Received: 21 July 2023 | Revised: 24 May 2024 | Accepted: 18 June 2024

DOI: 10.1002/met.2220

RESEARCH ARTICLE

Meteorological Applications
Science and Technology for Weather and Climate
Open Access
RMetS

What can we learn from nested IoT low-cost sensor networks for air quality? A case study of $PM_{2.5}$ in Birmingham, UK

Nicole Cowell | **Clarissa Baldo** | **Lee Chapman** | **William Bloss** | **Jian Zhong**

School of Geography, Earth and Environmental Sciences, University of Birmingham Ringgold Standard Institution, Edgbaston, Birmingham, UK

Correspondence
Nicole Cowell, Centre for Environmental Policy, Imperial College London, South Kensington, London, UK.
Email: n.cowell@imperial.ac.uk

Funding information
Natural Environment Research Council, Grant/Award Numbers: NE/S003487/1, NE/T001976/1; Engineering and Physical Sciences Research Council, Grant/Award Number: EP/P016782/1

Abstract
Low-cost sensing and the Internet of Things (IoT), present new possibilities for unconventional monitoring of environmental parameters. This paper describes a series of intersecting networks of particulate matter sensors that were deployed across the Birmingham conurbation for a 12-month period. The networks consisted of a combination of commercially available sensors and University developed sensors. Data from these networks were assimilated with data from a third-party Zephyr deployment, along with the DEFRA AURN network, which was hosted on an open-source online platform. This nesting of sensor networks allowed for new insights into sensor performance, including the accuracy of a large network to detect regional concentrations and the number of sensors needed for effective monitoring beyond indicative measurements. After comprehensive data validation steps, the sensors were shown to perform well during co-location with reference instrumentation (exhibiting slopes of 0.74–1.3). The sensors demonstrated good capability of detecting temporal patterns of regional $PM_{2.5}$ with the mean of the entire sensor network recording an annual mean $PM_{2.5}$ concentration within 0.2 μgm^{-3} of the regulatory network annual mean observation. Network-derived statistics for estimating urban background concentrations compared to a reference site increase in-line with the number of sensors available, however when assessing this for near-source concentrations the importance of sensor location rather than the number of sensors is highlighted. Overall, the network provided novel insights into local concentrations, detecting similar hotspots to those identified by a high-resolution model. The increased spatial coverage afforded by the sensor network has the potential to support higher resolution evaluation of models and provide unprecedented spatial evidence for air pollution management interventions.

KEYWORDS

ADMS-Urban dispersion model, Internet of Things (IoT), local particulate concentrations, low-cost sensors, particulate matter, sensor networks

1 | INTRODUCTION

1.1 | Clean Air Zones and air quality management

Birmingham is a large city in the United Kingdom, with the wider conurbation being home to a population of approximately 1.14 million people (Birmingham City Council, 2021b). Like many cities, it faces the challenge of improving its air quality for public health benefit, and in 2017 was highlighted as one of the first wave of cities in the United Kingdom to act to improve its roadside NO_2 concentrations by implementing air quality charging schemes (DEFRA, 2017).

Low emissions and Clean Air Zones (CAZ) are areas of action to improve air quality by targeting vehicular emissions, either by charging fees or by enhanced traffic management to reduce emissions (Williams et al., 2022). With the aim of reducing NO_2 exceedances, the CAZ is one of the most prominent measures recently introduced in Birmingham. Introduced on June 1, 2021, the CAZ applies to all roads inside of the inner ring road (excluding the ring road itself), 24 h a day, 365 days a year (Figure 1). The ring road (A4540) forms a circle around the city centre zone, drivers are charged a daily fee dependent on their vehicle engine standard, vehicles with diesel engines of Euro 6 or better or petrol engines of Euro 4 or better are exempt from charges (Birmingham City Council, 2018). The daily fee is £8 per day for cars, taxis, vans (LGVs) and £50 a day for coaches, buses and HGVs (Birmingham City Council, 2021a).

The approach is not unique to Birmingham. Other UK cities such as Bath, Bradford and Portsmouth already have a CAZ and, at the time of writing, there are plans for CAZs in Bristol, Manchester, Sheffield and Tyneside. However, not all CAZs are the same. Birmingham has a

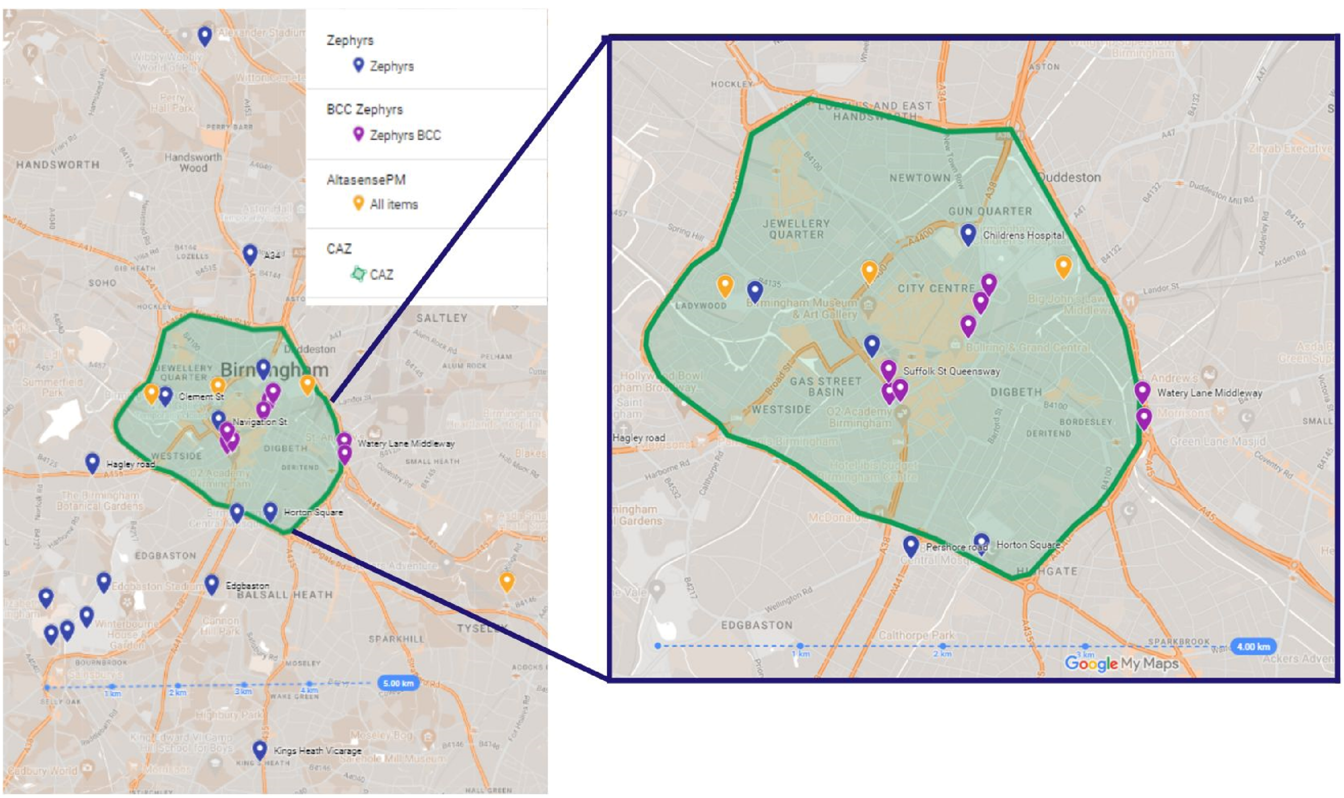

FIGURE 1 Map showing Birmingham Clean Air Zone and the location of the various sensors across Birmingham. It shows the CAZ area in green and captures the majority of the city centre attractions, shopping and the CBD. The A38 is a key road that runs through the city joining onto the M6 motorway—A major access route to the region.

class D CAZ meaning charges apply to all vehicle types that do not meet engine standards (GOV.UK, 2022). Other CAZ types may opt to only target certain vehicle types such as buses and lorries rather than cars. London also has a very similar scheme. The Ultra-Low Emission Zone or ULEZ was introduced in 2019 and expanded in 2021 and charges vehicles for entering based on the same Euro emissions standards as the Birmingham CAZ (Transport for London, 2022).

Initial studies on CAZ and low emissions zones demonstrate mixed results for improving air quality. Whilst generally successful at reducing their target pollutant of NO_2, their impact on PM has been found to be limited (Williams et al., 2022). For example, (Ma et al., 2021) study on the London ULEZ reported $PM_{2.5}$ responses from −6% to 4% change across roadside and background monitoring sites, with aggregated concentration change to $PM_{2.5}$ within the ULEZ deemed insignificant. This is important as $PM_{2.5}$ is a pollutant of increasing concern. As vehicle fleets shift towards lower-emission combustion engines, hybrid engines and electric vehicles the contribution of gaseous emissions from exhausts will reduce, but the impact of this transition on non-exhaust emissions of particulates will be limited (Harrison et al., 2021). Exposure to particulates has been linked to a number of health excess risks with links to; cardiovascular disease, respiratory disease, lung cancer, diabetes and adverse birth outcomes (Feng et al., 2016; Lu et al., 2015) In line with other studies, an initial analysis at the 6-month anniversary of the Birmingham CAZ reported a 13% reduction in average (defined in this paper as mean) NO_2 but no evidence of a reduction in $PM_{2.5}$ (Birmingham City Council, 2022). This report recognized that further data analysis was needed, which would now be possible by consulting a range of low-cost sensor networks now operational in the city. These provide a novel opportunity to evaluate concentrations at higher resolutions than traditional monitoring networks, providing an understanding of the exposure of particulates on the population alongside the impacts of management techniques.

