Transportation Research Part D 134 (2024) 104357

Contents lists available at ScienceDirect

Transportation Research Part D

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

The impact of a low traffic neighbourhood intervention on urban noise measured with low-cost sensors in Oxford, UK

Felix C.P. Leach [a,*], Jingyuan Yang [b], Varun Shankar [a], Stuart Cole [c], Katie Parnell [c], Mani Entezami [b], Suzanne E. Bartington [d]

[a] *Department of Engineering Science, University of Oxford, UK*
[b] *Department of Electronic, Electrical and Systems Engineering, University of Birmingham, UK*
[c] *Oxfordshire County Council, UK*
[d] *Institute of Applied Health Research, University of Birmingham, UK*

ARTICLE INFO

Keywords:
Urban noise
Low Traffic Neighbourhood
NDSI
Noise pollution
Acoustic energy
AudioMoth

ABSTRACT

Noise pollution, particularly in urban environments, is often caused by road traffic and is linked to increased risk of a range of adverse health outcomes. In recent years, Low Traffic Neighbourhoods (LTN) have been implemented in a number of UK towns and cities as an intervention to reduce road traffic and improve health and wellbeing among those living in residential areas. In this study, eight low-cost acoustic sensors (AudioMoth) were used to evaluate the effect of a LTN intervention on urban noise in a residential area of Oxford, UK. The acoustic energy and LAeq of the noise is evaluated before and after the introduction of the LTN at locations where traffic filters have been erected, other locations in the LTN, possible displacement locations, and a control location. In addition, source apportionment (anthropogenic or biotic) is undertaken using the Normalised Difference Soundscape Index (NDSI) using the frequency of the measured noise. The results show that in terms of acoustic energy almost all locations experienced a reduction in noise after the introduction of the LTN. In terms of the source apportionment, all locations except for the control location experienced more biotic noise after the introduction of the LTN. The results are also compared to other more traffic focussed locations in Oxford and the soundscape is much more biotic inside the LTN. Overall, the study demonstrates the impact of the LTN on urban noise, and the efficacy of this new sensing and analytical approach for evaluating noise pollution interventions.

1. Introduction

Noise pollution in urban environments is linked to increased risk of cardiovascular disease (Halonen et al., 2015), hypertension (van Kempen and Babisch 2012, Fuks et al., 2017), low birth weight (Smith et al., 2017), and obesity (Cai et al., 2020) amongst other adverse health outcomes, notably through sleep disturbances (Halperin 2014). In 2020, approximately 113 million people living in Europe were exposed to noise levels greater than 55 dB, a major source of which was road traffic noise (European Environment Agency, 2019). However, although air pollution has been a focus of policy in recent years, leading to reductions of many pollutants DEFRA (2019) (although there is further work to be done), noise pollution has remained constant and even increased in some areas (European

* Corresponding author.
E-mail address: felix.leach@eng.ox.ac.uk (F.C.P. Leach).

https://doi.org/10.1016/j.trd.2024.104357
Received 30 January 2023; Received in revised form 3 July 2024; Accepted 6 August 2024
Available online 13 August 2024

Nomenclature

BST	British Summer Time
ETRO	Experimental Traffic Regulation Order
GMT	Greenwich Mean Time
LTN	Low Traffic Neighbourhood
NDSI	Normalised Difference Soundscape Index
UK	United Kingdom

Environment Agency, 2019).

There have been numerous studies linking the presence of noise pollution to air pollution (Gulliver et al., 2015, Smith et al., 2017, Khan et al., 2018). In a sense, this is to be expected given that activities that generate noise in an urban environment (for example traffic, domestic machinery, aircraft) also typically produce air pollution. However, the link is not always causal, there are plenty of loud events and activities (for example shouting humans, animals, the wind/rain) which do not increase air pollutant emissions. Khan *et al.* in their review paper found mixed correlations ranging from 0.05 to 0.74 between air pollution and noise pollution (Khan et al., 2018).

When considering noise there are two parameters that are often investigated: the acoustic energy of noise and its frequency. It is known that human perception of noise depends on both of these parameters (Pujol, 2009; Marquart et al., 2021). When measuring acoustic energy, the primary measurement artefact is the proximity of the microphone to the source of the noise. However, in the field, other factors will play a role, notably the wind and the rain (in an urban environment rain is a particular confounding factor on roads when traffic drives through puddles / standing water).

When considering the frequency of noise, it is not just the human perception that may be of interest. Different sources produce noise at different frequencies, and it is possible to use this characteristic for source apportionment. One such technique that has been used is the Normalised Difference Soundscape Index (NDSI). NDSI is an attempt to quantify the ratio of biophony (natural noise) and anthropophony (human-generated noise) in sound data (Kasten et al., 2012). NDSI assumes that biophony and anthropophony occur in different frequency bands. Previous research has revealed that mechanical sounds are most prevalent in the frequency range 1–2 kHz and biological sounds are most prevalent between 2 and 8 kHz (Kasten et al., 2012). NDSI is calculated by taking the ratio of the spectral acoustic power for these two frequency bands (1–2 kHz and 2–8 kHz). Previous work has used NDSI in mostly natural environments (its origins are in measuring bird noise) (Kasten et al., 2012, Fuller et al., 2015), however there have been some studies applying it to urban environments considering urbanisation (Liu et al. 2020), source apportionment (Lawrence et al., 2022), and urban ecology (Wang et al., 2023).

A Low Traffic Neighbourhood (LTN) is typically a scheme implemented in a residential area of a town or city whereby bollards, planters, barriers, or equivalent restrictions are constructed on either a temporary or permanent basis on roads in order to limit or eliminate through traffic (Sustrans, 2020). Traffic can still approach the filter (bollards, planters, barriers, or equivalent restriction) from either side, but not pass through. LTNs are intended to reduce "rat-running" (traffic diversions from a major route to a minor and/or residential route to save time) and improve the quality of life inside the LTN (Pritchett et al., 2024). LTNs have been implemented for decades in the UK, however, there has been a recent increase in the number of LTNs implemented in the UK as part of the British government's Emergency Active Travel scheme response to the COVID-19 pandemic (Transport, 2020b) and commitment to increase cycling and walking as set out in 'Gear Change' (July 2020) (Transport, 2020a). The reasons behind implementing LTNs are numerous, but include controlling traffic flow, improving neighbourhood liveability, reducing road traffic injuries, reducing air pollution, reducing noise pollution, and promoting active travel (Laverty et al., 2021). Studies have shown LTNs leading to reductions in air pollution which might be expected also to lead to reductions in noise pollution, but this has not been studied (Yang et al., 2022).

The COVID-19 pandemic led to widespread changes in behaviour as a result of pandemic-related public health restrictions and other effects. Notably, traffic levels fell markedly in affected areas and air pollution changes as a result of these reductions have been widely studied and reported in natural experimental studies (Jephcote et al., 2021; Singh et al., 2022). In addition, some study of the impact of restrictions (in this case, namely, the closure of a school) on noise in an urban environment was undertaken by Kumar *et al.* (Kumar et al., 2022) who demonstrated a 3 dB increase in measured noise upon the re-opening of a school which they attribute to an increase in traffic.

Calibrated, regulatory measurements of noise are expensive and require very careful siting. These give an absolute measurement of noise in dB. However, given the constraints of an urban environment and the cost constraints imposed by needing a network of sensors, a network approach to explore the impact of an LTN on noise was previously challenging. However, recent advances in low-cost sensing technology have meant that data on noise can be obtained at a cost low enough to enable a network approach. This study, then, aims to investigate the impact of the implementation of a LTN on urban noise for the first time by considering a case study of a single LTN intervention in the east of the city of Oxford, UK, in an area called Temple Cowley. A network of eight low-cost noise sensors are deployed both before and after the LTN implementation and the results analysed to show the impact of the LTN on acoustic energy, LAeq, and source apportionment.

2. Experimental methodology

2.1. Low-cost noise sensor

The AudioMoth device (Hill et al., 2018; Hill et al., 2019) is a low-cost microphone combined with a data-logger. It is small, measuring 58 mm × 48 mm × 15 mm and easily powered by 3 x AA batteries (R6). It is capable of recording at sample rates up to 384 kHz, enabling the capture of all human-audible sounds as well as a part of the ultrasonic spectrum. The data recorded is an uncompressed.wav file which is saved on an internal microSD card. For this application the sampling rate was set to 48 kHz, which, therefore, will detect noise up to 24 kHz – just above the human perception limit. A photo of an AudioMoth, and its associated weatherproof housing, is shown in Fig. 1.

Clearly in some senses it would be advantageous to sample constantly, however there are some disadvantages with this. Notably, from the data it is possible to reconstruct the original sound – useful in some ways, but when deploying in an urban environment there are understandable privacy concerns. Secondly, with the AudioMoth, there is a trade-off between battery life and sampling time. The AudioMoths are deployed until their power runs out (or the batteries are changed, and device reset). The devices were set to log for five minutes, three times per hour (at 00, 20, 40 minutes past the hour), this strategy helps prolong the battery life of the device. With high performance AA batteries, the devices lasted ∼ 30 days. With standard AA batteries it was as low as 10 days.

2.2. Deployment locations

The AudioMoth devices were deployed on items of street furniture (such as lampposts or street signs) that were as close as possible to the area of interest, but high enough to avoid interference (i.e. > 2 m), and as far as practically possible from reflective surfaces, which is in line with approaches in the literature (Benocci et al., 2020). Because the devices are battery powered, requiring no external power supply, this proved relatively straightforward to achieve. A photo of a deployed device is shown in Fig. 2.

2.3. Low traffic Neighbourhoods (LTNs)

From 2021, Oxfordshire County Council introduced a trial of three Low Traffic Neighbourhoods (LTNs) within the Cowley area of East Oxford. The Cowley LTNs were introduced using Experimental Traffic Regulation Orders (ETROs) in 2021 (Oxfordshire County Council, 2021) and three areas, Temple Cowley, Church Cowley and Florence Park were chosen as priority areas in response to residents' complaints about traffic and to improve the cycle routes running through the neighbourhoods. This study specifically targeted impact within the Temple Cowley LTN, a total area of approximately one square kilometre and installation was completed on 22nd April 2021. There were four traffic filters (i.e. barriers such as a bollard or planter preventing traffic from travelling through the filter but traffic is able to approach the filter from either side, just not pass through) installed as part of the Temple Cowley LTN, sufficient to stop all through-traffic in the area. The study area, traffic filters, and the sensor deployment locations are shown in Fig. 3, a photo of an example traffic filter is shown in Fig. 4.

Eight AudioMoth devices were deployed on a mixture of boundary roads (where displacement traffic might be expected), the traffic filters within the LTN itself, a control location (where the LTN is expected to have no effect), and other locations within the LTN where a general reduction in traffic might be expected. Unfortunately, two AudioMoths were missing from their locations at the end of the first deployment (one at the Salegate lane filter, and one on the Hollow Way displacement location), so data for both deployments is only available for eight locations. These are shown in Fig. 3 and Table 1, where "Category" refers to whether a sensor is deployed in a location where displacement traffic might be expected ("Displacement"), at a traffic filter ("Filter"), at another location within the LTN where a general reduction in traffic might be expected ("LTN"), or at a location where the LTN is not expected to have an impact ("Control").

As part of a separate project measuring the impact of COVID-19 lockdowns on noise pollution, seven other sensors were deployed in other locations around Oxford including locations which might be seen as urban control (away from LTNs – Banbury Road, Iffley Road, Parks Road, St Clement's, Windmill School, and the A34 Highway), and one biotic control (Wytham Woods). These locations are

Fig. 1. AudioMoth (right) and its waterproof housing.

Fig. 2. AudioMoth deployed inside the Temple Cowley LTN, Oxford.

shown in Fig. 5. Because this was a different project, there is not an exact overlap on the dates between these sensors, but there is substantial data overlap during the March LTN deployment (pre-LTN). The sensors were identical to those deployed in this project as were the location and analysis methodologies, so results from these are directly comparable to those in this work.

