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Capturing the spatial and temporal variability of urban noise: do low-cost sensors offer a step towards higher resolution noise monitoring?

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Abstract
Populations are being exposed to environmental noise at levels that impact on both mental and physical health, with knock-on effects on productivity and economic performance. Current assessments of exposure are often based on noise levels at building façades, derived from sound propagation models and are usually limited to long-term average noise levels for periods of the day, night or over 24 hours (e.g. L_{den}). There is a particular lack of information on variations in noise throughout the diurnal cycle and over long time periods. In this study, we deployed 14 low-cost recorders to gather high resolution data on urban noise levels and compared results with those from a conventional noise propagation algorithm. Daily L_{Aeq} and diurnal variations in hourly L_{Aeq} showed considerable variation in space and time with the middle of the day generally noisiest. Some of these patterns were well captured by the propagation model although it tended to underestimate noise levels from all sources. Although more work is needed, we suggest that well-placed sensors have the potential to enhance exposure assessments e.g. on minor roads and where traffic is not the major noise source.

Keywords: noise pollution, CNOSSOS-EU, road traffic noise, noise façade, exposure

1 Introduction

Millions of people worldwide are currently being exposed to harmful levels of noise. In Europe alone, this figure is estimated to be around 100 million people [1]. There is growing evidence linking long-term noise exposure to auditory and non-auditory health effects, and premature death [2]. Given its pervasive nature and the extent of population affected, noise pollution is considered a major public health concern. The 2002/49/EC Environmental Noise Directive (END) was implemented with the overall aim of establishing a common framework to assessing exposure to environmental noise within the European Union (EU) [3]. Under the Directive, Member states are required to produce strategic noise maps to determine population's exposed to environmental noise and to apply action plans in areas that need further management for noise reduction. Since the implementation of the END, several steps have been taken towards the assessment and management of noise. Among these, was the establishment of a standardised framework, common noise assessment methods (CNOSSOS-EU) for the generation of strategic noise maps across EU Member States.

Noise mapping is undoubtedly a crucial tool in epidemiological studies, to visualise and determine who is being exposed to harmful levels of noise pollution. However, the way these strategic noise maps are produced might be underestimating noise levels at the building facades, and therefore the percentage of people being exposed. This is mainly because the methods used to calculate and assess noise levels at the building facades are based on sound propagation algorithms, heavily driven by annual traffic flows, the assumed primary source of noise. Underestimation might result from the lack of traffic counts in residential areas, or the prevalence of source noise other than traffic. Health study models are only as good as the data used to derive them, and yet limited work has been done on the total noise levels from all sources measured at buildings. There is a particular lack of information on variations in noise throughout the diurnal cycle and over longer time periods, and how these affect people. This emphasizes the need to investigate the benefit of using sensors capable of capturing noise from all sources, alongside noise propagation models.

In this study, we deployed 14 low-cost noise sensors across the city of Southampton, UK, to gather high temporal resolution data on variations in urban noise levels, and compared the results with a version of the CNOSSOS-EU noise modelling framework [3,4] and an alternative model[5]. We were motivated by considering the feasibility of improving exposure assessment at the façades of the buildings, by combining low-cost sensor data with the outputs from a CNOSSOS-EU noise model. This may be especially important at locations where temporal variability in noise cannot be captured by noise propagation models due to the poor availability of traffic flow data (e.g. in residential areas), and where the main source of noise is not traffic related. Although traffic is often the major source of noise within urban environments, especially along major roads and centres of activity, urban noise results from the combination of a multitude of sounds and noises from sources other than traffic

