Noise and air pollution during Covid-19 lockdown easing around a school site\textsuperscript{a})

Prashant Kumar,\textsuperscript{b)} Hamid Omidvarborna,\textsuperscript{c)} Abhijith Kooloth Valappil,\textsuperscript{d)} and Abigail Bristowe\textsuperscript{e)}

Global Centre for Clean Air Research (GCARE), Department of Civil and Environmental Engineering, Faculty of Engineering and Physical Sciences, University of Surrey, Guildford GU2 7XH, United Kingdom

ABSTRACT:
During the Covid-19 pandemic and resulting lockdowns, road traffic volumes reduced significantly leading to reduced pollutant concentrations and noise levels. Noise and the air pollution data during the lockdown period and loosening of restrictions through five phases in 2021 are examined for a school site in the United Kingdom. Hourly and daily average noise level as well as the average over each phase, correlations between noise and air pollutants, variations between pollutants, and underlying reasons explaining the temporal variations are explored. Some strong linear correlations were identified between a number of traffic-sourced air pollutants, especially between the differently sized particulates PM$_1$, PM$_{2.5}$, and PM$_{10}$ ($0.70 < r < 0.98$) in all phases and an expected inverse correlation between nitrogen dioxide (NO$_2$) and ground-level ozone (O$_3$) ($-0.68 < r < -0.78$) as NO$_2$ is a precursor of O$_3$. Noise levels exhibit a weak correlation with the measured air pollutants and moderate correlation with meteorological factors, including wind direction, temperature, and relative humidity. There was a consistent and significant increase in noise levels ($p < 0.01$) of up to 3 dB with initial easing, and this was maintained through the remaining phases. © 2022 Acoustical Society of America. https://doi.org/10.1121/10.0009323

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I. INTRODUCTION
> Road traffic is the main source of air and noise pollution in urban environments causing negative impacts on human health, especially on children in school environments (Khan et al., 2018). Many schools are located near busy roads providing access to school children, teachers, staff, and parents. Queues of idling cars during drop-off and pick-up hours emit disproportionately higher pollutants adjacent to schools, exposing the school children to air and noise pollution (Ibrahim and Richard, 2000; Kumar et al., 2020a). As a chronic stressor, noise has the potential to disrupt executive functioning in school children, which includes working memory, decision making, and self-regulation of emotions/behaviours (Belojevic et al., 2012). According to the European Environment Agency (2020), approximately 82 million people living in urban areas in Europe are exposed to noise pollution (Lden $\geq 55$ dB). Hänninen et al. (2014) found transportation noise (along with secondhand smoke and radon) second only to air pollution with respect to the environmental burden of disease in six countries (Belgium, Finland, France, Germany, Italy, and the Netherlands). Their study included only severe sleep disturbance (with a fairly low onset threshold of 35 dB), and heart disease from road traffic noise, the annoyance which has by far the largest and most widespread impact according to the World Health Organization (2018), was excluded. As transportation is a source of both air and noise pollution, research has explored correlations between air and noise pollution sourced from traffic. This has been done for two key reasons: first, identifying the variability in correlations between air and noise pollution is essential to understand their impacts on human health, and second, to explore the potential of proxy measures for the more difficult to measure pollutants. Examples include Davies et al. (2009) finding a moderate correlation between noise and NO$_2$ (0.53) and NOx (0.64) during a 2-week measurement period, Fecht et al. (2016) reporting moderate correlations between modelled noise and air pollution (0.34–0.55), and Khan et al. (2020) using an aggregate modelling approach and finding a weak to moderate correlation between noise and air pollutants (0.01–0.42) in two Danish cities. Dekoninck et al. (2015), however, find noise to be a good proxy for black carbon. A comprehensive review by Khan et al. (2018) showed a substantial variation in air and noise pollution correlation (0.05–0.74) among studies. Although moderate to strong correlations (up to 0.74) have been reported between noise pollution and some of the traffic-related air pollutants, a solid conclusion cannot be drawn. The number of road lanes, vehicles, presence of major intersections, and the spatial unit could influence the degree of correlation and variability in readings (Fecht et al., 2016; Hänninen et al., 2014).