2.4. Data processing

As noted in the Introduction, wind and rain has a significant impact on noise data, and that was observed in this work. On some days / locations, the wind or rain completely dominated the soundscape recorded by the AudioMoths. Some test points were necessarily discarded because the effect was so large as to saturate the microphone (any gaps in data will be as a result of this). For data that was not saturated but still affected, an attempt was made to explore the Kurtosis of the data to see whether wind and rain had characteristic values. Unfortunately, no clear patterns were seen, and it was decided not to pursue this potential data exclusion approach. Instead, the assumption is that the microphones are mounted sufficiently close together (all being in Oxford) that the wind and the rain will affect all sensors equally.

It should be noted that the sampling days straddled Greenwich Mean Time (GMT) to British Summer Time (BST) daylight saving time changes, all times presented in this work, and 24-hr window definitions, remain GMT.

2.4.1. Low-cost sensor calibration

AudioMoth devices record audio and the datasets are saved as waveform audio file format (.wav) files. Their accuracy of measurement was compared to a measurement microphone compliant with the IEC 61094–4 standard within anechoic chamber facilities at the University of Birmingham, shown in Fig. 6 when exposed to a pure (single frequency – 1 kHz) tone. The sound pressure units were compared in order to show that the AudioMoth device does not normalise the signals or manipulate the amplitudes so the event-to-event comparisons are correct. Time-frequency spectra are used for highlighting the frequency range variance from the different generated sounds.

The frequency results of the acoustic signals generated from both devices are plotted in Fig. 7. It can be seen that the frequency and acoustic pressure signals obtained from the AudioMoth data are very similar to those obtained from the GRAS 46AE microphone including over very short time periods (bottom plot in Fig. 7). It shows that the acoustic pressure collected from the AudioMoth has linear correlation to measurement microphones and the frequency response is virtually identical at the frequencies of interest.

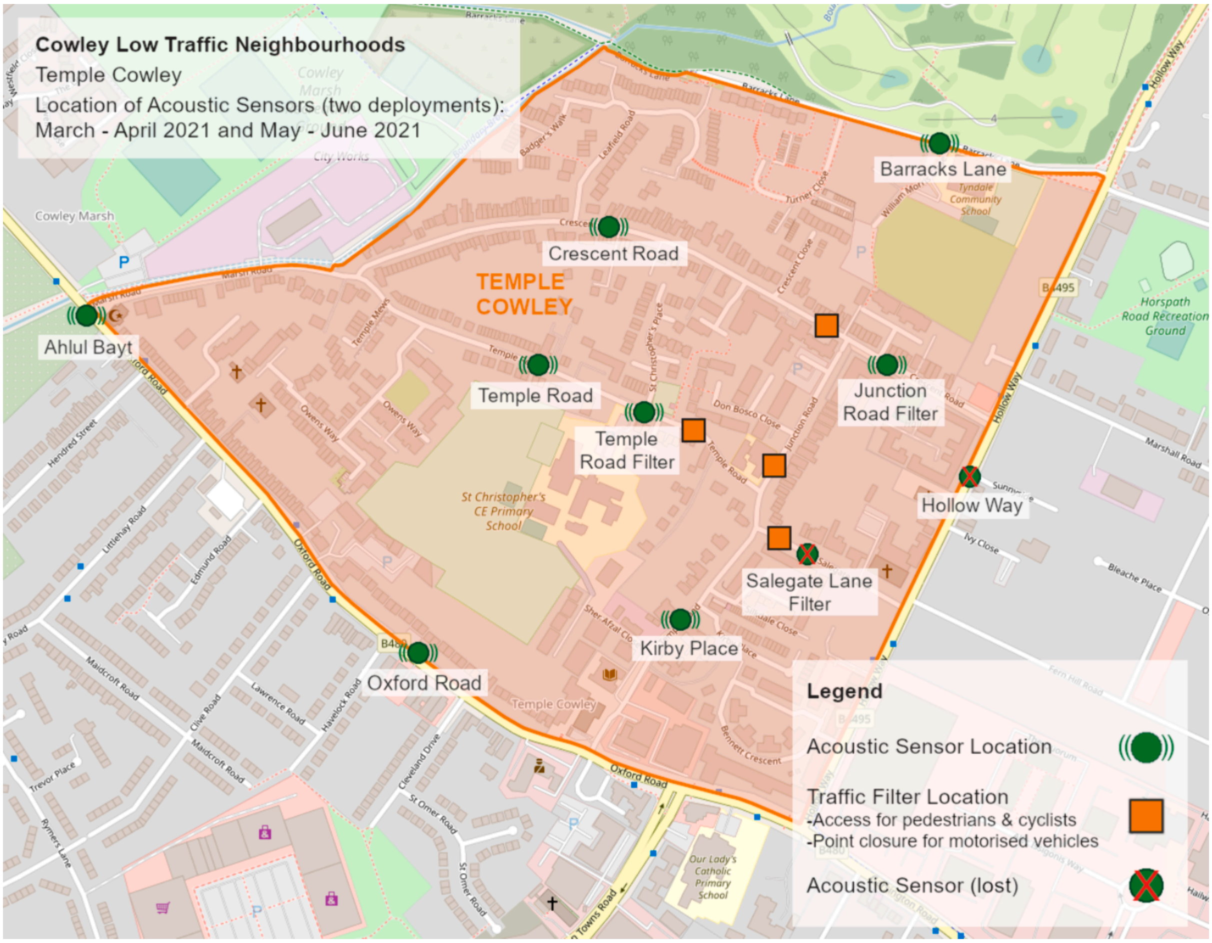

Fig. 3. Map showing locations of deployed AudioMoths (green circles) and traffic filters (orange squares) in the Temple Cowley LTN. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4. Photo of an LTN traffic filter in Oxford, UK.

Table 1
AudioMoth deployment dates, site categorisations, and sites in the Temple Cowley LTN.

LTN site	Category	Reference	Deployment 1 (Pre-LTN)	Deployment 2 (Post-LTN)
Ahlul Bayt	Displacement	AhB	15 Mar – 14 Apr	7 May – 3 June
Oxford Rd	Displacement	OxR	15 Mar – 10 Apr	7 May – 2 June
Kirby Place	LTN	Kir	15 Mar – 13 Apr	7 May – 3 June
Crescent Road filter	Filter	CrF	15 Mar – 13 Apr	7 May – 2 June
Barracks Lane	Control	Bar	15 Mar – 13 Apr	7 May – 2 June
Crescent Road	LTN	Crs	15 Mar – 13 Apr	7 May – 3 June
Temple Road	LTN	Tem	15 Mar – 13 Apr	7 May – 4 June
Temple Road filter	Filter	TemF	15 Mar – 14 Apr	7 May – 3 June

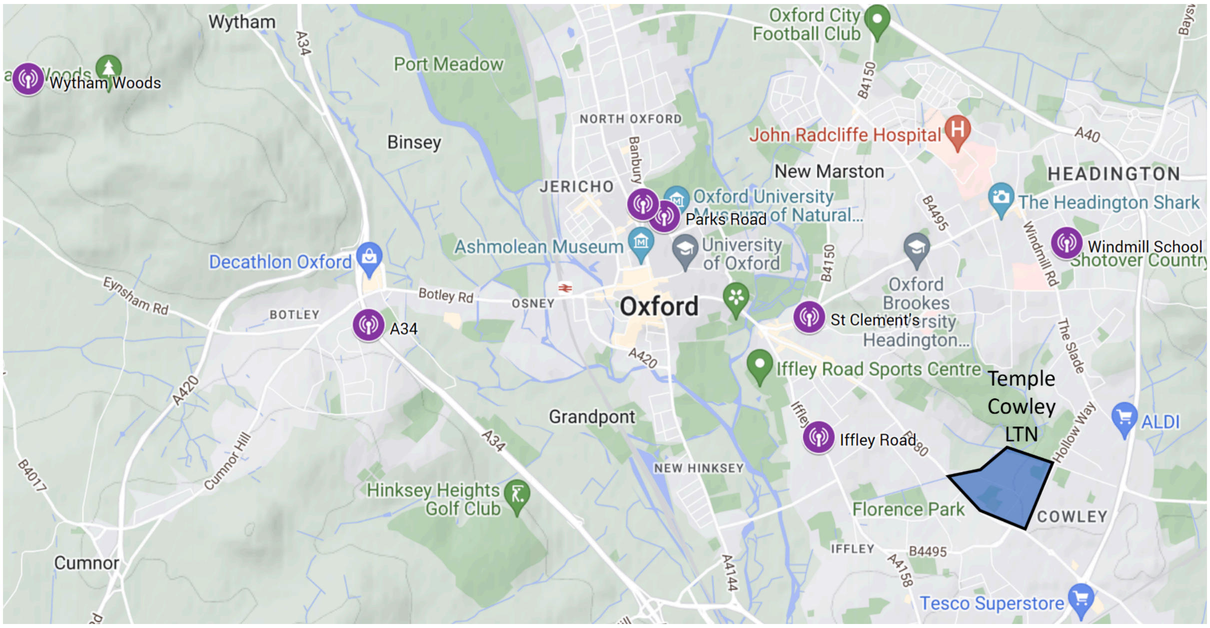

Fig. 5. Sensor locations outside the LTN, around Oxford (indicated by purple circular markers), the area of the LTN is in the shaded blue area in the southeast of the map. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4.2. Acoustic energy

The measured acoustic energy of a sound is significantly affected by its proximity to the microphone. For a study like this, where field locations are limited to lampposts and other similar pieces of street furniture, it is therefore impossible to control for this by, for example, locating the AudioMoths identical distances from the possible sources of noise that they would pick up or even an identical distance away from the road.

As a result, in the analysis of the data, the acoustic energy is rescaled by dividing by the maximum value for that location. This means that direct location-to-location comparisons are not possible, but trends both within and between locations over time *are* possible to discern.

Acoustic energy was then computed from the amplitude of the recorded signals by Welch's method (Welch 1967). This was then mean-averaged over the entire 5-minute recording window. This data can then be plotted and, for example diurnal trends seen, such as in Fig. 8. Here, not only can it be seen that there are noise peaks during daylight hours, and troughs at night (as would be expected) but further detail such as morning and evening peaks is visible on weekdays. However, it is clear that the weekends have the highest noise overall with either Friday or Saturday evenings showing peak noise. Given that the Temple Cowley area is almost entirely residential, it is not that surprising that noise peaks at the weekends, when most people are at home.

In order to measure the impact of the LTN, 5-minute mean averages are not so helpful (due to their large random variability), so the acoustic energy was then aggregated over 24-hr periods (i.e. 72 individual 5-minute recordings made up a 24-hr period).

Two methods were explored for this: (1) a simple mean average of the data and (2) integrating the signal to find the area. The reason for this is that the data showed perhaps one or two events per day that had extremely high acoustic energy on occasion (say an order of magnitude higher than all other data) but it may only have been one 5-minute sample where something loud happened very close to the microphone. This particular noise would then dominate the data. If such a noise was persistent then it was important to include it, but if it was a one-off then it was important it didn't skew the entire data set. For this reason, both methods were compared, and this is shown in Fig. 9.

Fig. 6. GRAS 46AE Free-filed microphone in anechoic chamber.