2 Methods

The AudioMoth [6] is a low-cost, open-source acoustic monitoring device, originally designed for monitoring wildlife. It uses a EFM32 Gecko processor, analog MEMS microphone and pre-amplifier with adjustable gain to record audio from 8000 to 384,000 samples per second onto micro SD card. Prices start at around £53 each and therefore offer potential for creating a network of audio samplers to be used as the basis for estimating spatially distributed sound energy levels. In this study, AudioMoth recorders were programmed to gather 60-second samples of acoustic data every 10 minutes from 9 May 2020 to 31 October 2020, either on or near the facades of 14 dwellings in the city of Southampton, UK. The devices used a sampling rate of 48 kHz, 16-bit depth and saved data as uncompressed wav files on SD cards. Data were collected every day except when batteries and SD cards were changed or the devices failed (due to water damage). The devices were calibrated using pure tones in deci-decades from 100 Hz to 19.95 kHz against a Brüel & Kjær Class 1 sound level meter (type 2250) in the anechoic chamber at the University of Southampton. Using the calibration data, finite impulse response filters were developed to correct the frequency responses before passing through Fast Fourier Transforms to extract A-weighted sound pressure levels (dBA).

To remove contamination due to wind and rain, recording times were matched against imputed meteorological data from two weather stations (src_id 25727 from MIDAS https://catalogue.ceda.ac.uk/uuid/dbd451271eb04662beade68da43546e1 and "Southampton Weather" from https://wow.metoffice.gov.uk/). Any recordings made when average wind speed exceeded 5 ms^{-1} or when rain was detected at either station were removed from analysis. The processed 60-second dBA (hereafter, "instantaneous") readings were binned into hours and the means calculated using logarithmic averaging. This process corrected for differences in sampling intensity caused by the removal of samples due to poor weather. This baseline dataset (hourly L_{Aeq}) was then used to calculate the standard acoustic measures L_{day}, $L_{evening}$, L_{night}, L_{A16} and L_{den}. To provide an indication of data variability within hourly L_{Aeq} values, we calculated 95% inter-quantile ranges from the raw data available for each hour. For simplicity, consideration is limited here to L_{Aeq} measures over various time periods, although other metrics could easily be derived from the wav recordings and may be more appropriate for spatio-temporal analysis. Using L_{Aeq} is advantageous because it is often the only metric type output from noise propagation models and this facilitates comparison between measured and modelled noise levels.

Modelled road-transport noise estimates were calculated in accordance to the 'Common framework for noise assessment methods' (CNOSSOS-EU) framework, developed by the European Commission (2002/49/EC). Annual Average Daily Traffic (AADT) counts and traffic speeds enter the model, along with information relating to the surface roughness of land cover, building heights, wind profiles and average temperatures in 2020. Topological information was derived from the Ordnance Survey (OS) MasterMap product, and hourly meteorological information at three stations within 30 km of Southampton city centre were accessed from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database. AADT counts by vehicle class for the entire UK road network in 2013 [7], were locally scaled to 2020 levels using the Department for Transport road traffic statistics at 46 sites across Southampton. CNOSSOS-EU model algorithms were implemented in PostgreSQL, following the protocol described in Morley *et al*. [4]. L_{day} was also extracted from a land-use regression type machine-learning model [5] for comparison.

3 Results

In total, 261,182 sound recordings were made which reduced to 173,325 for analysis after matching with the weather data (i.e. about one third were removed due to wind and rain). The instantaneous dBA measurements ranged from 32.2 to 85.0 dBA, with an average of 50.0 dBA. The lower value probably reflects the floor level of the AudioMoth as deployed, since the lower measurement limit in the anechoic chamber was estimated as 33.0 dBA from the calibration data. Hourly L_{Aeq} ranged from 37.3 to 71.0 dBA, with an average of 54.0 dBA. As the data were gathered during 2020 when the city was in lockdown due to the coronavirus pandemic, we ran simple regressions to check for long-term trends in daily L_{Aeq} and therefore whether combining the data across months would be safe. Significant trends were detected at only half the sites (Table 1) and changes were negative at three and positive at four locations. Among the sites with significant trends over longer runs of data (>150 days), changes were <4 dBA. We therefore do not consider it problematic to combine the data across months for the analyses here.