1.2 | IoT low-cost PM sensors

IoT sensors can take many forms ranging from commercial sensing units that come with a range of functionality, customer support and online data hosting to basic sampling units that require more manual support from the consumer. Prices can vary reflective of this range in product, from <£50 per unit for the most basic of samplers to £1000–5000 for the more complex devices. Many units come with additional costs that will also need to be considered including but not limited to; communication subscriptions such as cellular connection, servicing and replacement parts, online data storage and hosting and staffing needs. Low-cost sensors are growing in popularity, within both the research, government and local authority air quality community. The small stature, real-time measurement, portability and reduced cost of these units compared to traditional regulatory monitoring efforts make air quality sampling more accessible and are leading to an increase in the spatial resolution of air quality measurements (Zhang et al., 2018).

For particulate matter, many low-cost sensing units use an Optical Particle Counter (OPC) to measure particulates. OPCs use light scattering technology to detect particles being pulled through the unit and are commonly featured within low-cost sensor literature (Zhang et al., 2018). There are uncertainties introduced by environmental variables, namely temperature and relative humidity (RH). RH is particularly important to consider, due to the hygroscopic nature of particles, which varies with particle composition and can affect how particles are detected in the sampling chamber by affecting their size as particles swell when absorbing water. Literature has shown that with calibration against regulatory instrumentation and correction factors that account for RH, sensors are able to generate indicative particulate concentrations (Cowell et al., 2022; Crilley et al., 2018; Magi et al., 2020; Malings et al., 2019).

The PlantowerPMS5003 is a commonly used OPC within low-cost sensor units. It can be found in various instruments, including PurpleAir units and Earthsense Zephyrs. Previous work has demonstrated successful calibration and correction of humidity of this sensor for indicative measurement (Cowell et al., 2022, 2023). These studies use a multi-linear model developed against a FIDAS reference instrument to apply a correction dependent on sensor detected humidity. This method reported Pearson's R against a reference instrument of 0.81–0.91 and strong intersensory correlations which is important when wanting to deploy sensors as a network for spatial analysis (Cowell et al., 2022). However, the literature also reports challenges with this sensor being unable to effectively measure PM10 due to laser geometry and particle loss within the sampling chamber (Hagan & Kroll, 2020; Kuula et al., 2020; Ouimette et al., 2022), and more recent literature has recommended that the Plantower PMS5003 is not suitable for measuring coarse PM (Molina Rueda et al., 2023). The Zephyr unit which utilizes the PMS5003 has received MCERTS status for the indicative monitoring of $PM_{2.5}$ and PM_{10} (Earthsense, 2022a). In line with this certification, in February 2023 they updated their undisclosed calibration method, data used in this study was downloaded before these updates. However, due to the high levels of uncertainty found in scientific research evaluating the Plantower PMS5003 sensors, this paper does not use PM_{10} data and instead focuses on $PM_{2.5}$.

1.3 | Sensor networks

Despite the growing popularity with both local authorities and researchers alike, low-cost sensor networks for air quality have a tendency to be isolated deployments, generated and maintained by their own interested party with the focus of their own monitoring goal. Examples of such networks include the SAMHE project in UK schools (SAMHE Project, 2022), Coventrys' Earthsense Zephyr deployment (Earthsense, 2019) and the Aeroqual AQY network in California (South Coast AQMD, 2023). This can lead to multiple overlapping deployments which, if used together, could enhance hyperlocal understanding of air quality as well as provide an excellent opportunity to explore both the integrity and utility of data from such networks.

However, there are inevitable issues that arise from ad-hoc approaches to nested deployments of sensors. Data sharing can be an issue with data being hosted and collected by different bodies using different protocols and metadata standards (Topping et al., 2021). A further challenge is how to integrate and manage this data. Whilst there is an abundance of air quality data available, this is often of contrasting quality and standards ranging from regulatory networks to citizen science. Added to this, low-cost measurements and data can be presented in a confusing way making it hard for non-specialist users to understand (Kosmidis et al., 2018). Here, online platforms and big data storage offer potential solutions to this problem by allowing data from various sources to be automatically pulled onto an online platform for viewing and analysis (Chang et al., 2018).

This paper uses a cloud-based approach to collate the data from new deployments of IoT sensors across Birmingham nested within pre-existing IoT deployments and standard deployed instrumentation. The aim is to bring together a much wider selection of the available data to not only assess the particulate concentrations across the city but also to assess the wider applications of low-cost sensor data to increase understanding of variability in particulate concentrations across an urban environment.

2 | METHODS

2.1 | Data and instrumentation

This paper utilizes the Birmingham Urban Observatory, an online cloud-based platform that, amongst a range of other data, hosted an integrated array of AQ sensors. This included data from two university-based deployments of air quality sensors (AltasensePM—an in-house designed PM sensor and Earthsense Zephyrs), as well as Zephyr data from a network maintained by Birmingham City Council and standard observations from the DEFRA AURN. For this paper, 15-min mean data from the Urban Observatory online platform was used.

2.1.1 | AltasensePM

AltasensePM are an IoT-enabled particulate matter sensor. The AltasensePM connects a Plantower PMS5003 and SHT21 temperature/humidity sensor with an Arduino MKRFox1200 microcontroller via a custom PCB to connect the sensor to the Sigfox network. As previously stated, the PMS5003 is an optical particle counter that converts scattered light into a voltage and then particle count via an undisclosed algorithm (Sayahi et al., 2019). The PMS5003 is manufacturer-stated to report particles with a minimum particle diameter of 0.3 μm although a recent study has reported detecting particles smaller than this with the PMS5003 (Ouimette et al., 2022; Yong & Haoxin, 2016) and the sensor's inability to reliably measure coarse particles (Molina Rueda et al., 2023). The manufacturer reports uncertainty of $\pm 10\ \mu gm^{-3}$ for concentrations 0–100 μgm^{-3} and ±10% for concentrations 100–500 μgm^{-3} (Yong & Haoxin, 2016). AltasensePM make an instantaneous measurement every 15 min after running for 1 min to stabilize the fan and sensor. AltasensePM are co-located for ~8 weeks against a FIDAS at the Birmingham Air Quality Supersite (BAQS) urban background site for calibration and are corrected for the impact of humidity in real-time online via the Urban Observatory platform. Full details of the calibration can be found in Cowell et al. (2022).

2.1.2 | Zephyr

Zephyrs, by Earthsense, are a commercial sensing unit that can measure both gaseous and particulate pollutants and can be main or solar powered. The sample rate of the Zephyr is 10 s with an upload rate of 15 min in normal operation, reducing to 1 min sample rate with 60 min upload rate in winter mode which is utilized when there is low solar insolation during winter to extend the battery power within the unit (Earthsense, 2022b). Like AltasensePM, Zephyrs utilize a PlantowerPMS5003 but with an undisclosed algorithm to measure particulates and report estimate accuracy of 5 μgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} and limits of detection of 0.2, 1.3, and 1.4 $\mu g\ m^{-3}$, respectively (Earthsense, 2022b). Ideally, the solar panel powering the Zephyr will face due south with no obstructions or shadow as recommended by the supplier, however in a city centre this was sometimes challenging due to building/tree shadow and existing infrastructure limitations combined with limited access to alternative locations to install the units on. Therefore, some of the Zephyrs in the observatory experienced power outages/ data loss in the winter. Zephyrs undergo manufacturer calibration via co-location against a GRIMM EDM180 in an urban background environment in Derby, UK. Derby is a small city in the Midlands of the United Kingdom approximately ~35 miles from Birmingham. This suggests the Zephyr should be suitable for sampling in Birmingham as the literature suggests the best practice is calibrating sensors in an environment similar to that in which they will be deployed in, to allow calibrations to capture the impact of particulate composition on performance (Crilley et al., 2018; Zusman et al., 2020).

2.1.3 | DEFRA AURN

Data from the DEFRA AURN network were also hosted as third-party data on the Birmingham Urban Observatory. The Automatic Urban and Rural Network (AURN) is the largest network of regulatory-grade instruments in the United Kingdom, with current active sites and data spanning back to 1972. The goal of the network is to check for statutory air quality standards are being met and data is used for compliance reporting as set out under the Air Quality Standards Regulations 2010. Two sites were hosted on the platform, namely Ladywood and the A4540 (DEFRA, 2023a). These sites provide hourly average particulate data with the $PM_{2.5}$ data being used for this study. Ladywood is classified as an urban background site, situated in the east of the city centre region on a local residential street behind a small school (DEFRA, 2023b). Importantly, the Ladywood location is within the CAZ. The A4540 roadside site is classified as an urban traffic site and is located on the westerly stretch of the city's ring road, a major traffic route around the city centre (DEFRA, 2023b). The A4540 site is outside of the CAZ.

The DEFRA AURN locations provide hourly average data which was used in this study. Data from both low-cost sensor types are analysed using hourly means generated from the 15-min reported values, after validation explained in the next step. Due to the challenges around measuring PM_{10} outlined in Section 2.4, this analysis focuses on $PM_{2.5}$ from all sensors in the network (Zephyrs & AltasensePM). A further reference site on the University campus, BAQS, is also used within the study. This is an urban background site located outside of the CAZ on the University Campus to the south of the city centre. The instrument at BAQS used for comparing PM measurements is the PALAS FIDAS. R studio was used to analyse data via the OpenAir package (Carslaw, 2019; Carslaw & Ropkins, 2012).

2.2 | Sampling locations

Across Birmingham, a total of 28 locations were included in the network at various stages across the year (01.06.21–31.05.22) of sampling used in this project. A map of the sensor locations is presented in Figure 1. Twenty-four of the locations were monitored by Zephyrs (8 BCC Zephyrs, 16 UoB Zephyrs) with 4 monitored by AltasensePM. Thirteen locations were located inside the CAZ and 15 were outside of the CAZ. For analysis, sensors were grouped into site types using the (Department of Environmental Food and Rural Affairs, 2023) definitions of site type for the AURN as guidance for defining the sites. The majority of sites (19) were classified as urban traffic types and urban background was the second most prominent site type (6). There were also limited examples of urban industrial (1) and suburban background (2) sites from locations driven by work with partners outside of the city centre region. Most units were installed at heights of 2.5–3 m above ground level, so far as the infrastructure would allow. This height prevents tampering whilst sampling at a height similar to human exposure. Sensors were considered semi-mobile; this means units can be redeployed with relative ease to suit sampling needs. This is reflective in the sampling of this project, where some units were moved throughout the year to capture specific sites of interest.