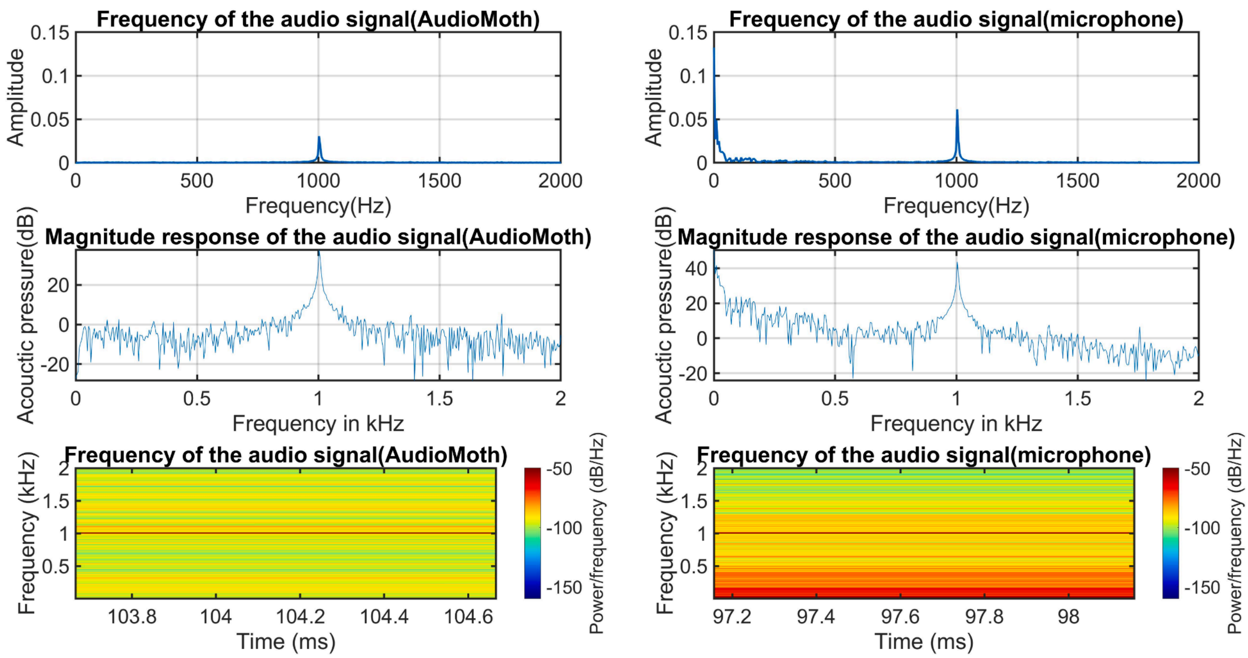

Fig. 7. Calibration results from the AudioMoth (left) and GRAS 46AE (right).

It can clearly be seen that at most points, there is a strong linear correlation between the two methods. However, for a small number of days the mean is much higher than the corresponding area. These days have a single 5-minute window where there is a very loud noise which is an anomaly which is not present in any other recording (for example someone shouting adjacent to the microphone or a car backfiring). As these noises dominate but are not relevant for the long-term nature of the study measurement period, it was decided

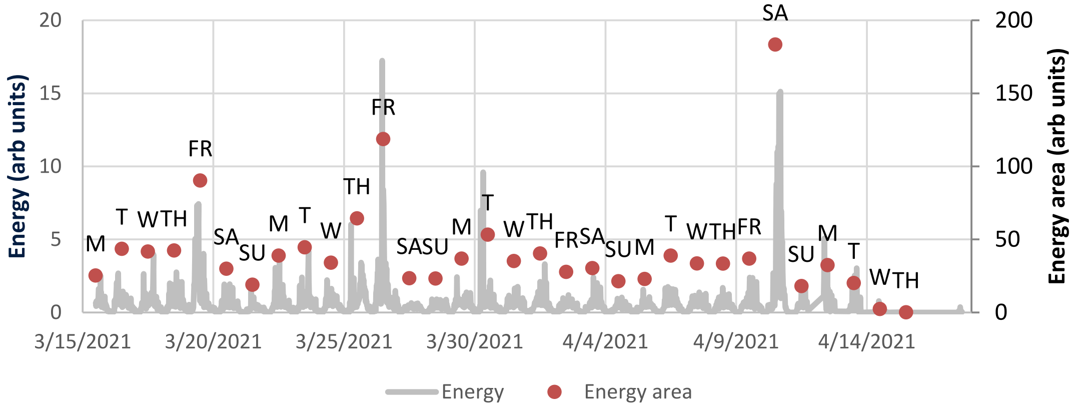

Fig. 8. Example of acoustic energy from a single AudioMoth during the first deployment. (data from Oxford Road, a displacement site). The days of the week are shown above the data.

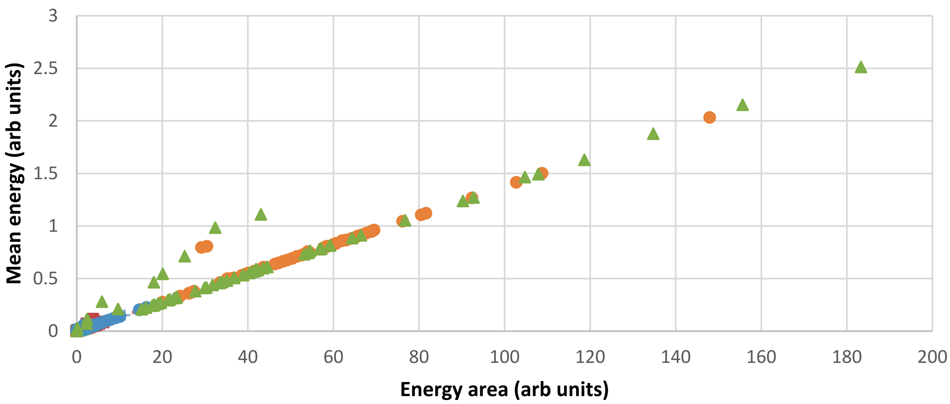

Fig. 9. Comparison between mean average acoustic energy and integrated area acoustic energy for all sensors aggregated over 24 h windows.

to continue with the area method for the analysis.

2.4.3. Anomaly investigation

Notwithstanding the use of the area method, there remains a challenge, as already noted, about what loud sounds may dominate the data. A balance needs to be struck, in order that the study effectively assesses the impact of the LTN (for example by excluding wind noise), whilst retaining sounds that will affect people's experience of noise. In this case if a sound was vehicle-related it was retained. For the LTN data, if fewer than 10 % of the days (generally 6 out of 63) were in the top 50 % of acoustic energy area, these were selected for further investigation by listening to the audio files and attempting to interpret the resulting sound. However, as points are excluded, then once the data is recalculated, a new set of points might be in the top 50 % of acoustic energy area. It is not practical to listen individually to every sound recorded as part of this study, so no further investigation was undertaken after this first exclusion.

Therefore, the data were analysed with all possible anomalies included (primary assessment) and with a first pass of anomalies excluded (secondary assessment). No further anomaly investigation was conducted beyond that. Table 2 shows all of the anomalies investigated, and whether or not they were excluded from the secondary assessment.

2.4.4. Laeq

LA_{eq}, the A-weighted, equivalent continuous sound level, is a very commonly used metric for analysis of noise (Fredianelli et al., 2022). Once calibrated, the LA_{eq} values obtained were identical between the audiomoths and the calibration microphone tested. In addition to the LA_{eq} values presented in this paper (which are mean averages), the 10th, 50th, and 90th percentiles are also calculated, shown as LA_{10} $LA_{50,}$ and LA_{90} respectively.

2.5. NDSI

The Normalised Difference Soundscape Index (NDSI), is used to apportion the measured noise from biotic and anthropogenic sources. NDSI assumes that biophony and anthropophony occur in different frequency bands as the sounds from man-made machinery, such as vehicle engines, are most predominant in the frequency range 1–2 kHz and biological sounds, such as birds tweeting, are most

Table 2
Anomalies investigated.

Sensor	Date and Time	Source of noise	Excluded from secondary assessment?
Kir	Thursday 01-Jun-2021 08:40	Electric saw	Y
Kir	Thursday 01-Jun-2021 09:00	Electric saw	Y
Kir	Thursday 01-Jun-2021 09:20	Electric saw	Y
Kir	Thursday 01-Jun-2021 10:40	Electric saw	Y
Kir	Thursday 01-Jun-2021 11:00	Electric saw	Y
Kir	Thursday 01-Jun-2021 11:20	Electric saw	Y
Kir	Thursday 01-Jun-2021 12:20	Electric saw	Y
Crs	Wednesday 17-Mar-2021 09:00	Street sweeping	N
Crs	Wednesday 19-May-2021 06:40	Electric saw	Y
AhB	Thursday 13-May-2021 10:40	Vehicle passing through surface water	N
AhB	Saturday 15-May-2021 16:40	Vehicle passing through surface water	N
Bar	Friday 26-Mar-2021 09:00	Passing car	N
Bar	Friday 26-Mar-2021 22:40	Rain	Y
Bar	Sunday 11-Apr-2021 10:00	Street sweeping	N
OxR	Friday 26-Mar-2021 11:00	Rain	Y
OxR	Saturday 10-Apr-2021 15:20	Street sweeping	N
OxR	Thursday 13-May-2021 10:40	Street sweeping	N
Tem	Wednesday 17-Mar-2021 11:40	Electric saw	Y
Tem	Sunday 04-Apr-2021 19:20	Alarm	Y
Tem	Friday 21-May-2021 10:20	Passing car	N
TemF	Thursday 25-Mar-2021 18:20	Passing car	N
TemF	Tuesday 06-Apr-2021 05:20	Passing car	N
TemF	Tuesday 18-May-2021 09:00	Vehicle engine	N
TemF	Thursday 20-May-2021 05:00	Machine noise	Y
TemF	Friday 21-May-2021 05:00:00	Machine noise	Y

prevalent between 2 and 8 kHz.

Examples of biophony and anthropophony have been compared to assess the efficacy of the NDSI method in this context. The time–frequency spectra of a sound which contains road noise including vehicles (sampled for 5 min) is analysed in Fig. 10. This is compared to a sound containing the noise of birds tweeting (also sampled for 5 min) analysed in Fig. 11. In these two figures, the main differences between frequency ranges are clear, as the noise from the road is mainly dominated by frequencies less than 2 kHz and noise from the birds are between 3–8 kHz. When calculating the NDSI, the sound pressure units will automatically cancel each other out, resulting in the NDSI being purely an index. Thus, no unit conversion was required from AudioMoth devices to sound pressure, which simplifies the processing.

NDSI is calculated from a given sound signal ($x(t)$) using equations 1–4.

$$X(\omega) = \mathscr{F}\{x(t)\}, \omega = 2\pi f \tag{1}$$

$$E_1 = \int_{\omega_{1,L}}^{\omega_{1,H}} |X(\omega)|^2 d\omega \tag{2}$$

$$E_2 = \int_{\omega_{2,L}}^{\omega_{2,H}} |X(\omega)|^2 d\omega \tag{3}$$

$$NDSI = \frac{E_2 - E_1}{E_2 + E_1} \tag{4}$$

where, $x(t)$ is the sound signal, $\mathscr{F}$ is the Fourier transform operator, $X(\omega)$ Fourier transform of $x(t)$, E is energy (proportional), $\omega_{1,L}$ and $\omega_{2,L}$ are lower cut off frequencies in rad/s, $\omega_{1,H}$ and, $\omega_{2,H}$ are upper cut off frequencies in rad/s, and f is frequency in Hz, E_1 is the anthrophony energy and E_2 is biophony energy

NDSI takes values of -1 for noise where all of the acoustic power is in the 1–2 kHz band (representing anthropogenic sources) and 1 for noise where all of the acoustic power is in the 2–8 kHz band (representing biotic sources).

While it is common to consider the NDSI using the above frequency bands (Kasten et al., 2012), it is of interest to test the methods sensitivity to these frequency bands. Hence, a sensitivity study was undertaken, extending the frequency ranges of the bands as low as 0.5 kHz for the anthropophony band and 11 kHz for the biophony band to ensure that the urban soundscape was being well characterised. The comparison between these two NDSIs for all data is shown in Fig. 12.