\textsuperscript{a)}This paper is part of a special issue on COVID-19 Pandemic Acoustic Effects.
\textsuperscript{b)}ORCID: 0000-0002-2462-4411.
\textsuperscript{c)}ORCID: 0000-0003-2865-5319.
\textsuperscript{d)}ORCID: 0000-0002-3678-3516.
\textsuperscript{e)}Electronic mail: a.l.bristow@surrey.ac.uk, ORCID: 0000-0002-9757-4929.
Although traffic is known as one of the main sources of noise pollution for schools in urban areas (Bhang et al., 2018; Clark and Paunovic, 2018; Minichilli et al., 2018; Zijlema et al., 2020), the pandemic and resulting lockdowns in many countries have provided a unique opportunity to observe significant changes in travel behaviour and impacts on noise and air pollution (Bar, 2021; Kumar et al., 2020b; Yang et al., 2021). The significance of this study is to continuously collect noise data on an hourly basis at a school site in a trafficked urban area, which is correlated with the environmental variables and air pollution data. This study aimed to investigate the changes in noise and air pollution levels at a primary school site in Guildford, UK, during 2021 through a series of lockdown eases. We first explored the levels of noise pollution in each phase. Then, we investigated the strength of any correlations between noise and air pollution at the school site during a subsequent easing of restrictions and possible ways forward for noise abatement and control.

II. METHODOLOGY

A. Study site

The Sandfield Primary School is located on a heavily trafficked conjunction of two busy roads in Guildford which exacerbates the air quality issues and may create air pollution hotspots at the school premises. This study is a collaboration between the school and Guildford Living Lab (GLL) at the Global Centre for Clean Air Research (GCARE) at the University of Surrey, UK. The collaboration builds upon community engagement and citizen-science activities on air quality with schools in Guildford (see Kumar et al., 2020c; Mahajan et al., 2020). Figure 1 shows the location of the school and the pollution monitor with respect to the roads. The location was determined by the need to identify a site inside the school grounds giving the smallest distance from both roads and the junction, and a requirement to be mounted in a safe place and face towards the South (as it is powered by a fixed solar panel). Apart from the capital and

| Sensor | Type | Range | LOD | Precision | Accuracy |
|--------|------|-------|-----|-----------|----------|
| Noise  | Omnidirectional mic | 35–100 dB | 20–20 000 Hz | >0.8 | 1 dB |
| PM     | Optical particle counter | 0–100 000 (PM$_{10}$) | 0 µg m$^{-3}$ | 0.9 | 5 µg m$^{-3}$ |
|        |                  | 0–150 000 (PM$_{2.5}$) | (PM$_{10}$ and PM$_{2.5}$) >0.9 | 4 ppb |
|        |                  | 0–250 000 (PM$_{10}$) | PM$_{10}$ > 0.85 | 5 ppb |
|        | All in µg m$^{-3}$ |                      |                |         |
| NO$_2$ | Electrochemical | 0–20 000 ppb | <1 ppb | >0.85 | 4 ppb |
| O$_3$  | Electrochemical | 0–20 000 ppb | <1 ppb | >0.9 | 5 ppb |
| CO     | Electrochemical | 0–1 000 000 ppb | <50 ppb | >0.8 | 20 ppb |

*Obtained from the manufacturer’s specification datasheet under standard test conditions (20 °C and 80% of RH) in the absence of any interfering gasses.
*Reported after extensive global colocation experiments against the reference.
*Best accuracy without any local scaling and calibration against the reference.
*Average noise is calculated using all noise samples over the period.
operating cost associated with each unit, performing single point monitoring to gain more understanding about the situation is quite common in research-led studies.

The United Kingdom (UK) was under stringent lock- down measures from January 2021 (beginning of Phase 1). These measures included: (i) stay at home, with limited exceptions; (ii) school closures; and (iii) closure of non-essential shops and services (Prime Minister’s Office, 2021). Some schools were open for children of key workers, including this one, but with small numbers of pupils and staff on site. On March 8 (beginning of Phase 2), schools reopened but other measures stayed in place. Subsequent changes on April 12 (beginning of Phase 3) saw the opening of non-essential retail and hospitality venues serving outside and on May 17 (beginning of Phase 4), indoor hospitality and larger outdoor gatherings including some sporting events with spectators. Finally, lockdown measures were removed from July 19 (beginning of Phase 5). Therefore, we defined five phases of lockdown ease: covering January 1 to March 7 (Phase 1); March 8 to April 11 (Phase 2); April 12 to May 16 (Phase 3); May 17 to July 18 (Phase 4); and July 19, 2021 onwards (Phase 5), accordingly.