As this paper takes advantage of a range of coinciding and separate sensor deployments, each with their own foci and goals, the rationale underpinning the choice of sampling locations is varied. For sensors deployed by the University team, were part of the WM-Air and Birmingham Urban Observatory projects. These projects had varied sampling agendas, including working with local stakeholders to support targeted monitoring at events and areas of interventions and more generic ambient sampling to assess PM concentrations across the city. However, the choice of locations was limited somewhat by restricted permissions to access street furniture for installing sensors, particularly at roadside environments (including around the CAZ). Table S1 outlines the rationale behind sensor locations of units deployed by the University of Birmingham managed sensors within the study. Birmingham City Council had its own rationale for its monitoring sites, which mostly targeted roadside environments on major transport routes. Therefore, these coinciding networks do not represent a planned spatial distribution across the city, however, they do represent a situation that is reflective of the sampling occurring in many urban centres. It is not uncommon for local authorities, citizen scientists, researchers and other interested parties to have overlapping air quality sampling where each user is deploying with their own goals. By combining the wealth of air quality data from different sources like this, there is room for opportunistic analysis of air quality in a city and this is a methodology that could be easily replicated in many cities to enhance air quality understanding by simply collaborating or data sharing. Whilst there are limitations, with sampling locations not being evenly distributed across the city, there are benefits in that these sampling networks are capturing some of the concerns of local stakeholders and therefore data analysis from these sites has room to support impactful change if interpreted carefully.

2.3 | Data validation

Best practice to ensure trust in low-cost sensor networks data is via thorough evaluation and data validation in real-world scenarios (Mahajan et al., 2021). Unlike regulatory instruments which have extensive certification and procedures to ensure that data quality standards are met, there is not set practice for validating low-cost sensor networks (Fishbain et al., 2017). (Lu et al., 2021; Mousavi & Wu, 2021) both propose quality control methods for PurpleAir PM sensors (that also utilize the PMS5003) that capture the low frequency of change, values greater than the sensor's effective measurement range, and data loss/completeness. They also propose removing outliers that deviate far from a time-averaged median, as these are likely not reflective of the true concentrations at the sensor site. (Bush et al., 2022) recommend a series of meteorological filters based on evidence of contexts in which sensor performance may be affected, including extreme temperatures and low humidity (which is not frequently experienced in this study location). From these suggestions, there are some clear traits of low-cost sensor data that need to be addressed through a validation method; sensor completeness, low frequency of change, extreme outlier values and impact of external factors. Therefore, this study utilized a 4-step data validation (drawn from the above literature) outlined below.

Step 1—75% completeness criteria 3 or more measurements an hour (sensors measure every 15 min), 18 h or more coverage a day, 23 days or more coverage a month cumulative. Hours/days/months that fell outside of this criteria were discarded.

Step 2—Meteorology filter Keep data that falls within the confines of manufacturer specifications $-10°C < t < 35°C$ and $RH > 35\%$ using temperature and humidity data from the Birmingham Air Quality Supersite (BAQS) located on the University of Birmingham campus.

Step 3—Static data Remove data with 5 h moving standard deviation = 0.

Step 4—Exclude outliers Exclude data based on a threshold defined from 3× the Median Absolute Deviation as shown below in Equations (1) and (2) drawn from (Lu et al., 2021), where X_i is the PM2.5 reading of the sensor, $\tilde{X}$ is the median of X_i in a month and $b = 1.4826$ (a set constant).

$$\mathrm{MAD} = b * \mathrm{median}\left(X_i - \tilde{X}\right), \quad (1)$$

$$X_i < \tilde{X} - 3 * \mathrm{MAD} \text{ or } X_i < \tilde{X} + 3 * \mathrm{MAD}. \quad (2)$$

After these steps, there were 121,037 data points retained (79.1% of the total hourly mean data points from the year long period were retained). The percentage of total data points from the year period retained after validation ranged from 36% to 96% by location, with the mean location retaining 76% of data after validation.

2.4 | High-resolution air quality model

The final part of the evaluation process was to overlay sensor data with a high-resolution air quality map of $PM_{2.5}$ (at 10 m × 10 m resolution) using ArcMap. The air quality map was derived from a local scale ADMS-Urban dispersion model, which takes into account explicit point and road sources, and grid sources (e.g., energy, industry, residential, waste, agriculture, natural and other sectors) at a 1 km^2 resolution from UK National Atmospheric Emissions Inventory (NAEI, 2019) for the baseline year of 2019. The model also accounts for the effect of the advanced canyon and urban canopy on the dispersion with building data (Digimap, 2019). The model adopts Generic Reaction Set (GRS) chemistry scheme to capture NOx-O3-VOC chemistry and sulphate chemistry to represent the formation of secondary particulate matter (Cambridge Environmental Research Consultants Ltd, 2020). When compared to reference grade station observations, the model performs well and full details of the West Midlands case study can be found in (Zhong et al., 2021). Only the Birmingham segment of the model was used in this study. The data for each site was averaged to overlay with the modelled air quality map. As discussed below, the model predictions are for a specific year—2019—which did not correspond to the sensor deployment dates. Therefore, absolute levels are expected to vary and only insight into spatial distribution of PM levels is considered here. This is discussed further in Section 3.3.

3 | RESULTS AND DISCUSSION

3.1 | Sensor performance

3.1.1 | Data capture

After quality control, the proportion of the year captured at each location varied considerably from 6.8% to 94.4%, with an average % cover of 51.2%. Hagley Road was the lowest performing location in terms of the percentage of year captured and this was due to the unit needing repair. Other low-performing sensors in this test are Perry Park and BAQS and this is due to the sensors only being deployed for a segment of the year. Many of the Zephyr units struggled for power during the winter months. Although the solar panel is designed to power the unit in winter mode with clear solar insolation this is not always possible in urban locations due to building/infrastructure shadows. This limits some of the Zephyr's presence in the winter. In contrast, AltasensePM were limited by their calibration/deployment cycles and battery life, as some units required refurbishment after an initial deployment round after suffering some environmental damage. This meant there was not always a unit available to switch out when the sensors came in for recalibration/new batteries. As the AltasensePM can only be reset in person due to the 1-way comms, this also led to some downtime. The issue of sensor capture completeness is not unique to this study, (Connolly et al., 2022) reported sensor presence within a low-cost sensor network being a major reliability issue with only 54% data capture with the outdoor segment of their network. It is evident that power and communications resilience needs investigation to ensure the future reliability of these types of sensors. However, the power of multiple nested networks ensures that whilst all the networks may not be functioning concurrently, sufficiently large sections should be operational to ensure some data coverage. No individual locations were excluded completely after data filtering as this allowed for sites to be looked at individually, even if only present for a short time, comparative to other sites for the equivalent reduced time periods. However, for some of the analysis below, sites were chosen that had >75% when looking at annual averages compared to a model or by location and data captured periods when making spatial conclusions. The complete details are outlined alongside the analysis. The representativeness of the overall network compared to regional concentrations from regulatory instruments is discussed in Section 3.1.3.

3.1.2 | Co-location of sensors

Using both urban background and urban traffic site sensors: reference instrument co-locations within the deployment network, it was generally shown that the lower-cost IoT sensors perform well and could provide indicative values (Figure 2). The urban background sites used were Ladywood AltasensePM versus Ladywood AURN, Clement St Zephyr versus Ladywood AURN (~200 m away) and BAQS Zephyr versus BAQS FIDAS. Slopes (ratio of sensor:reference instrument) for daily averages from these co-locations were 1.3 (R^2 0.62), 1.1 (R^2 0.91), and 0.98 (R^2 0.94) respectively. Notably, the Zephyr performed better than the AltasensePM in an Urban Background setting. This may be due to the additional external fan on the Zephyr unit which helps maintain airflow through the sensor. The Urban Traffic site was located at Watery Lane, ~160 m from the A4540 AURN site on the opposite side of the carriageway. This co-location has a sensor: reference slope of 0.74 (R^2 0.62). These slopes are reflective of previous values reported in the literature where the PlantowerPMS5003 and other similar low-cost OPCs tend to overread compared to reference instruments (Bulot et al., 2019) but still demonstrate reasonable closeness to the reference instrument concentrations. Some discrepancy in the roadside slope was to be expected given the location on opposite sides of the carriageway. Here, the A4540 AURN site is on an approach to a junction where there is occasional queuing traffic whereas the Watery Lane site is on the exiting carriageway which is less likely to queue. This highlights the importance of ensuring representative sampling, especially at near-source locations. Ideally, co-locations for checking device consistency against a reference instrument would occur in close proximity (i.e., on the same side of a carriageway) so that sampling is reflected in the same near-source environment and comparison can be made between units rather than between environments. However, deployment restrictions often lead to compromises.