It can clearly be seen from Fig. 12 that the results are insensitive to the choice of frequency range with a good linear correlation between both methods of calculating NDSI. The 0.5–11 kHz method gives slightly higher values, but this is to be expected given the proportionally wider range of the upper band relative to the 1–8 kHz method. As a result, it was decided to continue solely with the

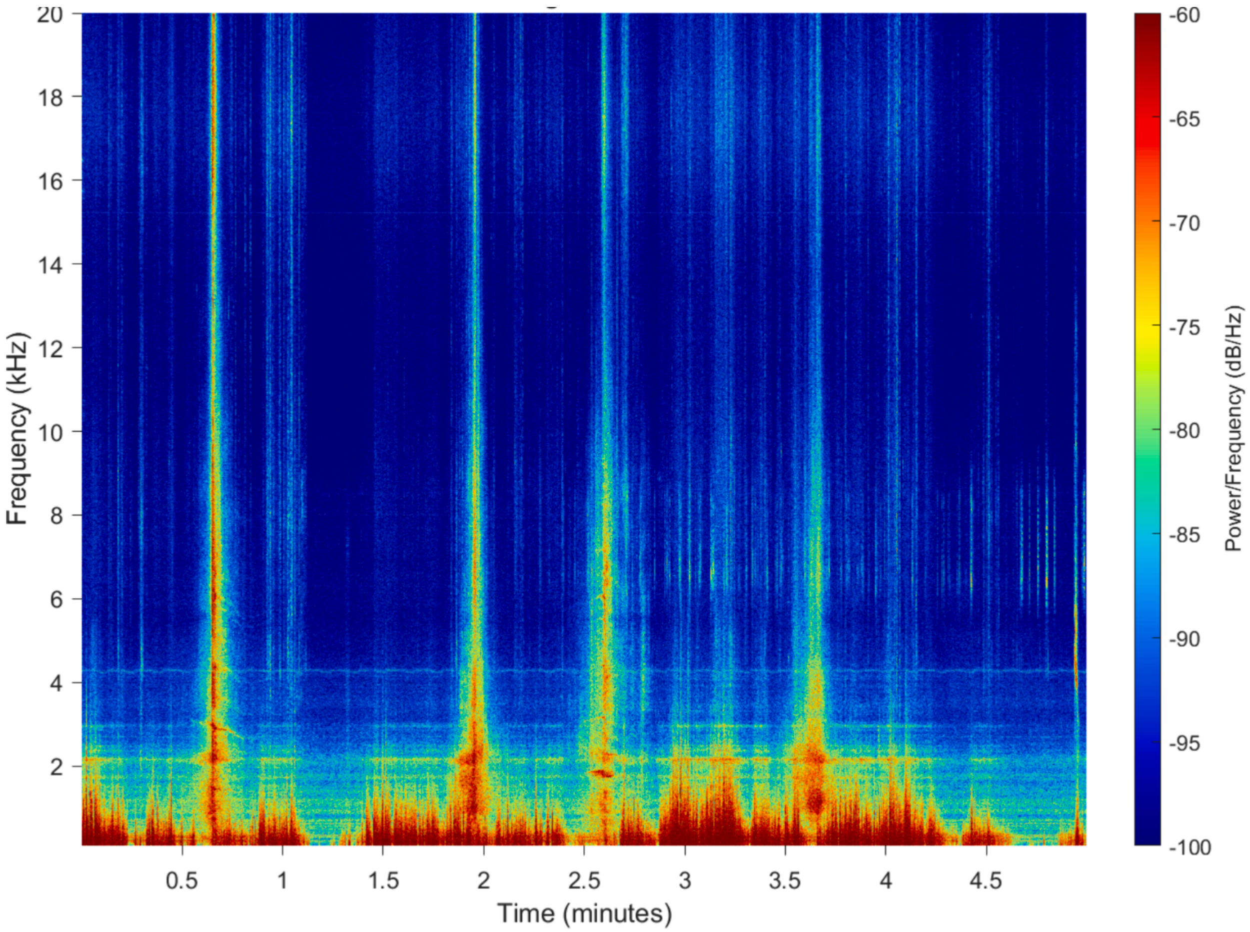

Fig. 10. An example of anthropophonic source – sound from road vehicles.

1–8 kHz method in order to provide data comparable to previous work (Kasten et al., 2012; Fuller et al., 2015).

Data was aggregated to a daily value using a similar approach to that of the energy – a mean of each individual 5-minute sample was taken, and then these samples were mean-averaged over a 24-hour period. The effect of this averaging is shown in Fig. 13 which is the time series of one sensor, and the comparison mean averages. Note that this is the NDSI calculation for the same data where energy was calculated in Fig. 8. Similar diurnal trends to the acoustic energy are seen, with the lowest values of NDSI (most biotic sound) occurring overnight.

3. RESULTS

The first set of results is presented without the anomalies excluded, and then subsequently the effect if anomalies are excluded is considered.

3.1. Acoustic energy

Table 3 presents the percentage change in acoustic energy after the implementation of the LTN restrictions for all of the sensors in the study.

3.1.1. Sensors located at modal traffic filters

A more detailed look can be obtained by considering the timeseries of the daily means of acoustic energy. Fig. 14 shows the timeseries of the daily means of acoustic energy for the sensors located at the traffic filters.

3.1.2. Sensors located inside the LTN

Similarly, Fig. 15 shows the timeseries of the daily means of acoustic energy for the sensors located inside the LTN.

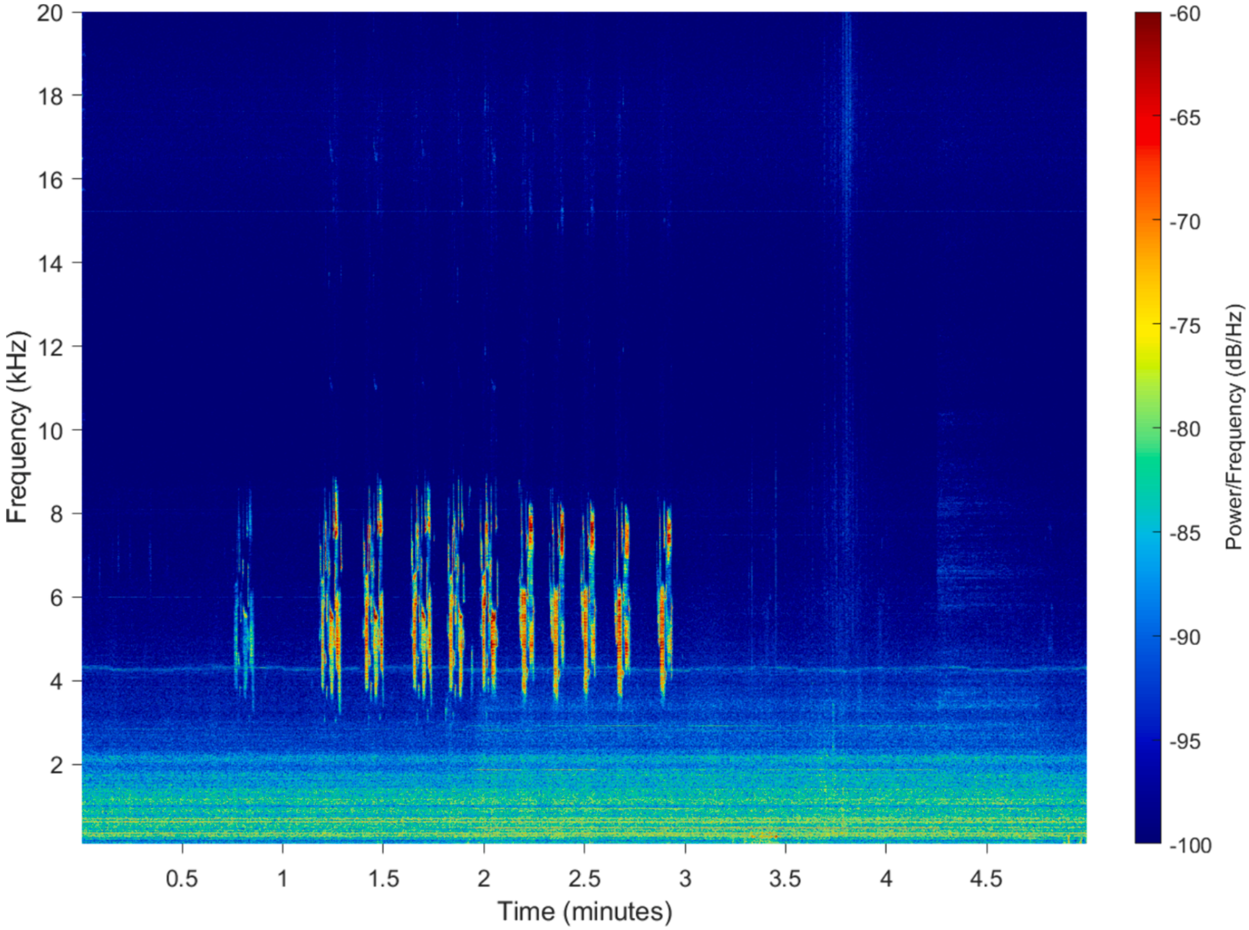

Fig. 11. An example of biophonic source – sound from birds tweeting.

3.1.3. Sensors located at possible displacement sites and control

Fig. 16 shows the timeseries of the daily means of acoustic energy for the sensors located at the possible displacement sites and the control site.

3.2. Laeq

Table 4 shows the change in LA_{eq} after the implementation of the LTN restrictions for all of the sensors in the study. The LA_{10} $LA_{50,}$ and LA_{90} data (Tables 5-7) show more detail.

3.2.1. Sensors located at filters

Fig. 17 shows the timeseries of the daily means of LA_{eq} for the sensors located at the traffic filters.

3.2.2. Sensors located inside the LTN

Fig. 18 displays the timeseries of the daily means of LA_{eq} for the sensors located inside the LTN.

3.2.3. Sensors located at possible displacement sites and control

Fig. 19 shows the timeseries of the daily means of LA_{eq} for the sensors located at the possible displacement sites.

3.3. NDSI

Table 8 shows the percentage change in NDSI after the implementation of the LTN restrictions for all of the sensors in the study. As a reminder, a lower NDSI means that the noise is considered more anthropogenic (human generated).

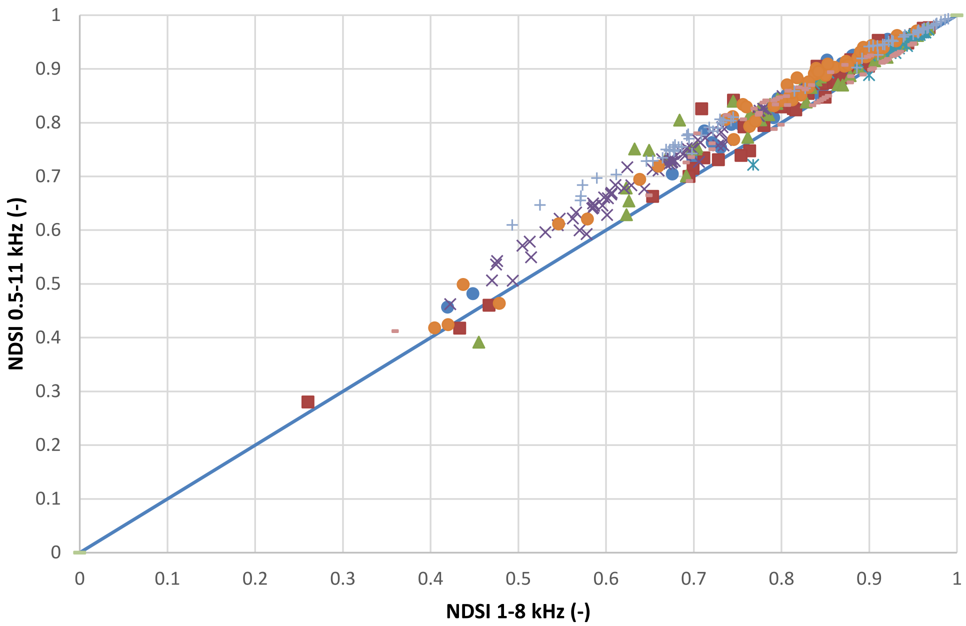

Fig. 12. Comparison between 1–8 kHz and 0.5–11 kHz NDSI methods for all sensors aggregated over 24 h windows. Different symbols refer to data from different sensors.

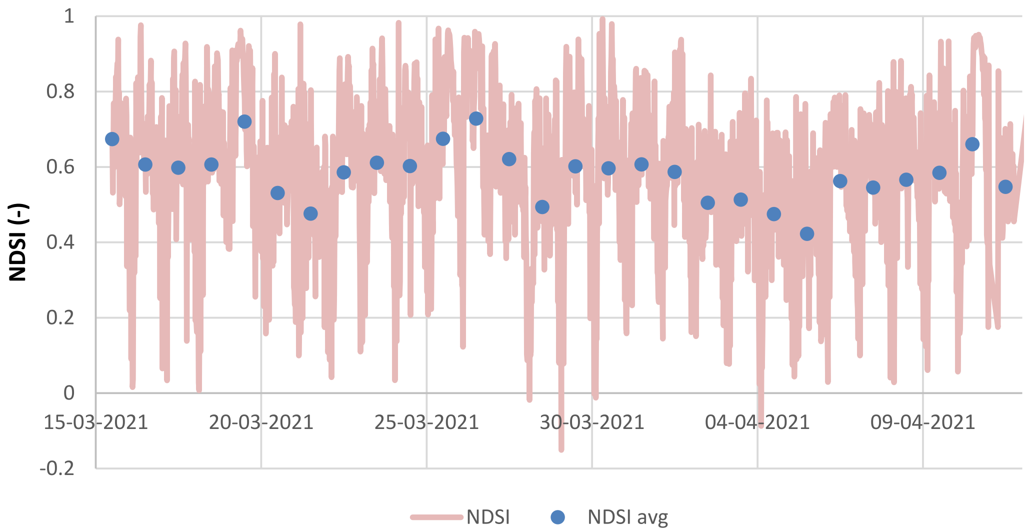

Fig. 13. Example of NDSI from a single AudioMoth during the first deployment. (data from Oxford Road, a displacement site).