Table 1. Linear trends in daily L_{Aeq} over the period of deployment.
Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Site	Start date	End date	Days deployed	Linear trend	dBA change over deployment
A	13/05/2020	20/06/2020	38	NS	
B	10/05/2020	31/10/2020	174	NS	
C	12/05/2020	28/06/2020	47	*	-5.0
D	10/05/2020	31/10/2020	174	***	-3.4
E	10/05/2020	31/10/2020	174	*	-2.8
F	17/06/2020	31/10/2020	136	***	4.3
G	11/05/2020	31/10/2020	173	***	2.7
H	17/05/2020	31/10/2020	167	NS	
I	16/05/2020	31/10/2020	168	NS	
J	11/05/2020	18/06/2020	38	NS	
K	13/05/2020	31/10/2020	171	***	3.7
L	11/05/2020	31/10/2020	173	*	-2.6
M	11/06/2020	18/06/2020	7	NS	
N	09/05/2020	31/10/2020	175	NS	

Plots of daily L_{Aeq} across the days of the week (Fig. 1) showed considerable variation both spatially and temporally. Apart from the obvious difference that some sites were noisier than others, the degree of variation between days also differed among sites with some (e.g. A and K) showing little difference and others (E, L and M) suggesting a weekend effect. Propagation models usually do not consider weekend differences. The vertical bars in Fig. 1 also indicate differences between L_{Aeq} on individual days of 20 dBA or more, suggesting potentially marked variations in exposure and annoyance.