It is also important to consider similar challenges when assessing co-location between sensors themselves at near-source sites. Co-location of sensors can allow for checks to ensure device consistency. Previous research has shown that the AltasensePM demonstrates good inter-sensor linearity between devices as showcased in

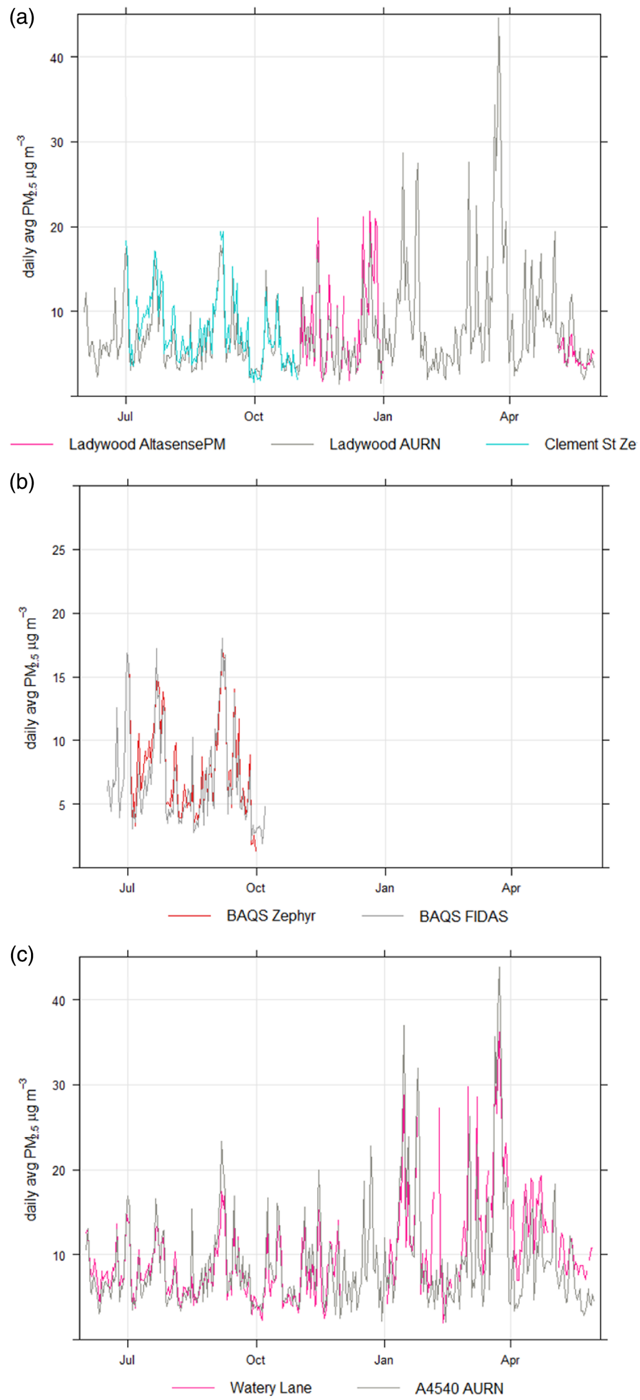

FIGURE 2 Co-location daily average time plots of (a) urban background Ladywood site, (b) urban background BAQS site and (c) roadside A4540 site.

(Cowell et al., 2022) where Pearson's R between sensors ranged from 0.93 to 0.99 for $PM_{2.5}$. However, when using nested networks from different sources, field co-locations can be insightful in understanding the co-linearity between the devices that may be managed externally. If sampling near-source (such as roadside environments as explored in the Watery Lane and reference site co-location above) it is essential that sensors are located in very close proximity (i.e., ideally on the same piece of street furniture), otherwise it is hard to decipher whether any differences or similarities between sensors are reflective of source emissions or sensor performance. An example of this from the nested network is a near-co-location of Zephyrs located across the major junction in the city centre.

The local authority network also provided an opportunity to explore small-scale spatial variability. Here, three Zephyrs were clustered, with one sensor in the middle of the junction and two located on different approaches immediately before the Holloway Circus junction. Holloway Circus and Holloway Head Zephyrs were located ∼90 m apart with a third zephyr unit (Suffolk St Queensway) located ∼160 m from the other two. Figure 3 shows the inter-sensor correlation between Holloway Circus and Holloway Head with a slope of 1.1 and R^2 of 0.96, with shading/colouring relating to correlation with the Suffolk Street Queensway unit. This appears to show the sensors in strong agreement despite their varying locations across the carriageway. This suggests that at this junction, the sampling locations (of which two are on similar junction approaches) experience similar concentrations and there is less variation or may be reflective of sensor performance, highlighting that sensors are not detecting any potential differences. A suggestion for future networks would to be consider a period of co-location of all sensor types at one near-source site if possible, to help provide further insight. Small-scale clusters, such as those described, can represent best practices when deploying networks. Over time, the insights collected identify redundancies within the network. This then allows for redundant sensors to be deployed elsewhere.

3.1.3 | Insights into regional concentrations

The sensor network was able to detect trends and patterns in regional particulate concentrations throughout the year. The annual average $PM_{2.5}$ mass concentration for the study period from the entire low-cost sensor network is 8.56 μgm^{-3} which is comparable to the average from the 3 DEFRA AURN sites of 8.37 μgm^{-3}, further demonstrating the ability of the sensor network to accurately detect regional air quality. Despite the sampling locations of the network only representing a small area of the city, the sensor network average also estimated concentrations within <2 μgm^{-3} of the 2019 high-resolution model, which estimates citywide annual average

Meteorological Applications
Science and Technology for Weather and Climate
Open Access
RMetS

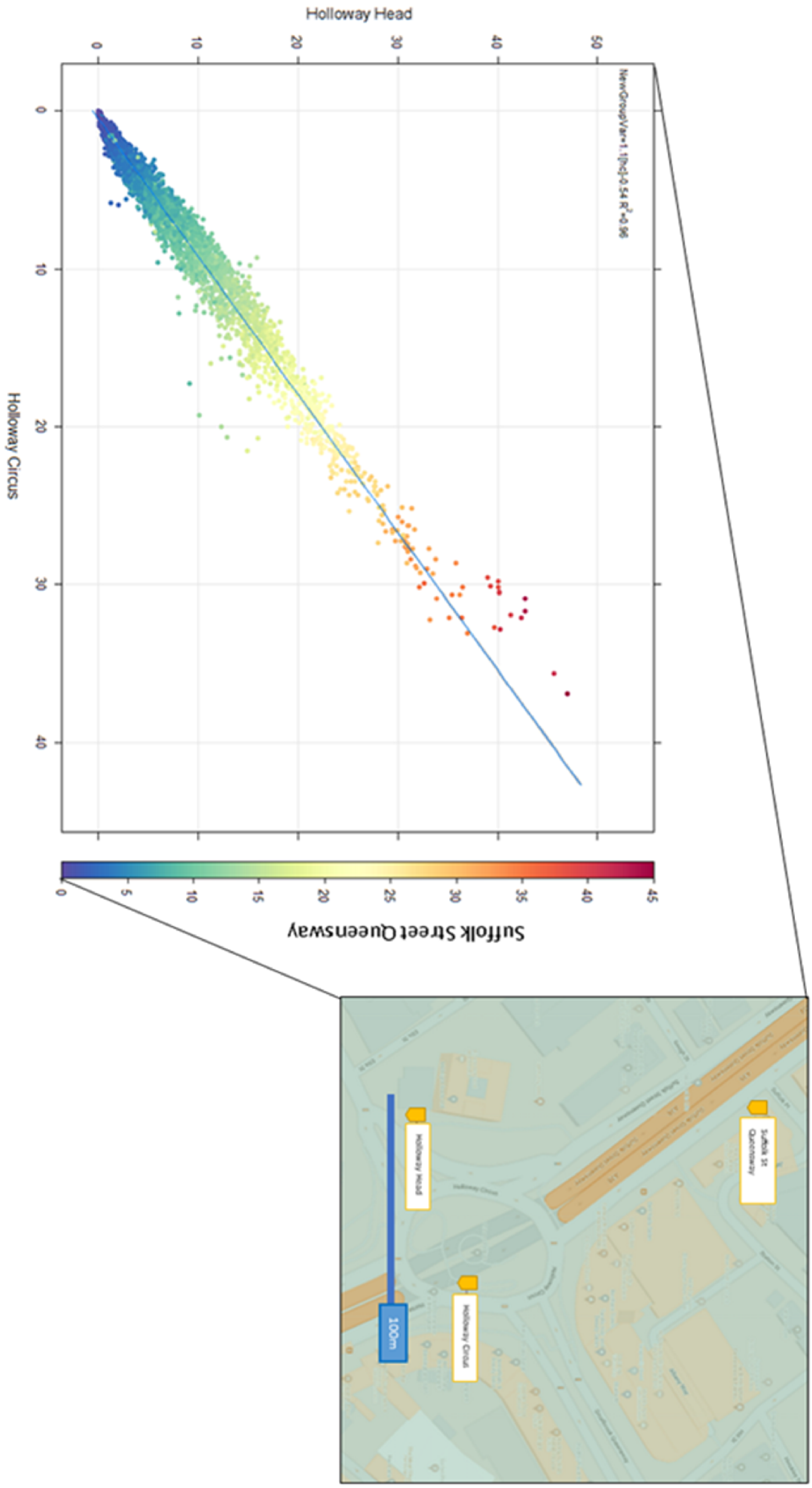

FIGURE 3 Hourly average data points of Zephyrs in near-co-location inside the CAZ and city centre of Birmingham. All three roadside sites are located within ~90–160 m of each other across a busy junction on a major road. Holloway Head and Holloway Circus are the closest located at ~90 m apart, and the colour of the plot is by Suffolk St Queensway location which is ~160 m away.

concentrations at 10.3 μgm^{-3}. 80.6% of monthly averages across all sites were >WHO annual guidelines (5 μgm^{-3}) and monthly averages ranged from 2.2 to 22.9 μgm^{-3} As shown in Figure 4a, sensors detected monthly patterns and the overall variability tracks across the city. Units also detected a dust storm that hit the United Kingdom