Table 3
Percentage change in acoustic energy after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Percentage change
Ahlul Bayt	Displacement	0.36	0.34	−5%
Oxford Rd	Displacement	0.23	0.25	8 %
Barracks Lane	Control	0.34	0.33	−4%
Crescent Road	LTN	0.25	0.20	−21 %
Temple Road	LTN	0.21	0.20	−3%
Kirby Place	LTN	0.03	0.06	142 %*
Crescent Road filter	Filter	0.41	0.34	−17 %
Temple Road filter	Filter	0.24	0.23	−2%

*a relatively small absolute increase on a low baseline leading to a very large percentage increase.

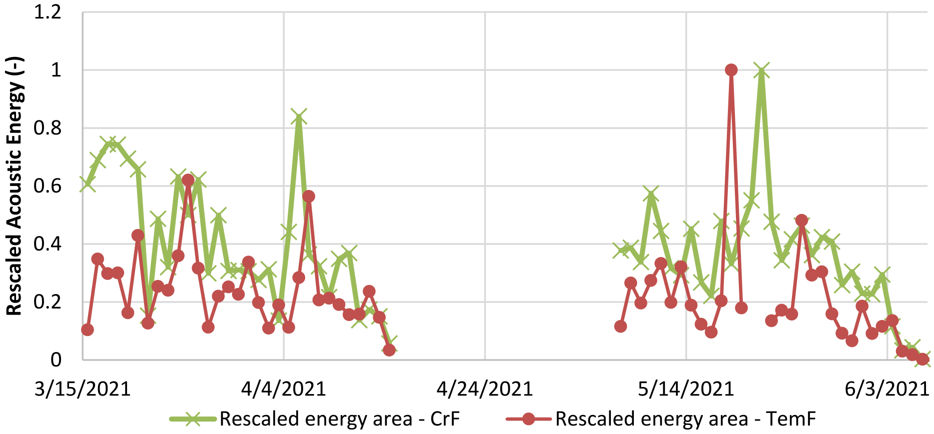

Fig. 14. Timeseries of the daily means of acoustic energy for the sensors located at the modal traffic filters.

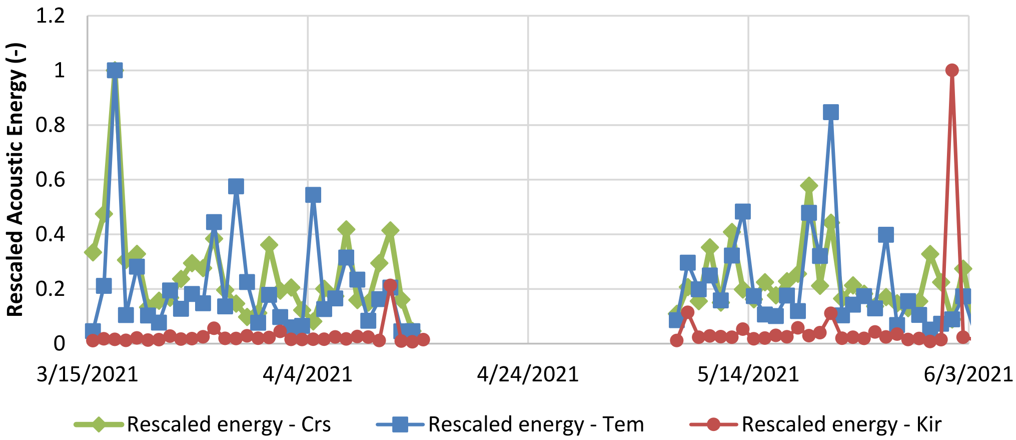

Fig. 15. Timeseries of the daily means of acoustic energy for the sensors located within the LTN.

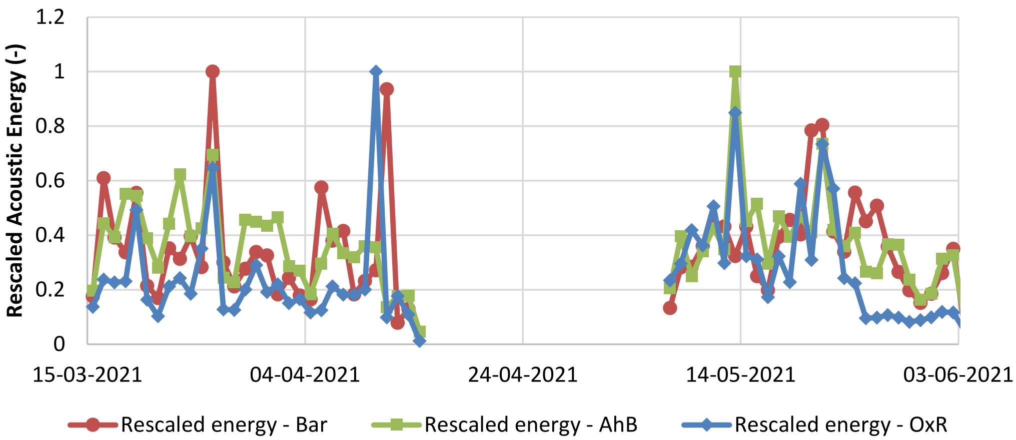

Fig. 16. . Timeseries of the daily means of acoustic energy for the sensors located at the possible displacement sites and control location (Bar).

3.3.1. Sensors located at filters

Similar to the acoustic energy analysis, examining the timeseries of the daily means of NDSI reveals further insights. Fig. 20 shows the timeseries of the daily means of NDSI for the sensors located at the traffic filters.

Table 4
Change in LA_{eq} (dB) after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	51.3	50.9	−0.4	−1%
Oxford Rd	Displacement	50.7	50.6	−0.1	0 %
Barracks Lane	Control	35.7	36.6	0.9	3 %
Crescent Road	LTN	34.8	35.2	0.4	1 %
Temple Road	LTN	34.1	36.6	2.6	8 %
Kirby Place	LTN	37.4	39.1	1.6	4 %
Crescent Road filter	Filter	39.4	41.4	2.1	5 %
Temple Road filter	Filter	38.5	40.0	1.5	4 %

Table 5
Change in L_{10} (dB) after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	38.9	39.9	0.9	2 %
Oxford Rd	Displacement	37.1	38.4	1.3	3 %
Barracks Lane	Control	30.8	31.1	0.3	1 %
Crescent Road	LTN	29.9	30.0	0.1	0 %
Temple Road	LTN	28.1	28.2	0.2	1 %
Kirby Place	LTN	29.1	29.5	0.4	1 %
Crescent Road filter	Filter	33.0	31.6	−1.5	−4%
Temple Road filter	Filter	30.3	31.3	0.9	3 %

Table 6
Change in L_{50} (dB) after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	53.7	53.0	−0.8	−1%
Oxford Rd	Displacement	53.7	52.0	−1.7	−3%
Barracks Lane	Control	35.4	36.2	0.8	2 %
Crescent Road	LTN	34.6	35.2	0.6	2 %
Temple Road	LTN	33.9	36.8	2.9	8 %
Kirby Place	LTN	38.3	39.5	1.2	3 %
Crescent Road filter	Filter	39.7	42.0	2.4	6 %
Temple Road filter	Filter	39.1	40.1	1.0	3 %

Table 7
Change in L_{90} (dB) after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	59.3	58.8	−0.5	−1%
Oxford Rd	Displacement	58.1	59.3	1.2	2 %
Barracks Lane	Control	40.9	42.3	1.4	4 %
Crescent Road	LTN	39.6	39.8	0.2	1 %
Temple Road	LTN	40.3	43.6	3.3	8 %
Kirby Place	LTN	44.0	46.7	2.7	6 %
Crescent Road filter	Filter	45.8	49.4	3.6	8 %
Temple Road filter	Filter	45.8	47.3	1.5	3 %

3.3.2. Sensors located inside the LTN

Fig. 21 displays the timeseries of the daily means of NDSI for the sensors located inside the LTN.

3.3.3. Sensors located at possible displacement sites and control

Fig. 22 shows the timeseries of the daily means of NDSI for the sensors located at the possible displacement sites.

3.4. Relationship between NDSI and energy

It is of interest to establish whether there is a relationship between the NDSI of a sound and its energy for the sounds collected through this study. For example, are loud noises persistently more anthropogenic? Fig. 23 shows the relationship between acoustic energy and NDSI for all of the daily means over all sensors throughout the study. It can be seen that there is no clear correlation at all between the two parameters, further emphasising the importance of considering both variables independently.

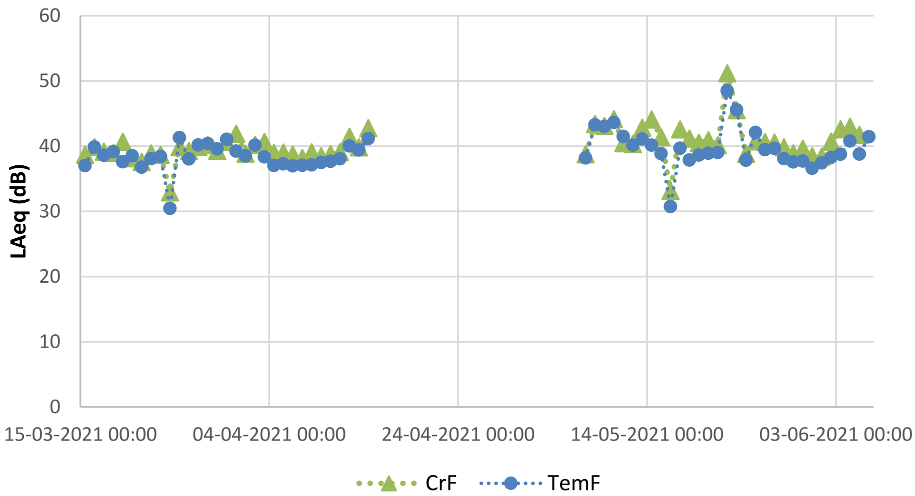

Fig. 17. Timeseries of the daily means of LA_{eq} for the sensors located at the traffic filters.

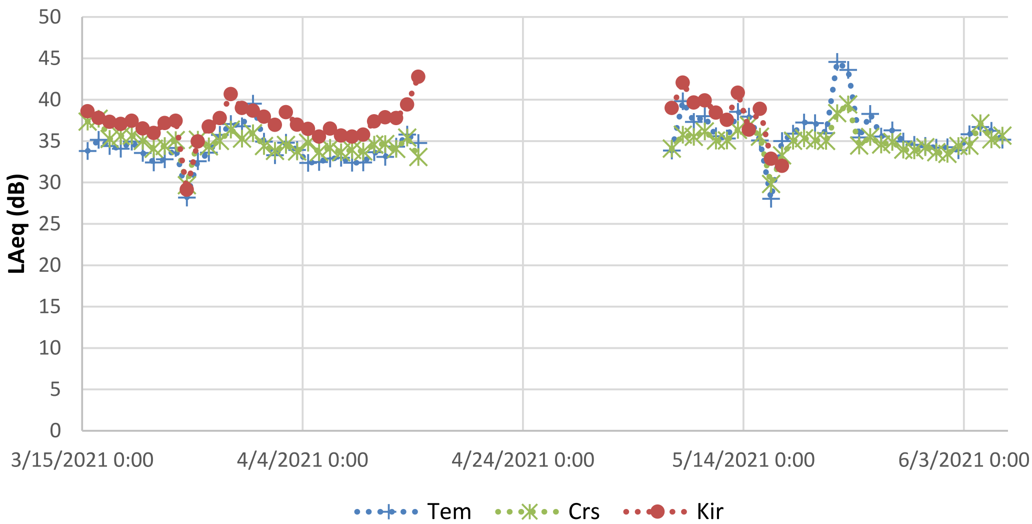

Fig. 18. Timeseries of the daily means of LA_{eq} for the sensors located in the LTN.