B. Instrumentation

The wireless air quality compact system called AQMesh (AQMesh, 2020) is an ambient air quality multisensor unit capable of measuring particulate matter (PM) of different size fractions (PM1, PM2.5, and PM10), electrochemical gas sensors [nitrogen dioxide (NO2), carbon monoxide (CO), and ozone (O3)], air pressure (accuracy of 5 mb), temperature (accuracy of 2 °C, relative humidity (accuracy of 5%), and an omnidirectional microphone for noise measurement (accuracy of 1 dB). For the noise analysis, daily average (Lday) (7 AM to 7 PM), evening average (Levening) (7 PM to 11 PM), and night average Lnight (11 PM to 7 AM) of noise level during different phases for weekdays and weekends are defined accordingly. The specification of the main sensors is listed in Table I. The versions of the AQMesh platform for gas protocol and particle protocol were 5.1 and 3.0, respectively. The NO2 sensor is designed to reject O3 and thus, minimise O3-NO2 cross sensitivity issues. The recorded raw data were uploaded via a Subscriber Identity Model (SIM) card through General Packet Radio Services (GPRS) communication to a cloud database. While the AQMesh can provide 15 min averaged data, a standard averaging period of 1 h during the period of January to October 2021 is reported here to reduce random noise. Hourly and daily average equivalent noise (L_{eq,1h} and L_{eq,24h}) were downloaded from this server for data analysis.

The meteorological data were obtained from Royal Horticultural Society Garden Wisley, United Kingdom [National Grid Reference (NGR) = 5062E 1579 N; altitude = 38 m], which is the closest station to Guildford. All datasets were screened for quality control and quality assurance. The deployed AQMesh pod was calibrated by the
manufacturer (Environmental Instruments Ltd, Stratford-upon-Avon, UK) prior to setup and left in operation for a minimum of 2 weeks for stabilisation as advised. The AQMesh exported file comes with a status tag; only data points with valid tags were retained here. Additionally, all negative, N/A, and out-of-spec entries (see Table I) were visually removed from the clean file. Although AQMesh is not designed for regulatory purposes, studies have shown its reliable performance in relative terms (Castell et al., 2018; Margaritis et al., 2021; Wahlborg et al., 2021). The cleaned dataset was analysed using the open-source Openair tools (Carslaw and Ropkins, 2012) in the statistical computing software, R (R Development Core Team, 2013).

III. RESULTS

A. Noise pollution

Aggregate data for Great Britain shows road traffic levels running at 60%–70% of “normal” levels before March 8 (far higher than in the 2020 first lockdown periods) with goods vehicles at or above normal levels and car use at 50%–60%. After March 8, levels increase to 80% in March and 90% in April approaching normal levels by May and June. It is worth noting that within this car, traffic is running below comparator year levels (90%+) while light and heavy good vehicles are above at around 110% and this continues into October 2021. Interestingly, the largest gap between the comparator year and 2021 is at weekends where traffic levels are consistently higher than they were in a “normal” year; this is most clear for heavier vehicles running 120%–130% of normal—especially on Sundays (Department for Transport, 2021). We, therefore, expect to see some changes in local traffic levels and behaviours, especially at a newly reopened school site. The level of average noise pollution is plotted under different phases of lockdown eases, including $L_{\text{eq,1h}}$ (Fig. 2; both on weekdays and weekends), $L_{\text{eq,24h}}$ (Fig. 3), daily $L_{\text{day, evening}}$, and $L_{\text{night}}$ (Fig. 4), and the overall average of each phase (Fig. 5). The data in Fig. 2 seem to support this premise with a small but consistent increase in noise levels.
especially after Phase 1. On an hourly basis, as shown in Fig. 2, the relative difference started to increase from morning hours around daily commuting time (at around 6:00 am) and continued into the evening (at around 8:00 pm). Figure 2 indicates a similar pattern at weekends, which is in line with the national traffic data. During the lockdown ease period (Phase 2–5), the noise level exceeded by up to 15 dB the recommended average exposure limit of 53 dB Lden (World Health Organization, 2018). As our noise measure is not weighted, the exceedance is probably higher. This is a repeated trend, which is also visible in $L_{eq,24h}$ (Fig. 3) as well as $L_{day}$, $L_{evening}$ and $L_{night}$ (Fig. 4). As shown in Fig. 3, starting from Phase 2, school reopening on March 8, $L_{eq,24h}$ (95% confidence interval) reached to almost the same level as upcoming phases, which indicated that further loosening of restrictions did not make a significant change.

The average noise level in the monthly plot (Fig. 3) reveals a steady growth in the fitted line. The average noise levels before and after March 8 were found to be statistically significantly different ($p < 0.01$) using a pairwise t-test. It can be concluded that the school reopening on March 8 was also significant in permitting more freedom of movement for many parents. Despite the comparatively low noise pollution in Phase I, the least variation in $L_{day}$ is detected, starting from the school reopening phase, as shown in Figs. 2 and 4. Notably, the modest difference in $L_{eq,24h}$ during latter phases, see Fig. 5, was extended to weekends, when only $<2$ dB difference was recorded, as shown in Table II. Such noise pollution from road traffic could result in adverse health effects to both school children and nearby residents.