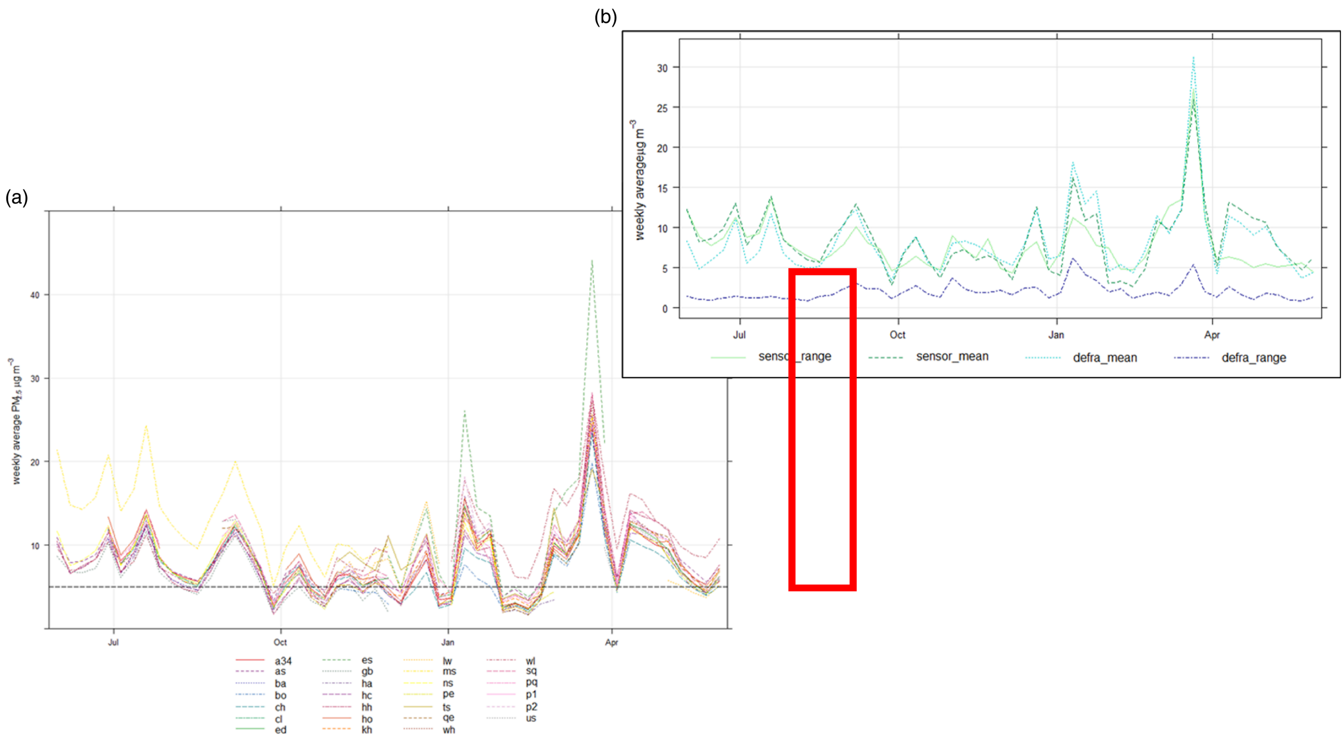

FIGURE 4 (a) Weekly average PM2.5 by site (Identified by code in appendix). The horizontal black dashed line demonstrates the WHO annual average guideline concentration of 5 μgm^{-3} and the red box highlights the peak associated with a regional dust storm and (b) weekly averages of the mean and the variation between sampling sites (range) of the sensor network and DEFRA AURN network measurements (DEFRA AURN sites Ladywood urban background site and A4540 Ringroad urban traffic site. Sensor network takes into account all sensor sites present at any given time stamp).

in March 2022 and this is clearly shown in Figure 4. This insight is not novel to low-cost sensors, the AURN sites already provide regional coverage of the city. However, seeing the low-cost network replicating events, values and patterns detected by the regulatory instruments add to the confidence in network performance. Figure 5 demonstrates that the greater the number of individual sensor readings available during an observation (1 h average), the more representative of regional urban background concentrations the sensor network averages are. As sensor numbers increase, the network urban background/urban traffic average falls closer to a 1:1 ratio with the relevant DEFRA site, particularly during urban background sampling. This shows that although sensors are sampling in a wide variety of locations and detecting local trends, when averaged together in large numbers they can be used as a proxy for regional concentrations. For urban background locations, with just 5 sensors available in a network regional concentration estimates from the network average fall within ~10% of the DEFRA regulatory urban background measurement with strong correlation (sensor network average: regulatory station slope = 0.899 and $R^2 = 0.807$). This is a vast improvement when only two sensors are present where although the slope remains within a ~10% difference range (sensor network average: regulatory station slope = 1.12), the correlation between sensors and regulatory instrument is weak with R^2 of 0.52. This pattern is less clear for Urban Traffic sites despite the fact that the network had greater quantities of roadside sensors than urban background sensors. The linear fit between sensor: regulatory measurement fluctuates with sensor numbers, performing similarly well at 2 and 10 sensor presence (slope = 0.776, 0.776, $R^2 = 0.802$, 0.782 for 2 and 10 sensors, respectively), but less so at 5 and 14 (max number) of sensors (slope = 0.618, 0.436 and $R^2 = 0.725$, 0.476 for 5 and 14 sensors, respectively). This may be reflective of the sampling location of the roadside sensors versus the DEFRA roadside location rather than the number of sensors or that we are comparing to the one roadside DEFRA location within the network area. The DEFRA location is a busy section of a major traffic route that often experiences congestion whilst the majority of the sensor locations were less busy roads due to a lack of available street furniture for installation on the busiest traffic routes. Therefore, the generally poor linear fit

Meteorological Applications Science and Technology for Weather and Climate Open Access RMetS

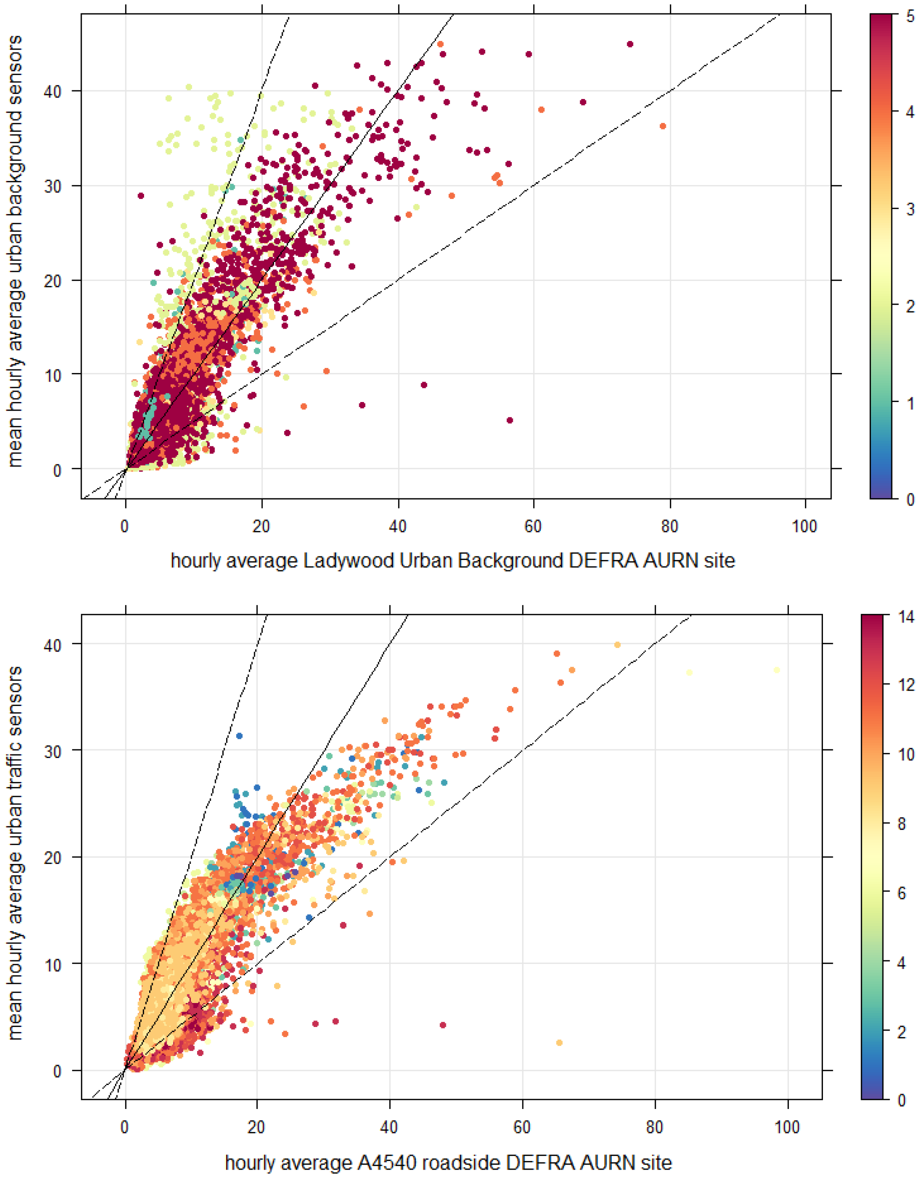

FIGURE 5 DEFRA AURN location versus sensor network mean separated for Urban Background and Urban Traffic sites with coloured by a number of sensor observations at each mean point. Solid line denotes the 1:1 relationship.

between the sensor network and reference may be explained by the sensor location. This highlights the risk around relying on a small number of locations as indications of city wide levels and the potential benefits of low-cost sensors to increase sampling resolution. However, it is clearly important to ensure low-cost sensors are deployed in larger quantities across a range of site locations if the goal is to achieve accurate insight into regional air quality. For roadside or near point source sites, the accuracy of regional concentration estimates may fluctuate in line with the number of sensors, especially where units are directly capturing variations associated with near-source sampling. However, this does outline the benefit of low-cost approaches, enabling a clearer picture of hyperlocal variations under various weather conditions.

3.1.4 | Insights into local spatial variability in concentrations

The novelty of low-cost sensor insight into air quality is clearly highlighted when the local variability in particulate matter is assessed. Unlike their regulatory counterparts, the high spatial resolution of the network allows for the evaluation of hotspots and spatial variability across the city. The two regulatory AURN sites across the city centre demonstrated average concentration ranging from 7.8 to 9.06 μgm^{-3} for the study period, however, sensors reported averages of 6.18–13.16 μgm^{-3} across all sites. This is also shown in Figure 4b which compares variation (range) between sites over time. The average range (defined as the difference in concentration recorded between sites at the same timestamp, maximum

TABLE 1 $PM_{2.5}$ concentration range and mean for sensor sites with >75% capture over the entire sample period and DEFRA AURN regulatory instruments for the sample period.

