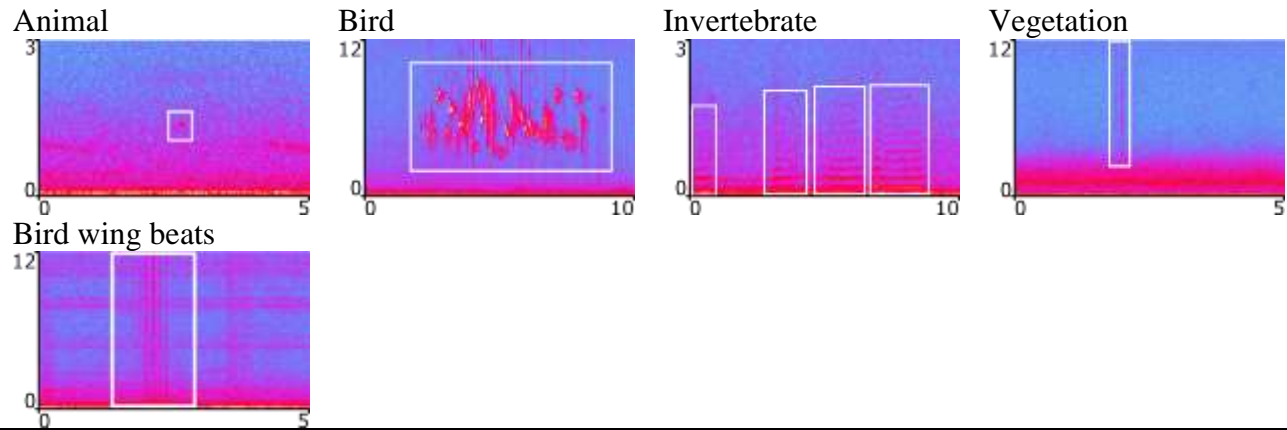
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BR4	C	18/08/2015	25/08/2015	51.38261	-0.00868	Medium
DA5	NR	24/08/2015	01/09/2015	51.42268	0.156502	Medium
CM16 7NP	NR	08/09/2015	15/09/2015	51.65396	0.101227	Low

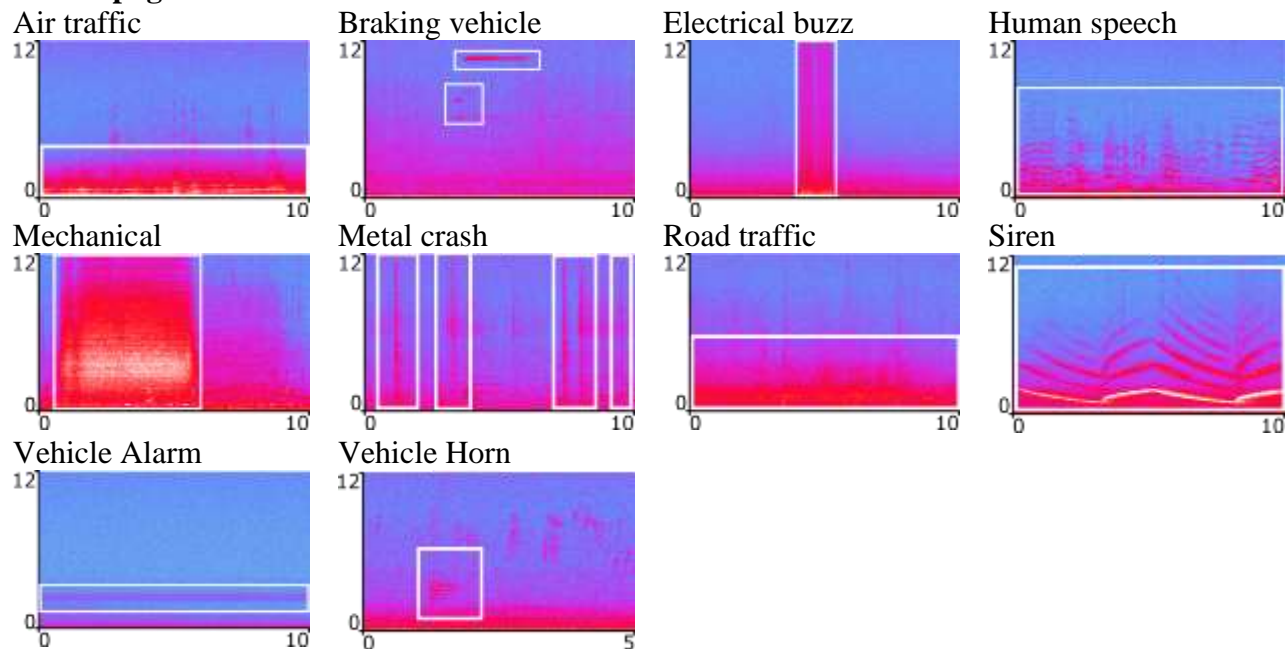
682

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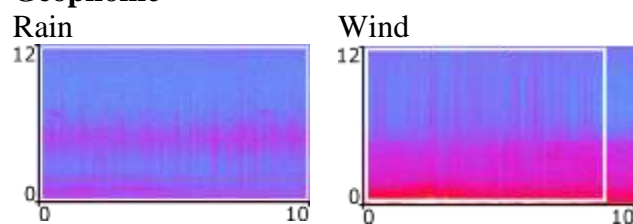
Biotic



Anthropogenic



Geophonic



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

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

691 REFERENCES

692 Ioffe, S. & Szegedy, C. (2015) Batch normalization: Accelerating deep network training by
693 reducing internal covariate shift. *Proceedings of the 32nd International Conference*
694 *on Machine Learning*, pp. 448-456. Lille, France.

695 Kingma, D. & Ba, J. (2015) Adam: A Method for Stochastic Optimization. *Proceedings of*
696 *the International Conference on Learning Representations 2015*. San Deigo, USA.

697 Maas, A.L., Hannun, A.Y. & Ng, A.Y. (2013) Rectifier nonlinearities improve neural
698 network acoustic models. *Proceedings of the 30th International Conference on*
699 *Machine Learning*. Atlanta, USA.

700 Srivastava, N., Hinton, G.E., Krizhevsky, A., Sutskever, I. & Salakhutdinov, R. (2014)
701 Dropout: a simple way to prevent neural networks from overfitting. *Journal of*
702 *machine learning research*, **15**, 1929-1958.

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