### B. Correlations between pollutants

The Pearson correlation coefficients ($r$), as plotted for all phases in Fig. 6, show a strong linear correlation between some traffic-sourced pollutants, especially amongst PM$_1$, PM$_{2.5}$ and PM$_{10}$ ($0.70 < r < 0.98$) with that between PM$_1$ and PM$_{2.5}$ always above 0.90. The inverse NO$_2$–O$_3$ correlation ($r = -0.68$ to $-0.78$) is expected as NO$_2$ is one of the precursors of ground-level O$_3$. However, there was a time (Phase 4) when no correlation was found between NO$_2$–O$_3$.

Other correlations between air pollutants vary from moderate to weak either positive or negative correlations ($r < 0.70$), which are shown by moderate/light cool/warm colours and smaller font size. Noise has moderate correlations with wind direction and temperature (positive correlation) and relative humidity (negative correlation), while there is no evident correlation with any of the air pollutants. Moderate to weak positive correlations ($0.29 < r < 0.53$) between noise and O$_3$ were observed. The relatively weak

| Day     | Phase      | $L_{eq,24h}$ | $L_{day}$ | $L_{evening}$ | $L_{night}$ |
|---------|------------|-------------|----------|---------------|-------------|
| Weekday | Phase I    | 58.0 ± 5.8  | 62.8 ± 1.9 | 58.7 ± 2.3    | 51.4 ± 3.4  |
|         | Phase II   | 60.1 ± 6.6  | 65.9 ± 1.0 | 60.5 ± 1.2    | 52.7 ± 3.4  |
|         | Phase III  | 60.5 ± 7.3  | 66.8 ± 1.2 | 61.2 ± 2.0    | 53.3 ± 2.2  |
|         | Phase IV   | 60.4 ± 6.9  | 66.4 ± 1.5 | 60.8 ± 2.1    | 52.9 ± 2.0  |
|         | Phase V    | 59.9 ± 6.5  | 65.9 ± 1.1 | 60.8 ± 1.2    | 52.4 ± 1.7  |
| Weekends| Phase I    | 56.4 ± 5.7  | 60.6 ± 2.3 | 58.1 ± 2.8    | 50.9 ± 5.0  |
|         | Phase II   | 58.5 ± 6.0  | 63.4 ± 1.5 | 59.3 ± 1.2    | 52.3 ± 4.3  |
|         | Phase III  | 59.5 ± 6.7  | 65.5 ± 1.7 | 60.1 ± 2.0    | 51.8 ± 2.5  |
|         | Phase IV   | 59.5 ± 6.4  | 65.0 ± 1.5 | 61.5 ± 3.4    | 51.9 ± 1.0  |
|         | Phase V    | 58.8 ± 5.8  | 63.8 ± 1.2 | 60.0 ± 1.8    | 52.4 ± 1.8  |

FIG. 6. (Color online) Correlation matrix among hourly $L_{eq,1h}$, meteorological parameters and air pollutants during the sampling period (January to end of October 2021) at the school site. The intensity of shading represents the strength of the correlation. Very weak correlations ($R < 0.1$) are shown in white and smaller font size.
correlations between noise and other air pollutants are probably due to the monitoring station being some distance from the roadside. Further investigations are warranted to also explore the impact of other factors, such as the meteorological parameters (e.g., wind speed and direction) or traffic flow conditions in future studies. For example, Weber and Litschke (2008) also concluded that the homogeneous spatial distribution of noise as compared to the inhomogeneous distribution of PMs could lead to weaker correlations. Correlations between noise and air pollutants have been found to be higher along highways and major roads, roads with multiple lanes, and sampling very close to roads (r = 0.53 between L_{eq,5min} and NO_{2}; Davies et al., 2009), which was not the case here.

IV. CONCLUSION

The study showed a noticeable increase in noise levels in the school site, Guildford, UK, most notably after the March 8 reopening of schools. The data show that the level of noise pollution in the school site exceeds the World Health Organization guideline of 53 dB L_{den}. It is likely that the elevated noise pollution is due to an increase in road vehicles after loosening the restrictions. As lockdown eased, noise levels increased by up to 3 dB throughout the week, suggesting the potential for greater noise disturbance at weekends than pre-pandemic. Significant correlations were found between traffic-related air pollutants, especially the different sized particulates. Published literature has reported variations from modest correlation to strong correlations (0.05 and 0.74) between noise pollution and some of the traffic-related air pollutants (Khan et al., 2018). Correlations are usually higher when measured close to the source (i.e., roadside) and weaken with distance. Moreover, unlike noise, the dispersion of air pollutants from the source into the surrounding areas is also driven by atmospheric dispersion conditions, such as wind speed and wind direction. A relatively weaker correlation observed in our case reflects these generic features observed elsewhere as our monitoring was carried out ~20–30 m away from the source to explain the correlations observed in our case.

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