Location	Sensor or regulatory instrument	$PM_{2.5}$ concentration 5th–95th percentile range (μgm^{-3})	Mean $PM_{2.5}$ concentration (μgm^{-3})
Watery Lane	Sensor	2.48–24.02	9.88
Navigation St	Sensor	1.65–20.88	8.31
Holloway Head	Sensor	0.89–20.53	7.74
Holloway Circus	Sensor	1.25–18.1	7.2
Geog Building	Sensor	1.27–19.09	7.16
Children's Hospital	Sensor	1.32–17.91	7.1
Albert St	Sensor	1.85–20.49	8.51
A34	Sensor	1.12–20.19	7.68
A4540	Regulatory	2.55–23.76	9.06
Ladywood	Regulatory	1.78–21.34	7.8

Note: The two regulatory DEFRA AURN sites were chosen because they fall into the ~39 km^2 area covered by the sensor network. One other regulatory station in the Birmingham area (Acocks Green) was not used as this is >2 km away from the nearest sensor and is not considered a city centre location.

concentration recorded minus minimum concentration recorded) of DEFRA measurements across the 2 city centre sites is 1.99 μgm^{-3} whereas the average range of the sensor network was 7.92 μgm^{-3}. This highlights how the lack of spatial coverage from the DEFRA sites leads to an underestimate in variability. The sensor network shows a range of concentrations recorded that is of a similar magnitude to the mean concentrations for the year, demonstrating hyperlocal site variation.

Table 1 shows the range in peak concentrations (concentrations within the 95th percentile for sensors that captured >75% of the study year) is 6.11 μgm^{-3} whereas the regulatory instruments only show a range of 2.42 μgm^{-3}.

This demonstrates how the current coverage of the regulatory network does not capture the areas of high PM which could be in exceedance of future target levels. As a result, there is a clear need for increased coverage of monitoring in urban areas to capture these exceedances with low-cost sensors being well placed to help resolve. This is further emphasized by the high-resolution model, which experiences $PM_{2.5}$ concentration ranging from 8.57 to 20.23 μgm^{-3} showing further how regulatory instrument networks are not capturing the wide distribution of concentrations.

Moor St (MS on Figure 2) is an example of a detected pollution hotspot with continuously higher concentrations than other locations, likely due to the proximity of the train station, bus stops and traffic. This echoes the results of (Johnston et al., 2019) who reported their small AQ network of 6 low-cost sensors (including the Plantower PMS5003) was suitable for detecting local PM trends and (Morawska et al., 2018) who reported low-cost sensor networks can detect pollution hotspots.

Clearly, there is a need for an increase in spatial resolution of particulate monitoring to further understand the variability eluded from this network. Whilst expansive networks are not needed to detect regional patterns such as dust storms, the increased granularity of $PM_{2.5}$ data from the sensor network can capture important insight into local particulate exposures that are missed by the low spatial coverage of regulatory instruments. In the United Kingdom, the Environmental Targets (fine particulate matter) (England) 2023 set out national targets for particulate matter, including suggestions for monitoring efforts (Secretary of State, 2023). These regulations propose that the West Midlands Urban Area (which covers most of Birmingham and some surrounding neighbourhoods) will require a minimum of 15 monitoring sites (10 at urban or suburban background, five near sources such as roadside locations) by 2028 (Secretary of State, 2023). This network demonstrates the relatively easy scalability of low-cost sensing networks to meet and exceed these targets at a significantly lower cost than regulatory monitoring site expansion. Whilst the majority of the 28 locations featured in this paper were near source sites, the mobility of the units would make it easy for this to be adjusted to reflect the requirements. As previously shown, five sensors can give good insight into regional urban background concentrations and performance is expected to increase with sensor numbers, especially if locations chosen are well representative of a region as a whole. Low-cost sensors are likely to be the most feasible option for meeting these requirements in most places due to their affordability. However, it will be important to ensure that if meeting these guidelines using low-cost technology, that sampling strategy is carefully considered to ensure representative coverage of the urban area. This is especially true, as demonstrated in this paper, for near source monitoring (such as roadside). Fundamentally, the location of a sensor is more important than sensor quantities in these instances. However, as highlighted in Section 3.1.2, achieving this may need an acceptance of some short-term redundancy in the network. Overall, sampling guidelines will need to evolve beyond just the quantity of sensors, to consider which sources are important and the area range that these sources will be likely to affect as part of sampling design.

3.2 | Impact of implementation of the Birmingham CAZ on PM concentrations

There are limitations in drawing conclusions from the spatial analysis of network data in this study with respect to the CAZ, namely missing data and the lack of baseline measurement from the sensors. The lack of baseline means that any spatial analysis is reflective of a post-CAZ environment only and it is not possible to assess if PM concentration change has been introduced by the CAZ, as prior concentrations at the measurement sites are unknown. This was heightened by the context of the coronavirus pandemic, which drastically altered travelling habits in the period immediately prior to and during the CAZ deployment, further limiting the value of any comparison data. Therefore, any analysis here referring to the CAZ is only capturing the current spatial context and cannot be used to definitively draw impacts of the implementation, only similarities or differences between the interior and exterior zones. Due to gaps in the data available at various sites over the year, there is limited opportunity to do cluster analysis and compare seasonal differences between sites. As such, the analysis is limited to annual means of groups of sensors that share characteristics (such as roadside, or urban background locations, inside or outsize CAZ locations). Comparisons can then be made between the city centre and non-city centre environments, and different traffic routing options. Although detailed conclusions about the efficacy of the CAZ cannot be drawn from this analysis, it does provide useful further insight into the use of nested sensor networks in this application.

Figure 6 shows the outputs when all sites inside the CAZ are averaged and compared to the average of relevant non-CAZ sites (sites located outside or on the CAZ boundary, excluding Perry Park as these sites are more reflective of suburban background where as QE/Women's hospital campuses have idling ambulances and different traffic behaviour and alternate sources that are not reflective of rest of the city). Within this analysis, the total number of sensors inside the CAZ was 12 and outside of the CAZ was 10, however, the number of sensors 'present' at each reading varies over time due to sensor outages and performance issues. The average number of sensors present in the CAZ during this analysis was 7.4 and outside of the CAZ was 4.7. This allowed for analysis of local changes across an area, as the network averaging and sensor density meant that there was always data available both inside and outside of the CAZ, however, data averages could be skewed if too few sites were reporting across the year. By grouping units this way, the mean $PM_{2.5}$ concentration of the CAZ is reported as slightly higher ($8.65\ \mu gm^{-3}$) than outside the CAZ ($8.11\ \mu gm^{-3}$) and a Mann–Whitney–Wilcoxon Test reports the CAZ versus outside of CAZ averages to be statistically different at $p = 0.05$ (p-value $= 8e^{-9}$). The average values are extremely close and reflect past reports that CAZ/ULEZ (Ma et al., 2021) have limited impact on PM concentrations. There are some discernible differences in the diurnal profile. The area outside CAZ seems to experience a greater afternoon reduction in concentrations, suggesting that different sources are impacting the concentrations. This may be reflective of the different site types captured in the crude averaging here. Urban background sites are being mixed with roadside which could be skewing data. Instead, a more effective way of assessing spatial variation is to split sites by their environment type. Therefore Figure 7 shows the split of roadside versus urban background for inside and outside of the CAZ. Generally, concentrations at both the background and traffic sites inside the CAZ are higher than their outside CAZ counterpart. However, again it is important to note that there are fewer urban background sites within the CAZ than outside (only 3 sites) and of those sites, often only 1 or 2 sites were active at a time due to sensor outages/movements. This may also be reflected in Figure 7 where the background concentrations in the CAZ appear to be higher than the traffic concentrations with large variability. This suggests there is too much site variability between the few background sites within the CAZ to fully compare against roadside concentrations without more locations. This falls in line with our above findings that network insights increase with sensor numbers.

Due to the high number of roadside sensors, individual traffic routes can also be assessed. Six roadside sites were selected for their proximity to two major traffic routes; either the A38 which is the direct route through the CAZ, or the A4540 which is the major alternate route