3.5. Comparison of NDSI with other locations in Oxford

This study was (in part) running at the same time as another study investigating the impact of COVID-19 restrictions on noise in Oxford (locations shown in Fig. 5). It is possible to compare the NDSI values between the Temple Cowley LTN locations (Fig. 3) and other locations around Oxford (Fig. 5) for the roughly 20 days of overlap. This is shown in Fig. 24.

3.6. Exclusion of anomalies

Data considered anomalies in Table 2 were removed from the dataset and the percentage changes in Table 3 and Table 8 recalculated over the study period.

3.6.1. Acoustic energy

Table 9 presents the percentage change in acoustic energy after the implementation of the LTN restrictions for all of the sensors in the study.

3.7. Laeq

Tables 10-13 present the percentage change in LA_{eq}, L_{10}, L_{50}, and L_{90} after the implementation of the LTN restrictions for all of the

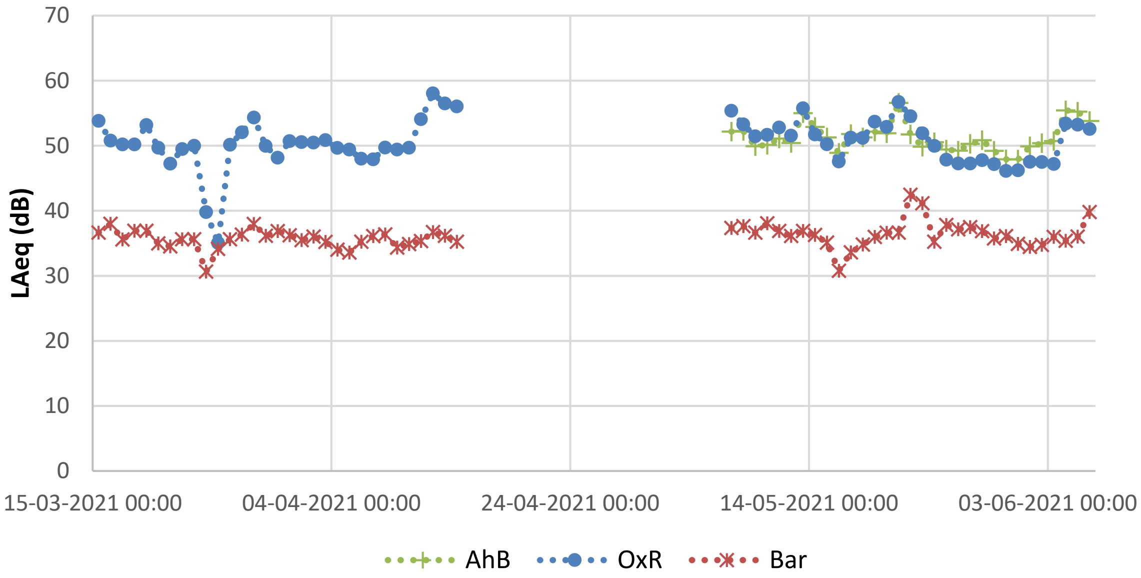

Fig. 19. Timeseries of the daily means of LA_{eq} for the sensors located at the possible displacement sites and control location (Bar).

Table 8
. Percentage change in NDSI after the implementation of the LTN restrictions for all sensor locations.

LTN site	Category	Pre-LTN	Post-LTN	Percentage change
Ahlul Bayt	Displacement	0.90	0.97	5 %
Oxford Rd	Displacement	0.60	0.70	20 %
Barracks Lane	Control	0.90	0.75	−18 %
Crescent Road	LTN	0.80	0.89	15 %
Temple Road	LTN	0.80	0.82	7 %
Kirby Place	LTN	0.71	0.90	27 %
Crescent Road filter	Filter	0.80	0.86	8 %
Temple Road filter	Filter	0.80	0.86	4 %

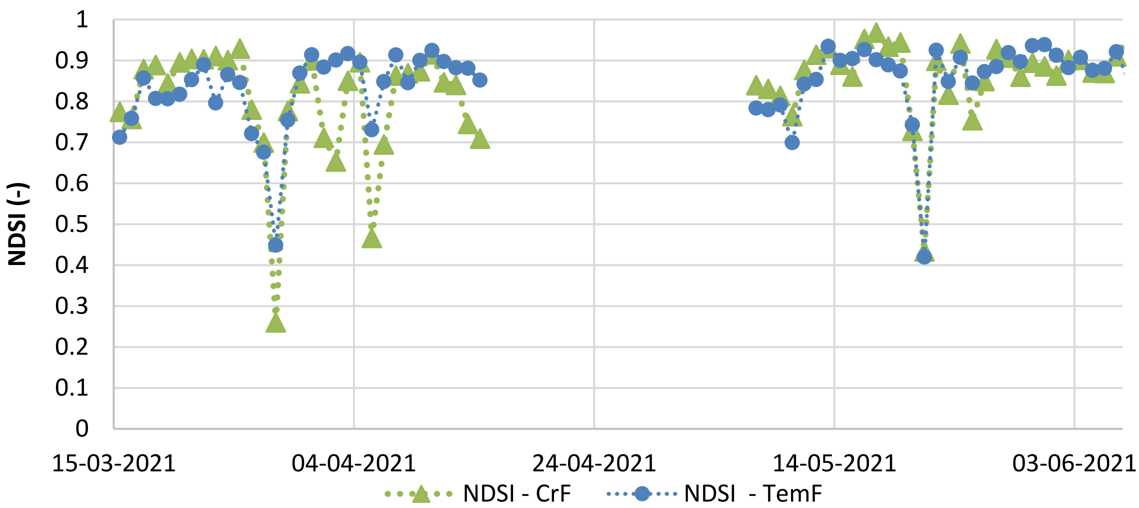

Fig. 20. Timeseries of the daily means of NDSI for the sensors located at the traffic filters.

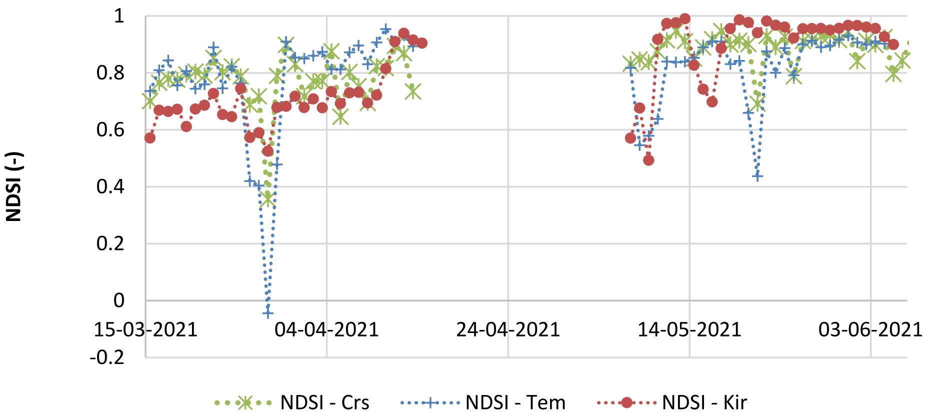

Fig. 21. Timeseries of the daily means of NDSI for the sensors located in the LTN.

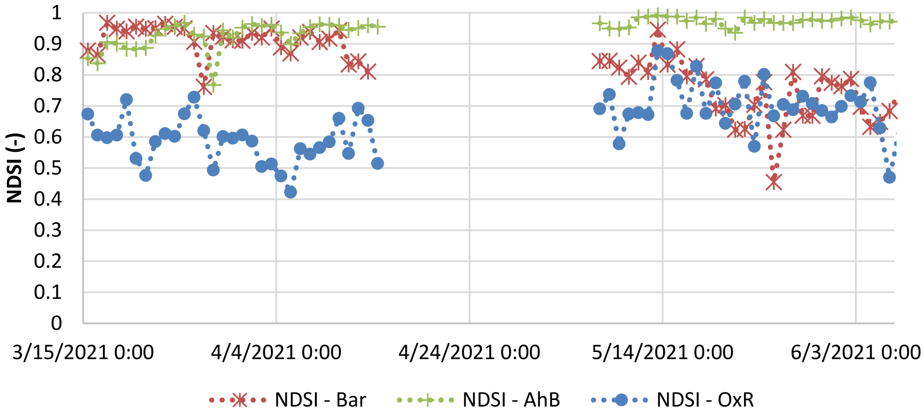

Fig. 22. Timeseries of the daily means of NDSI for the sensors located at the possible displacement sites and control location (Bar).

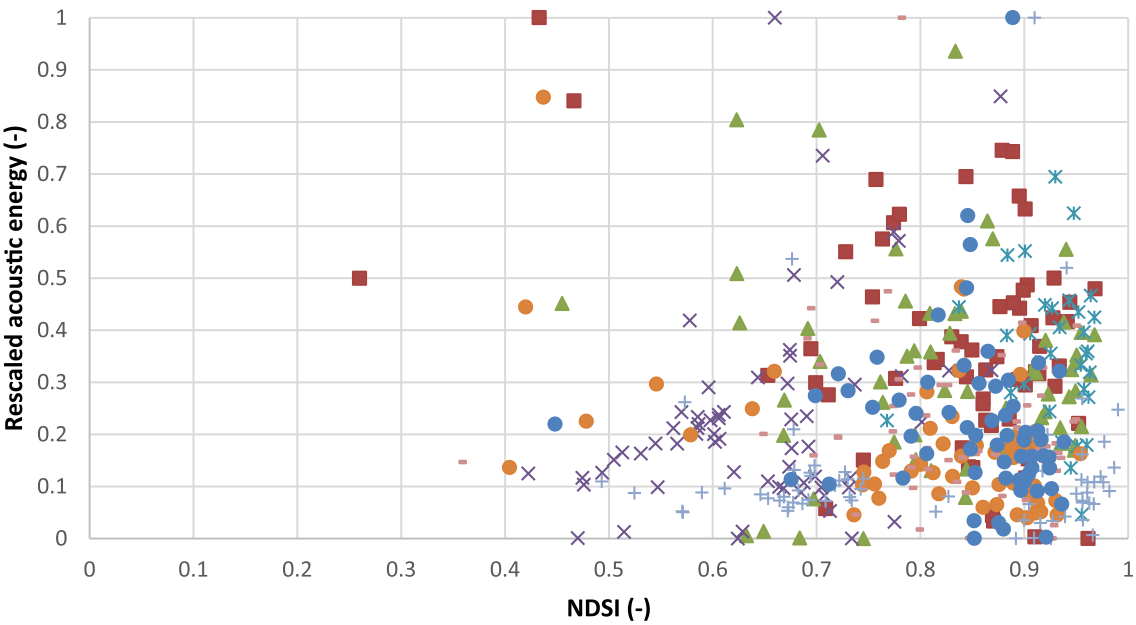

Fig. 23. Comparison of NDSI and acoustic energy for all data (24-hour means) in the study.

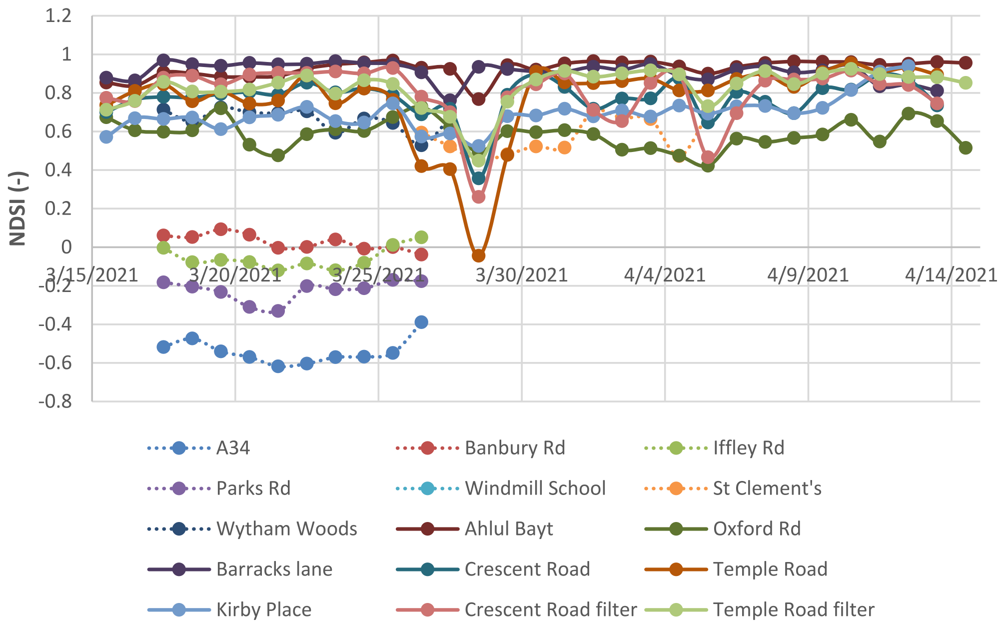

Fig. 24. NDSI values for AudioMoth sensors in Temple Cowley (solid lines) and wider Oxford (dash lines) locations.