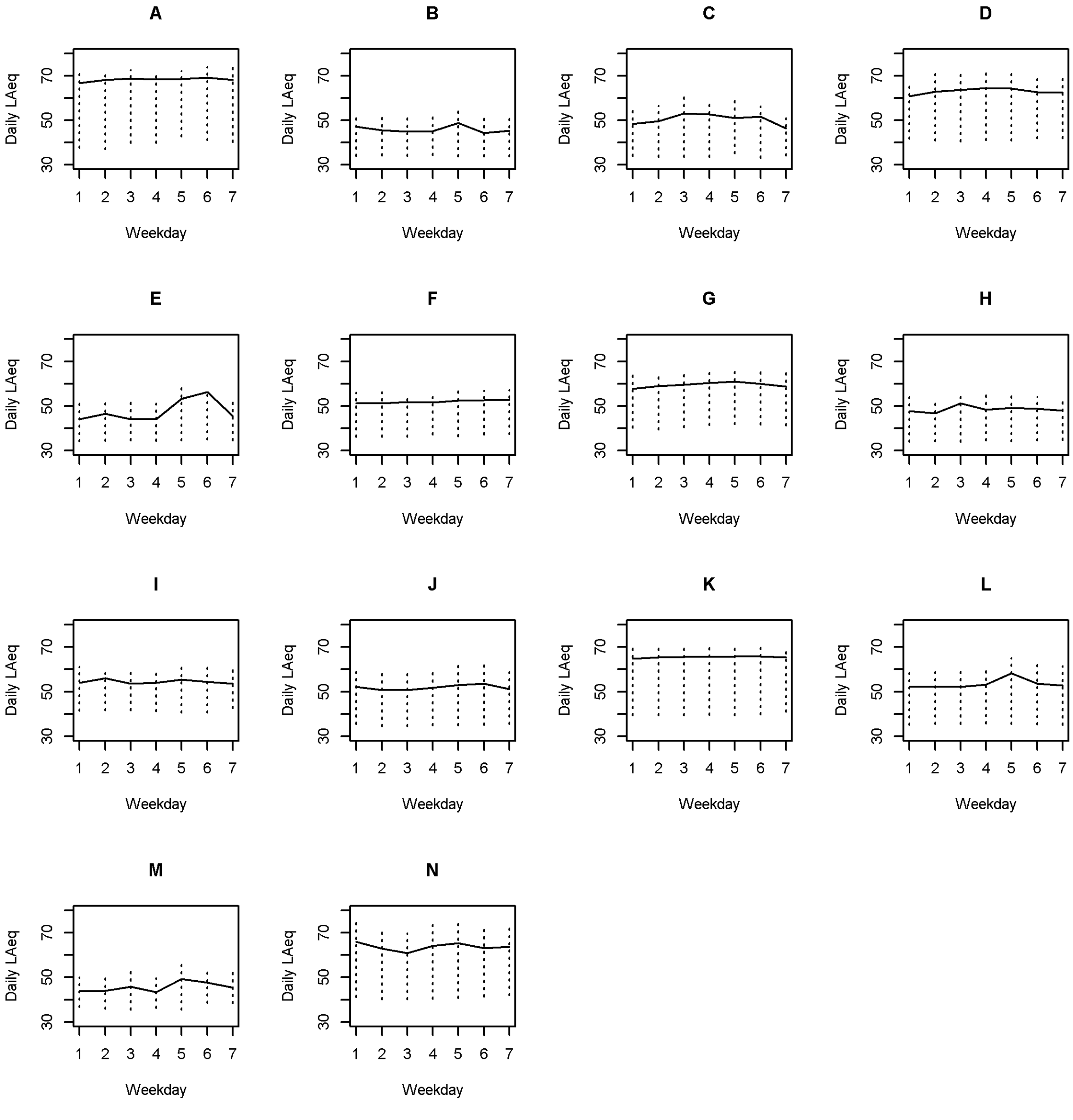

Figure 1. Variations in daily L_{Aeq} with day of the week (Monday = day 1) across the 14 sites. The vertical dotted lines show the 95% interquantile ranges of the data values.

Diurnal variations in hourly L_{Aeq} noise levels differed strongly among sites (Fig. 2), although all suggested at least some tendency for the middle of the day to be the noisiest time. However, the patterns of variability indicated various groupings across the city, such as the broad plateau at sites A, G and K, contrasting with the sharper peaks at C and E. Some of these patterns were captured remarkably well by the CNOSSOS-EU model (e.g. A, B, D, G, H, I and K) although the elevation of the lines (dashed red v. solid black) frequently differed with the CNOSSOS-EU model usually underestimating the noise levels. There was also marked variation within individual hours across the sites. For example, whereas sites A, K and N showed the greatest variation at night-time, the middle of the day was more variable at sites C and L. The overall impression from Fig. 2 is that many sites displayed hourly L_{Aeq} levels above the thresholds recommended by WHO [8] at least some of the time.