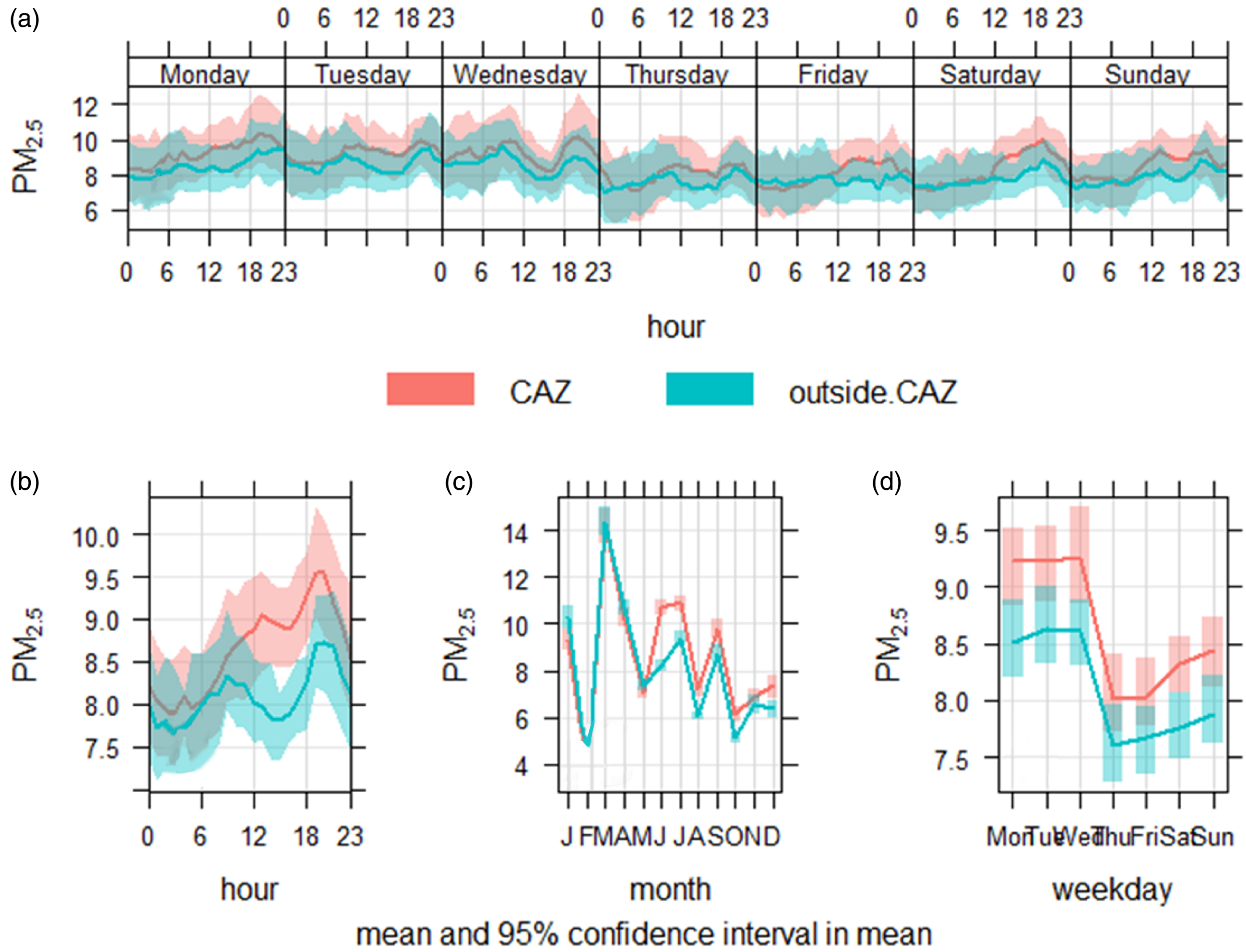

FIGURE 6 CAZ versus outside CAZ $PM_{2.5}$ temporal variation by (a) hourly day of the week, (b) diurnal, (c) month and (d) daily week day. CAZ refers to the average of all units inside the CAZ boundary. Outside CAZ refers to all units outside the CAZ boundary apart from the 2 Perry Park locations, the QE Main Entrance, University Train Station and Women's Hospital. This is because these sites are all campus or park locations determined by work with project partners to capture the park or campus air quality, and are unlikely reflective of the rest of the city.

avoiding CAZ charges. Both the A38 and A4540 typically consist of between four and six lanes of traffic during the sampling stretch and sensors are located directly on or near the roads. The A38 stretch covered by sensors has a speed limit of 30 mph whereas the A4540 ranges from 30 to 40 mph. Traffic is expected to be different at A38 versus the A4540, as the A38 section captured by the monitoring sites here is within the CAZ whilst the A4540 is an alternate route to bypass CAZ charges for non-compliant vehicles. Sites were selected for their similar data capture periods and averaged to make an A38 data set and an A4540 data set. Figure 8 shows the comparison of A38 to A4540, including diurnal profiles. The A38 and A4540 have similar diurnal profiles of $PM_{2.5}$ concentrations, and the A38 experiences lower concentrations (average 4.5% lower) than the A4540 (7.82 μgm^{-3} for A38 and 8.59 μgm^{-3} for A4540). Again, a Wilcoxon test shows a statistical difference between the A38 and A4540 sites with $p = 2.2e^{-16}$. Whilst a limitation of the network sampling locations means that this captures one south-easterly stretch of the ring road and A38, it may be possible to draw new insights into concentrations across different parts of the city such as novel information around PM exposure on previously un-monitored streets.

In summary, this example demonstrates that a low-cost sensor network can provide insight into spatial patterns but also highlights the importance of site selection. Where traditional monitoring may only cover a few sites within a city, the nested sensor network allowed for capturing greater spatial density across the city and highlighted features that may be hotspots or data skews such as a site-specific source affecting readings. As there are more sites, data can be filtered by site types to create averages that give insight into spatial differences across

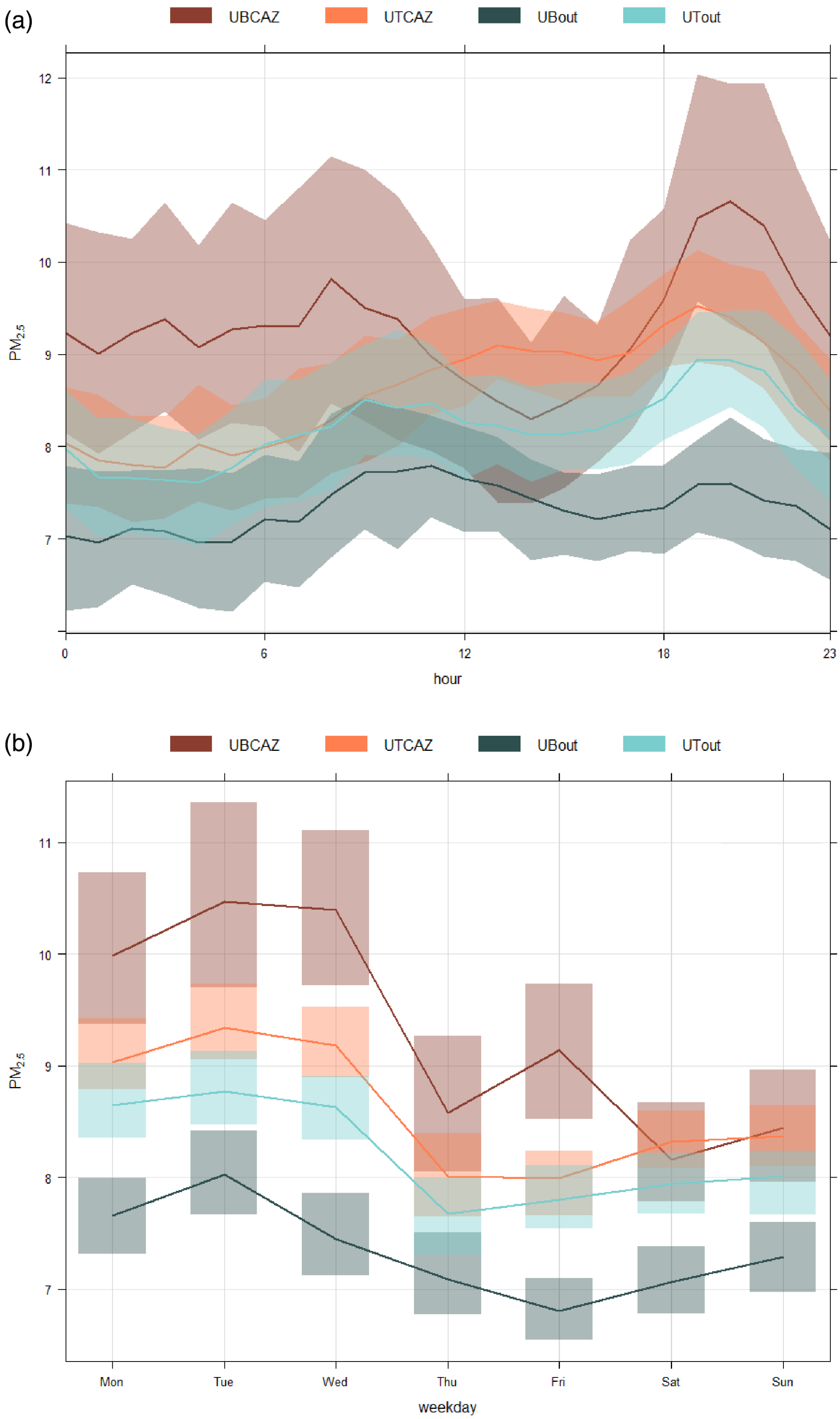

FIGURE 7 Diurnal (a) and weekly (b) time variation profile of $PM_{2.5}$ averaged by site type. UBCAZ, Urban Background within CAZ; UTCAZ, Urban Traffic within CAZ; UBout, Urban Background outside CAZ; UTout, Urban Background outside CAZ.

traffic management areas. Without delays to sensor deployments from the pandemic, a baseline dataset would be available, and the network should be suitable for pulling out spatial patterns over time as a result of changing traffic management.

3.3 | Comparison with a high-resolution model

Figure 9 shows the overlay of sensor averages for the entire study year with the high-resolution air quality map