Table 9
Percentage change in acoustic energy after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Percentage change
Ahlul Bayt	Displacement	0.36	0.37	5 %
Oxford Rd	Displacement	0.23	0.29	25 %
Barracks Lane	Control	0.32	0.37	17 %
Crescent Road	LTN	0.25	0.21	−19 %
Temple Road	LTN	0.17	0.20	20 %
Kirby Place	LTN	0.13	0.15	19 %
Crescent Road filter	Filter	0.42	0.40	−6%
Temple Road filter	Filter	0.24	0.23	−7%

Table 10
Change in LA_{eq} (dB) after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	51.3	50.9	−0.4	−1%
Oxford Rd	Displacement	50.6	50.5	−0.1	0 %
Barracks Lane	Control	35.7	36.6	0.9	3 %
Crescent Road	LTN	34.8	35.2	0.4	1 %
Temple Road	LTN	34.1	36.6	2.6	8 %
Kirby Place	LTN	37.4	39.1	1.6	4 %
Crescent Road filter	Filter	39.4	41.4	2.1	5 %
Temple Road filter	Filter	38.5	39.9	1.5	4 %

Table 11
Change in L_{10} (dB) after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	38.9	39.9	0.9	2 %
Oxford Rd	Displacement	37.1	38.4	1.3	3 %
Barracks Lane	Control	30.8	31.1	0.3	1 %
Crescent Road	LTN	29.9	30.0	0.1	0 %
Temple Road	LTN	28.1	28.2	0.2	1 %
Kirby Place	LTN	29.1	29.5	0.4	1 %
Crescent Road filter	Filter	33.0	31.6	−1.5	−4%
Temple Road filter	Filter	30.3	31.3	0.9	3 %

Table 12
Change in L_{50} (dB) after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	53.7	53.0	−0.8	−1%
Oxford Rd	Displacement	53.7	52.0	−1.7	−3%
Barracks Lane	Control	35.4	36.2	0.8	2 %
Crescent Road	LTN	34.6	35.2	0.6	2 %
Temple Road	LTN	33.9	36.8	2.9	8 %
Kirby Place	LTN	38.3	39.5	1.2	3 %
Crescent Road filter	Filter	39.7	42.0	2.4	6 %
Temple Road filter	Filter	39.1	40.1	1.0	3 %

Table 13
Change in L_{90} (dB) after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Absolute change	Percentage change
Ahlul Bayt	Displacement	59.3	58.8	−0.5	−1%
Oxford Rd	Displacement	58.1	59.3	1.2	2 %
Barracks Lane	Control	40.9	42.3	1.5	4 %
Crescent Road	LTN	39.6	39.7	0.2	0 %
Temple Road	LTN	40.3	43.5	3.3	8 %
Kirby Place	LTN	44.0	46.7	2.7	6 %
Crescent Road filter	Filter	45.8	49.4	3.6	8 %
Temple Road filter	Filter	45.8	47.2	1.4	3 %

sensors in the study with the anomalies excluded (compare with Tables 4-7).

3.8. NDSI

Table 14 presents the percentage change in NDSI after the implementation of the LTN restrictions for all of the sensors in the study with the anomalies excluded (compare with Table 8).

4. Discussion

When considering the change in acoustic energy before and after the introduction of the LTNs (Table 3), it can be seen that one of the displacement sites displays a minor decrease in noise and one shows a minor increase. Almost all other sensors show a decrease in noise at the control, across the LTN, and at traffic filters. One sensor (Kirby Place) shows an incredibly large increase in acoustic energy; however, this is a large percentage increase off a very low baseline noise (the pre-LTN baseline is only 3 % of the loudest day recorded).

The timeseries results of acoustic energy reveal further detail. When considering the modal traffic filters (Fig. 14), it can be seen that the noisiest days (days with the highest acoustic energy) typically have 2–3 times higher acoustic energy than an average day. It can also be seen that after the implementation of the LTN, there is greater variation, with occasional days having higher acoustic energy but these occur less frequently, and there is less acoustic energy overall. However, at the sensors located inside the LTN (Fig. 15) it can be seen that there is not much visible change before and after the implementation of the LTN (although the single day at Kirby place really does dominate the results for that sensor). Finally, at the sensors located at the possible displacement sites and the control site (Fig. 16), it can be seen that these sites show more "peaky" behaviour than those inside the LTN or at filters, however, again, there is no clear trend visible in the timeseries before and after the LTN implementation.

When considering the change in LA_{eq} before and after the introduction of the LTNs (Table 4), it can be seen that all sensors but one show a slightly higher LA_{eq} after the implementation of the LTN, in contrast to the acoustic energy data. Barracks Lane, the control location, shows a 3 % increase in LA_{eq}, whereas, interestingly, the displacement locations are lower than this and almost all of the LTN and filter locations are higher than this. Similar characteristics have been observed in the literature before, with some studies

Table 14
Percentage change in NDSI after the implementation of the LTN restrictions for all sensor locations with anomalies excluded.

LTN site	Category	Pre-LTN	Post-LTN	Percentage change
Ahlul Bayt	Displacement	0.93	0.97	5 %
Oxford Rd	Displacement	0.59	0.7	20 %
Barracks Lane	Control	0.91	0.75	−18 %
Crescent Road	LTN	0.77	0.89	15 %
Temple Road	LTN	0.77	0.82	7 %
Kirby Place	LTN	0.69	0.89	29 %
Crescent Road filter	Filter	0.80	0.86	8 %
Temple Road filter	Filter	0.83	0.86	4 %

questioning the applicability of LA_{eq} to traffic noise particularly in these low traffic and low-speed traffic environments (Brown and De Coensel, 2017). The LA_{10} $LA_{50,}$ and LA_{90} data (Tables 5-7) shows more detail – the LA_{10} data is significantly reduced at the LTN and filter sensors – showing the quieter moments have become quieter whereas the $LA_{50,}$ and LA_{90} show that the louder moments have become louder – particularly the LA_{90}, the loudest periods.

Similar to the acoustic energy analysis, examining the timeseries of the daily means of LA_{eq} reveals further insights. When considering the sensors located at the traffic filters (Fig. 17) it can be seen that the LA_{eq} is generally higher after the implementation of the LTN. At the sensors located inside the LTN (Fig. 18), there is not much difference observed between the sensors in LA_{eq} values before or after the LTN was implemented. At the possible displacement sites (Fig. 19), similar LA_{eq} values are seen for the Ahlul Bhayt and Oxford Road sensors, while the Barracks Lane (control) sensor shows a clear increase in LA_{eq} after the implementation of the LTN. This is likely to be because the Barracks Lane sensor is located next to a school, and through the study period, the school Easter holidays took place (1st – 19th April 2021). This is clearly seen with a lower LA_{eq} during the first deployment, than the second, when the school was open.

The NDSI analysis is an attempt to quantify the ratio of biophony (natural noise) to anthropophony (human-generated noise). As a reminder, a lower NDSI means that the noise is considered more anthropogenic. When considering the percentage change in NDSI after the implementation of the LTN restrictions (Table 8), It can be seen that all sensors but one show a more biotic noise characteristic after the implementation of the LTN. The sensor that shows a more anthropogenic noise characteristic after the LTN intervention, Barracks Lane, is the control location, which shows an 18 % more anthropogenic noise character.

The timeseries of the daily means of NDSI for the sensors located at the traffic filters (Fig. 20) shows that the NDSI is more consistently biotic (higher value) after the implementation of the LTN with the exception of one day (21st May 2021). The NDSI for the sensors located inside the LTN (Fig. 21) shows that, similarly to the filter sensors, there is a clear pattern of more biotic noise after the implementation of the LTN – although with occasional days where more anthropogenic noise is recorded. For the sensors located at the possible displacement sites (Fig. 22), similar NDSIs are seen for the Ahlul Bhayt and Oxford Road sensors, while the Barracks Lane (control) sensor shows a clear decrease in NDSI (more anthropogenic noise) after the implementation of the LTN. This is likely to be because the Barracks Lane sensor is located next to a school, and through the study period, the school Easter holidays took place (1st – 19th April 2021). This is clearly seen with a higher NDSI during the first deployment, than the second, when the school was open.

When comparing the NDSI values between the Temple Cowley LTN locations (Fig. 3) and other locations around Oxford (Fig. 5), it can be seen that, overall, the NDSI values in Temple Cowley (a mostly residential area) are far more biotic than those at the other (mostly very traffic-oriented locations) in Oxford. The lowest values recorded (i.e. most anthropogenic noise) were for the sensor located on the A34, which would be expected, and this demonstrates the value of the NDSI methodology for the study of urban noise in this example.

When considering the effect of excluding the anomalies (Table 9 for acoustic energy, Tables 10-13 for LA_{eq}, L_{10}, L_{50}, and L_{90}, and Table 14 for NDSI), it can be seen that both of the displacement sites now display a small increase in acoustic energy (compared to only one previously), as does the control location, and now two LTN sensors also show an increase. However, the very large increase in noise at Kirby Place is now not shown, with a much more probable rise shown following the exclusion of the anomaly (in this case an electric saw). The Filter sensors are still showing a decrease in noise. With regards to LA_{eq}, L_{10}, L_{50}, and L_{90}, the data is broadly unchanged here –L_{10} and L_{50} being entirely unchanged with (as might be expected given that anomalies were defined as being unusually loud noises) and minor variations seen in LA_{eq} and L_{90}. NDSI is broadly unchanged – with almost all sensors showing an increase in biotic noise after the implementation of the LTN restrictions – 10 % if aggregated across sensors. These results should be treated with caution, however, as further anomalies would need to be investigated to really get a rigorous set of excluded data, and this was not undertaken.

In the absence of other studies into the impact of an LTN on noise pollution it is impossible to know whether the results in this paper are generalisable to other LTNs or a specific to the intervention studied. However, the results do agree with (Yang et al., 2022) assuming that the correlations between air and noise pollution seen in (Khan et al., 2018) hold. It is interesting to note that the LA_{eq} and acoustic energy data show different results. This reveals that even if there is a reduction in noise from an LTN, the perception by residents may not always reflect this. Further study to investigate this difference in other examples would be of interest. However, it is clear that, in this study, there has been a clear increase in biotic sounds after the implementation of the LTN – and generalising this finding with future studies would be of great benefit.

5. Conclusions

Eight noise monitors have been successfully deployed throughout Temple Cowley, a residential area of Oxford, UK over a period spanning the introduction of a LTN there. The results show the power of this network approach for noise monitoring, in this case, following a substantial traffic intervention for acoustic energy, LAeq, and source apportionment via the NDSI approach.

The results show that, in terms of acoustic energy, almost all of the locations experienced a reduction in noise after the introduction of the LTN. One location, Oxford Road, a possible displacement location, experienced an 8 % increase. In terms of LAeq, an alternative measure, there was a mixed set of results with quieter periods (L_{10}) showing a decrease in noise and louder periods (L_{90}) showing an increase.

In terms of the source apportionment of the sound, all locations except for the control location (Barracks Lane) experienced more biotic sounds after the introduction of the LTN. This shows that the introduction of the LTN has reduced the amount of noise which is believed to be human generated (anthropogenic) everywhere measured by a total of about 10 % (with larger decreases in the LTN). It should be noted that correlation is not necessarily causal – and there may be other effects (seasonal influences and the impact of the COVID-19 restrictions for example) that may be responsible for this, but this observational study cannot decouple these.