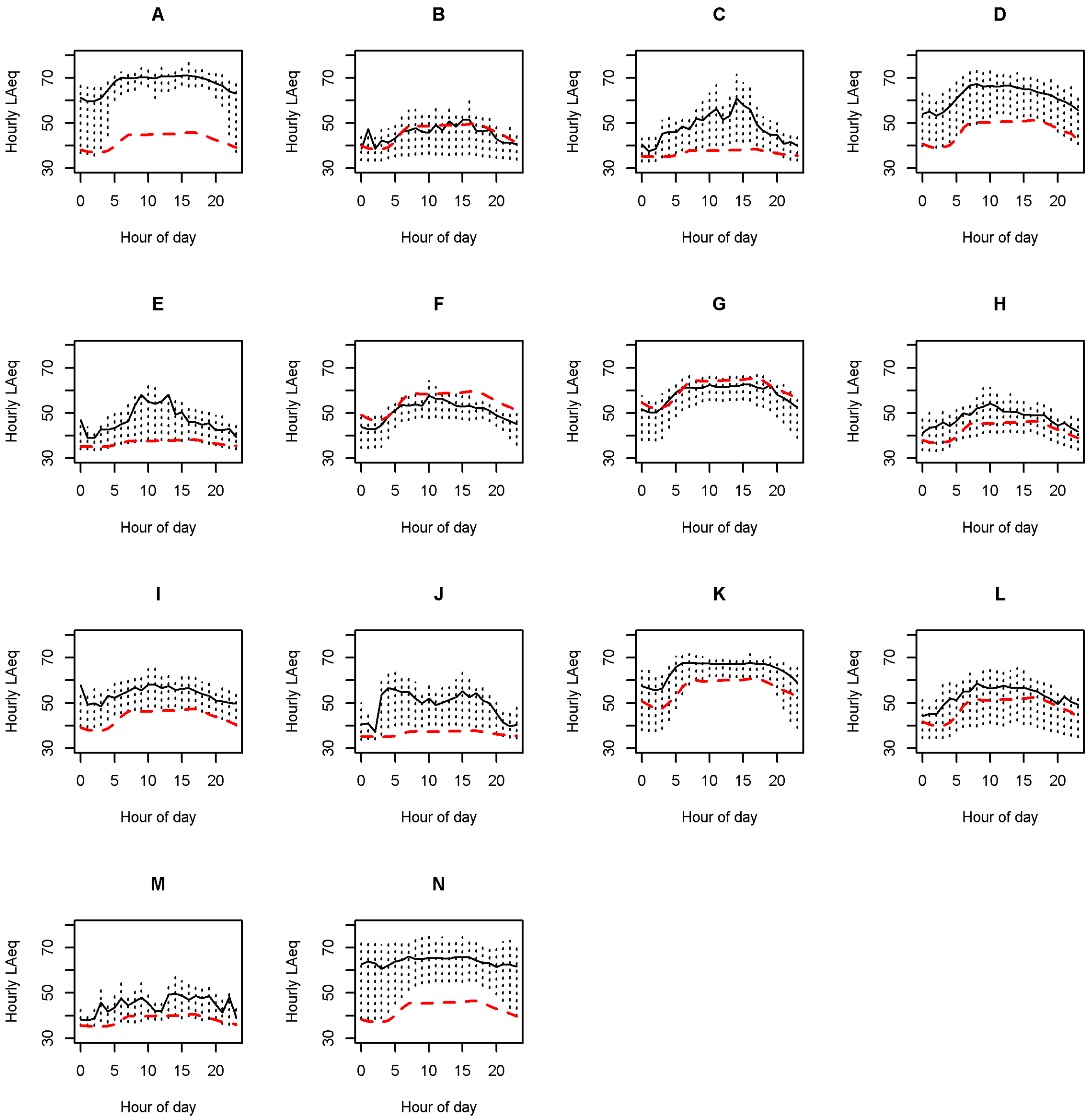

Figure 2. Variations in hourly L_{Aeq} among the 14 sites (solid black line) with the vertical dotted lines show the 95% interquantile ranges of the data values. The dashed red line shows the output from the CNOSSOS-EU model.

Among all the noise metrics examined, the field values exceeded the modelled values with bias typically between 7 and 11 dBA (Table 2). This strongly suggests that in this city, propagation models based on traffic counts markedly underestimate noise levels from all sources (see Conclusions for possible explanations). The machine-learning model [5] showed a smaller difference than the CNOSSOS-EU model [4] from the sensor data, slightly overestimating L_{day}, but this perhaps is not surprising since it was also derived from field measurements. Even so, it only weakly matched the rank order of measured values from this study, suggesting scope for improvement.

Table 2. Comparison of estimated dBA metrics for the 14 sites in Southampton based on field measurements and the CNOSSOS-EU model [4] and Machine-Learning (ML) [5]. Bias [9] estimates by how much the measured values exceed the modelled values (mean ± 95% confidence interval).