However, there were some anomalies identified within the acoustic energy data, and upon detailed listening to these a first pass was made at excluding them. This did not affect the source apportionment (NDSI) but made the acoustic energy picture much more mixed. A more robust (and resource intensive) approach to anomaly exclusion will be required to really understand this and have confidence in the data under this approach. Timeseries analysis of the data provides additional detail, which can be used further to ascertain diurnal trends and further to understand anomalies.

What this study cannot do, because of the design of the experiment where sensors are attached to street furniture, is understand whether the magnitude of the changes in acoustic energy (or NDSI) is large enough to have an impact on people's health. However, given the changes shown in this work, such as follow-on study including measures of residential noise exposure in absolute terms would clearly be beneficial. In addition, there remains scope to integrate noise and air quality data to advance current knowledge of environmental health impacts of urban traffic interventions.

This study is, to the authors' knowledge, the first deployment of low-cost audio sensors in an urban environment for this type of study. In addition, it is the first use of the NDSI for noise source apportionment to measure noise after an urban policy intervention, so new approaches have been developed and tested. By comparing the data from this study, with temporally-overlapping data from more traffic-oriented locations in Oxford, the utility of the NDSI methodology for noise source apportionment in the urban environment is demonstrated in this case. Overall, this project has shown the AudioMoth device, and the associated analysis developed, to be a very useful technique for understanding the impacts of introducing an LTN on noise pollution and could be used, in the future, for developing a statistical model for estimating changes in noise levels caused by a LTN intervention.

Funding

This research was funded by The Natural Environment Research Council, grant number NE/V010360/1.

CRediT authorship contribution statement

Felix C.P. Leach: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jingyuan Yang:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Varun Shankar:** Formal analysis, Data curation. **Stuart Cole:** Resources, Methodology, Data curation, Conceptualization. **Katie Parnell:** Resources, Project administration, Methodology, Investigation, Conceptualization. **Mani Entezami:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Suzanne E. Bartington:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would also like to thank the study steering committee, in particular John Gulliver, for their technical contributions and administrative support. Oxford City Council and Oxfordshire County Council are thanked for advice and support in deployment of several sensors. The following individuals and organisations hosting or facilitating the hosting of sensors: the Department of Engineering Science, University of Oxford; a resident on St Clement's Street; a resident on Westminster Way; Exeter College, University of Oxford; Keble College, University of Oxford; and Wytham Woods, University of Oxford.

References

Benocci, R., Bisceglie, A., Angelini, F., Zambon, G., 2020. Influence of traffic noise from local and surrounding areas on high-rise buildings. Appl. Acoust. 166, 107362 https://doi.org/10.1016/j.apacoust.2020.107362.

Brown, A.L., De Coensel, B., 2017. "Noise event measures for road traffic.". Proceedings of ACOUSTICS 2017 Perth: Sound, Science and Society - 2017 Annual Conference of the Australian Acoustical Society, AAS 2017.

Cai, Y., Zijlema, W.L., Sørgjerd, E.P., Doiron, D., de Hoogh, K., Hodgson, S., Wolffenbuttel, B., Gulliver, J., Hansell, A.L., Nieuwenhuijsen, M., Rahimi, K., Kvaløy, K., 2020. Impact of road traffic noise on obesity measures: Observational study of three European cohorts. Environ. Res. 191, 110013 https://doi.org/10.1016/j.envres.2020.110013.

Department for the Environment, Food, and Rural Affairs, 2019. Clean Air Strategy 2019. https://www.gov.uk/government/publications/clean-air-strategy-2019.

Department for Transport, 2020a. Active travel fund: local transport authority allocations. 2020. Accessed 11 August 2024; Available from: https://www.gov.uk/government/publications/emergency-active-travel-fund-local-transport-authority-allocations.

Department for Transport, 2020b. Gear Change: A bold vision for cycling and walking. https://assets.publishing.service.gov.uk/media/5f1f59458fa8f53d39c0def9/gear-change-a-bold-vision-for-cycling-and-walking.pdf.

European Environment Agency, 2019. Environmental noise in Europe — 2020. EEA Report No 22/2019. https://www.eea.europa.eu/publications/environmental-noise-in-europe.

Fredianelli, L., Carpita, S., Bernardini, M., Del Pizzo, L.G., Brocchi, F., Bianco, F., Licitra, G., 2022. Traffic Flow Detection Using Camera Images and Machine Learning Methods in ITS for Noise Map and Action Plan Optimization. Sensors 22 (5), 1929.

Fuks, K.B., Weinmayr, G., Basagaña, X., Gruzieva, O., Hampel, R., Oftedal, B., Sørensen, M., Wolf, K., Aamodt, G., Aasvang, G.M., Aguilera, I., Becker, T., Beelen, R., Brunekreef, B., Caracciolo, B., Cyrys, J., Elosua, R., Eriksen, K.T., Foraster, M., Fratiglioni, L., Hilding, A., Houthuijs, D., Korek, M., Künzli, N., Marrugat, J., Nieuwenhuijsen, M., Östenson, C.-G., Penell, J., Pershagen, G., Raaschou-Nielsen, O., Swart, W.J.R., Peters, A., Hoffmann, B., 2017. Long-term exposure to ambient air pollution and traffic noise and incident hypertension in seven cohorts of the European study of cohorts for air pollution effects (ESCAPE). Eur. Heart J. 38 (13), 983–990. https://doi.org/10.1093/eurheartj/ehw413.

Fuller, S., Axel, A.C., Tucker, D., Gage, S.H., 2015. Connecting soundscape to landscape: Which acoustic index best describes landscape configuration? Ecol. Ind. 58, 207–215. https://doi.org/10.1016/j.ecolind.2015.05.057.

Gulliver, J., Morley, D., Vienneau, D., Fabbri, F., Bell, M., Goodman, P., Beevers, S., Dajnak, D., Kelly, F.J., Fecht, D., 2015. Development of an open-source road traffic noise model for exposure assessment. Environ. Model. Softw. 74, 183–193. https://doi.org/10.1016/j.envsoft.2014.12.022.

Halonen, J.I., Hansell, A.L., Gulliver, J., Morley, D., Blangiardo, M., Fecht, D., Toledano, M.B., Beevers, S.D., Anderson, H.R., Kelly, F.J., Tonne, C., 2015. Road traffic noise is associated with increased cardiovascular morbidity and mortality and all-cause mortality in London. Eur. Heart J. 36 (39), 2653–2661. https://doi.org/10.1093/eurheartj/ehv216.

Halperin, D., 2014. Environmental noise and sleep disturbances: A threat to health? Sleep Sci 7 (4), 209–212. https://doi.org/10.1016/j.slsci.2014.11.003.

Hill, A.P., Prince, P., Piña Covarrubias, E., Doncaster, C.P., Snaddon, J.L., Rogers, A., 2018. AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment. Methods Ecol. Evol. 9 (5), 1199–1211. https://doi.org/10.1111/2041-210X.12955.

Hill, A.P., Prince, P., Snaddon, J.L., Doncaster, C.P., Rogers, A., 2019. AudioMoth: A low-cost acoustic device for monitoring biodiversity and the environment. HardwareX 6, e00073.

Jephcote, C., Hansell, A.L., Adams, K., Gulliver, J., 2021. Changes in air quality during COVID-19 'lockdown' in the United Kingdom. Environ. Pollut. 272, 116011 https://doi.org/10.1016/j.envpol.2020.116011.

Kasten, E.P., Gage, S.H., Fox, J., Joo, W., 2012. The remote environmental assessment laboratory's acoustic library: An archive for studying soundscape ecology. Eco. Inform. 12, 50–67. https://doi.org/10.1016/j.ecoinf.2012.08.001.

Khan, J., Ketzel, M., Kakosimos, K., Sørensen, M., Jensen, S.S., 2018. Road traffic air and noise pollution exposure assessment – A review of tools and techniques. Sci. Total Environ. 634, 661–676. https://doi.org/10.1016/j.scitotenv.2018.03.374.

Kumar, P., Omidvarborna, H., Valappil, A.K., Bristow, A., 2022. Noise and air pollution during Covid-19 lockdown easing around a school site. J. Acoust. Soc. Am. 151 (2), 881–887. https://doi.org/10.1121/10.0009323.

Laverty, A.A., Goodman, A., Aldred, R., 2021. Low traffic neighbourhoods and population health. BMJ 372, n443. https://doi.org/10.1136/bmj.n443.

Lawrence, B.T., Hornberg, J., Haselhoff, T., Sutcliffe, R., Ahmed, S., Moebus, S., Gruehn, D., 2022. A widened array of metrics (WAM) approach to characterize the urban acoustic environment; a case comparison of urban mixed-use and forest. Appl. Acoust. 185, 108387 https://doi.org/10.1016/j.apacoust.2021.108387.

Liu, Q., Liu, Z., Jiang, J., Qi, J., 2020. A new soundscape analysis tool: Soundscape Analysis and Mapping System (SAMS). Appl. Acoust. 169, 107454 https://doi.org/10.1016/j.apacoust.2020.107454.

Marquart, H., Ueberham, M., Schlink, U., 2021. Extending the dimensions of personal exposure assessment: A methodological discussion on perceived and measured noise and air pollution in traffic. J. Transp. Geogr. 93, 103085 https://doi.org/10.1016/j.jtrangeo.2021.103085.

Oxfordshire County Council, 2021. Agenda for Delegated Decisions by Cabinet Member for Environment (including Transport) on Thursday, 21 January 2021, 10.00 am. https://mycouncil.oxfordshire.gov.uk/documents/g6041/Printed%20minutes%20Thursday%2021-Jan-2021%2010.00%20Delegated%20Decisions%20by%20Cabinet%20Member%20for%20Environment%20.pdf?T=1.

Pritchett, R., Bartington, S., Neil Thomas, G., 2024. Exploring expectations and lived experiences of Low Traffic Neighbourhoods in Birmingham, UK. Travel Behav. Soc. 36, 100800 https://doi.org/10.1016/j.tbs.2024.100800.

Pujol, R., 2009. and P. Minary, Journey into the World of Hearing. Accessed; Available from: http://www.cochlea.org/en/hear/human-auditory-range.

Singh, A., Bartington, S.E., Song, C., Ghaffarpasand, O., Kraftl, M., Shi, Z., Pope, F.D., Stacey, B., Hall, J., Thomas, G.N., Bloss, W.J., Leach, F.C.P., 2022. Impacts of emergency health protection measures upon air quality, traffic and public health: evidence from Oxford, UK. Environ. Pollut. 293, 118584 https://doi.org/10.1016/j.envpol.2021.118584.

Smith, R.B., Fecht, D., Gulliver, J., Beevers, S.D., Dajnak, D., Blangiardo, M., Ghosh, R.E., Hansell, A.L., Kelly, F.J., Anderson, H.R., Toledano, M.B., 2017. Impact of London's road traffic air and noise pollution on birth weight: retrospective population based cohort study. BMJ 359, j5299. https://doi.org/10.1136/bmj.j5299.

Sustrans, 2020. *What is a low traffic neighbourhood?* 2020. Accessed: 26 May 2022; Available from: https://www.sustrans.org.uk/our-blog/get-active/2020/in-your-community/what-is-a-low-traffic-neighbourhood.

van Kempen, E., Babisch, W., 2012. The quantitative relationship between road traffic noise and hypertension: a meta-analysis. J. Hypertens. 30 (6).

Wang, J., Li, C., Lin, Y., Weng, C., Jiao, Y., 2023. Smart soundscape sensing: A low-cost and integrated sensing system for urban soundscape ecology research. Environ. Technol. Innov. 29, 102965 https://doi.org/10.1016/j.eti.2022.102965.

Welch, P., 1967. The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. IEEE Trans. Audio Electroacoust. 15 (2), 70–73. https://doi.org/10.1109/TAU.1967.1161901.

Yang, X., McCoy, E., Hough, K., de Nazelle, A., 2022. Evaluation of low traffic neighbourhood (LTN) impacts on NO2 and traffic. Transp. Res. Part D: Transp. Environ. 113, 103536 https://doi.org/10.1016/j.trd.2022.103536.