Site	L_{day}			$L_{evening}$		L_{night}		L_{Aeq16}		L_{den}	
	Measured	CNOSSOS-EU	ML model	Measured	CNOSSOS-EU	Measured	CNOSSOS-EU	Measured	CNOSSOS-EU	Measured	CNOSSOS-EU
A	70.4	45.2	60.8	67.1	42.1	65.2	39.0	69.8	44.6	72.9	45.5
B	48.6	49.0	50.8	43.8	45.5	43.3	41.4	47.9	48.4	50.8	48.1
C	55.0	38.0	55.6	43.4	36.5	44.4	35.5	53.8	37.7	54.2	41.5
D	65.8	50.6	60.7	60.5	47.3	58.5	42.6	65.0	50.0	66.9	49.5
E	53.7	37.9	54.2	43.5	36.4	43.2	35.5	52.5	37.5	53.0	41.5
F	54.5	58.8	63.0	48.9	55.1	48.5	50.8	53.6	58.1	56.2	57.5
G	61.7	64.5	60.4	59.0	60.3	56.0	56.1	61.2	63.7	63.9	62.8
H	51.1	45.7	55.5	45.2	42.3	45.5	39.0	50.2	45.1	53.0	45.5
I	56.5	46.7	55.4	51.5	43.5	52.9	40.1	55.7	46.1	59.8	46.7
J	52.6	37.5	52.1	45.9	36.2	52.5	35.4	51.6	37.2	58.5	41.4
K	67.4	60.1	59.8	64.8	56.6	62.4	52.2	66.9	59.5	70.1	59.0
L	56.6	51.7	69.6	51.3	48.1	50.3	43.5	55.7	51.0	58.2	50.4
M	47.3	40.0	57.7	46.7	37.8	43.0	36.0	47.1	39.5	50.7	42.2
N	65.3	45.8	62.6	62.5	42.7	63.0	39.4	64.7	45.2	69.7	45.9
Bias		9.6 ± 5.04	-0.8 ± 3.76	7.4 ± 4.77		10.2 ± 4.79		9.4 ± 4.98		11.4 ± 4.70	

4 Conclusions

To our knowledge, this is one of the first applications of the AudioMoth [6] for the monitoring and assessment of anthropogenic noise in urban areas. AudioMoth devices have many of the characteristics recommended for low cost noise sensors [10] and with appropriate frequency response correction (necessary to calculate dBA), we encourage their application in further studies.

Our preliminary analysis of the noise levels recorded at building facades and the output of the CNOSSOS-EU model shows both marked similarities in some respects and strong differences in others. The key to moving forward is to understand how these similarities and differences arise, and therefore what can be done to ensure noise assessments capture population exposure to both source-specific noise and total noise. The similarities in the patterns of diurnal variations between measured and modelled noise levels is encouraging. Since the primary determinant of this pattern in the CNOSSOS-EU model is traffic counts and traffic speed, this might suggest that the changes in measured noise similarly reflect traffic flows. However, the elevations of the curves in Figure 2 indicate substantial differences in the levels of measured and modelled noise. A possible explanation might be that traffic was not the dominant source of noise in the city, yet the pattern of change might suggest it is. Both the CNOSSOS-EU model and the recordings were made during the coronavirus lockdown when flights, trains and ship movements were minimal, and many businesses were closed. Given this, it is not easy to identify an alternative dominant noise source. Indeed, if traffic noise is not the primary source, relying solely on traffic counts to model noise might lead to underestimations of exposure. Further work is needed to assess the spatial variations in the coincidence of the curves in Figure 2 because this might indicate the cause of the differences. Traffic counts are not available for all roads and the methods used to extrapolate them to all roads may introduce unknown errors into noise models. Well-placed sensors have the potential to capture differences across space and time that can enhance exposure assessments from existing noise propagation algorithms through some form of integrated model.

While it may be argued that sensors are advantageous because they capture noise from all sources, this can also be a disadvantage as not all sounds are equally annoying. For example, a bird singing next to a recorder may dominate a recording and produce a high L_{Aeq} yet result in minor annoyance with no harm to anyone nearby. Such events, however, tend to be episodic and should not impact longer term noise measurements from well-placed sensors. A key issue in any noise exposure assessment is that summary indices such as equivalent noise levels conceal a multitude of issues. As Wunderli *et al.* [11] highlight, "*...[L_{Aeq}] is the best of all the bad noise exposure metrics*". Even so, we know far too little about how long term exposure to intermittent noise affects people compared with short-term exposure at higher volumes with the same L_{Aeq}. Full spectrum sound recordings from sensors offer the potential for the development of far more appropriate indices through post-processing than noise propagation models can currently provide. More studies are needed to look at the utility of low-cost sensors to supplement noise models (e.g. in epidemiological studies for sensitivity analysis on the relationship of changes in noise levels and health conditions), or provide alternative exposures where total noise levels are of interest.

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