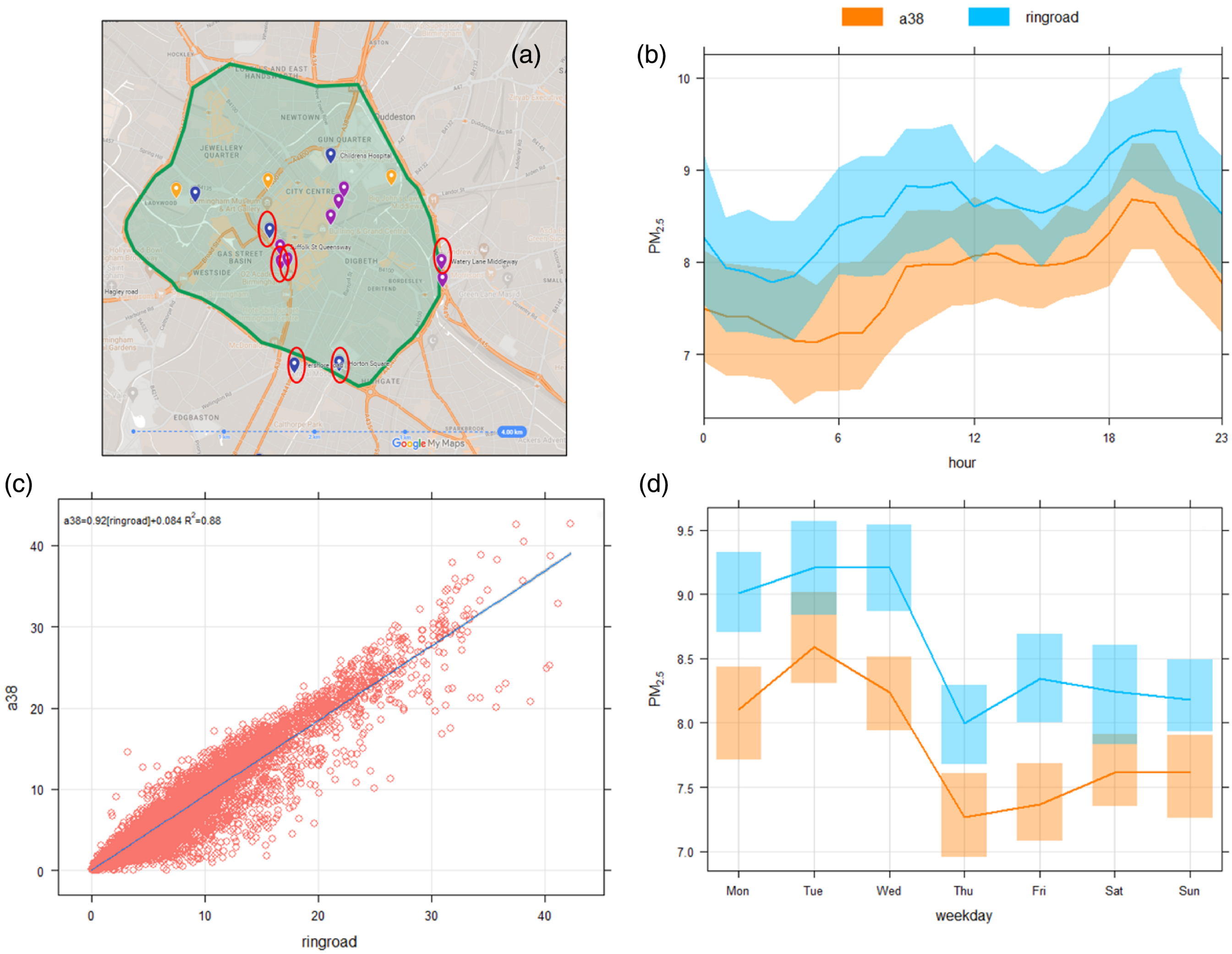

FIGURE 8 A38 (inner CAZ) versus A4540 (CAZ boundary) ring road traffic route $PM_{2.5}$ comparison. (a) Sensors included within this analysis are circled on the network map. (b) Diurnal profile of average A38 (CAZ restricted) route sensors versus average A4540 (not CAZ restricted) route sensors. (c) Scatterplot of the average A38 route versus average A4540 route. (d) Weekly profile of average A38 route versus average A4540 route.

of $PM_{2.5}$ based on a 2019 baseline. The sensors record concentrations lower than the maximum concentrations reported by the model; the model maximum concentration is about 10 μgm^{-3} higher than the sensors' mean concentrations when assessing the entire map, however, when drawing out individual site comparisons between map cells and sensor locations, the average difference between model and sensor is 4.02 μgm^{-3} and the median difference is 3.61 μgm^{-3}. The difference between individual sensor locations ranges from 2.5 to 7.3 μgm^{-3}. One limitation of this methodology is that sensors are being compared to 2019 data, simulating a different calendar year to the observations, with different meteorology, emissions, traffic fleet and commuter behaviours. As a result, analysis between the model and sensors is only indicative, exploring relative location-to-location variability. There is a need to further consider how this may be impacted by changing annual weather/emissions. For example, this may reflect why the sensors are reading low to the model, as the model is based on pre-Coronavirus pandemic conditions, since there has been a shift in working patterns. Alternatively, the model may just be reading high compared to real-world observations. A benefit of the sensor-based approach would be the ability to look at year-to-year patterns with an extended deployment, this could inform future models on temporal changes in concentrations capturing modal shifts such as the uptake of home working and the impact on emissions from commuters. Despite the baseline year difference, there are some similarities in location-to-location variability between sensor observations and the model. Roadside locations report high concentrations with hotspots around key urban features such as Moor St station and the A38/A4540 ring road major traffic routes and urban

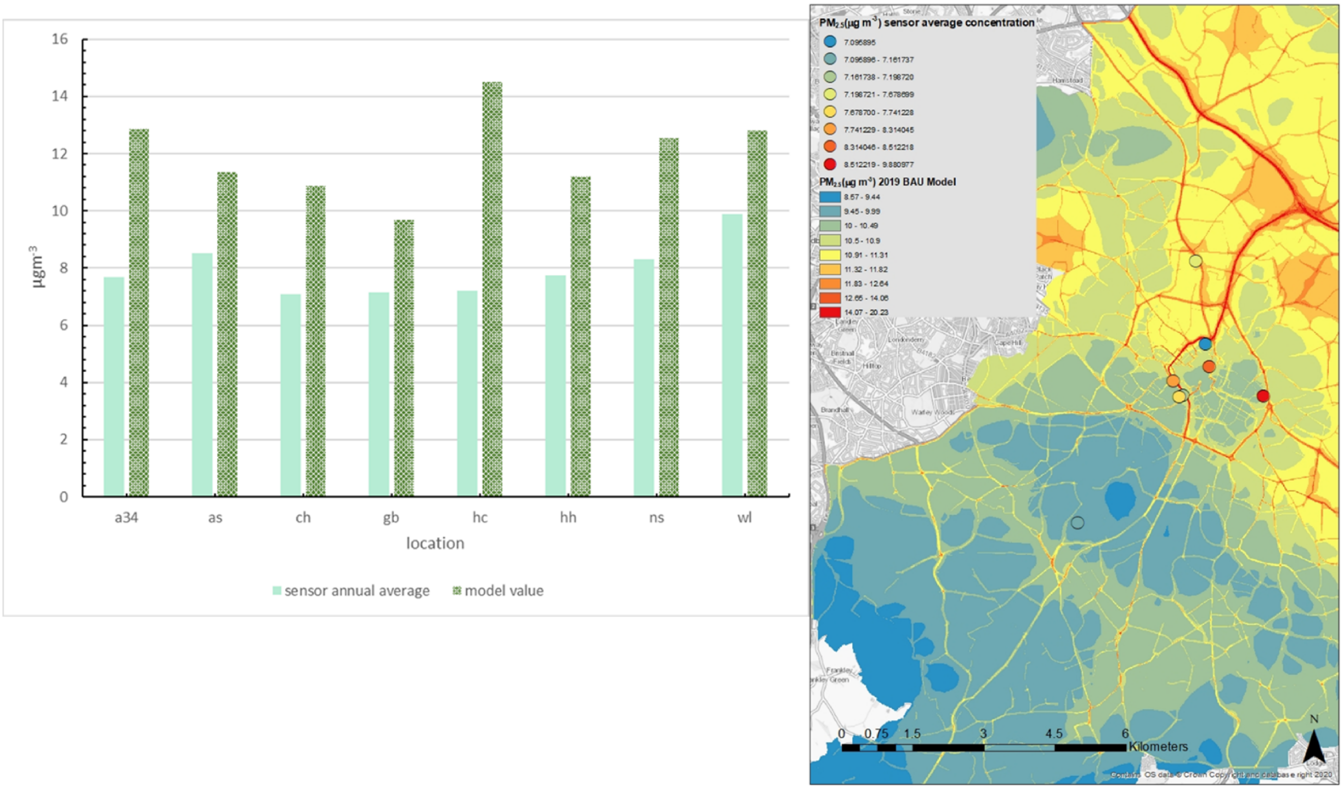

FIGURE 9 Overlaying the average concentration at a sensor location (for sites >75% annual capture) with the ADMS-Urban model (Zhong et al., 2021). Generated using ArcMap and OpenStreetMap. The scale for the model and the sensors is different but scaled to show the relative highs and lows of each in the same colour scheme. The bar chart shows the annual average value at the overlayed sensor sites versus the comparative model value for that cell.

background sites to the south of the city centre report lower concentrations. Figure 9 shows locations with >75% annual capture and outliers removed. Whilst this insight is limited in the amount of spatial coverage at high temporal capture, there are more sites available for evaluating the observation-to-model ratio than in the original model evaluation by Zhong et al. (2021) as spatial coverage of $PM_{2.5}$ for the city was enhanced by the sensor network. This past evaluation compared 2016 baseline model against three sites for $PM_{2.5}$ concentrations that were available across the region, and found the model performed generally well although slightly underestimated concentrations. The deployment of a nested network of sensors (such as our sensor dataset presented here) provides an opportunity to reassess model evaluations for future baseline years against a spatially enhanced set of observations.

3.4 | Lessons learned from a low-cost sensing network for particulate matter

This nested network can be viewed as a test bed for IoT low-cost sensor networks. Such networks are an emerging approach and as such it is important to evaluate them to enable future best practices. The large amounts of data available bring great potential for how we understand and manage air quality, but often this data are collected by many different groups and is rarely bought together as a single network (Topping et al., 2021). This data were also provided as open access via the Birmingham Urban Observatory. This meant that anyone could access and use this data as needed, increasing data accessibility to those who do not have as much funding for monitoring such as community groups and educational projects. Whilst open-access data sharing is an opportunity, it also comes with challenges. Non-specialist audiences may not be aware of the caveats and data validation needed alongside low-cost sensor data and this may lead to misinformation, especially as quantifying the scientific value of such sensors is challenging (Luo et al., 2018; Topping et al., 2021). The Birmingham Urban Observatory project added a caveat to the online description of low-cost sensor units, suggesting that they are providing indicative measurements. The calibrations for the AltasensePM were automated within the online platform so end users received the adjusted values rather than raw values (all data pulled from the Zephyrs also had undergone manufacturer calibration before being pulled via the API to the Urban Observatory platform but the methods for calibration are undisclosed). Future work could also try to embed some form of data validation into an online platform to flag data that may be potentially erroneous. All data handling, metadata and validation processes should be as transparent as possible (respecting manufacturers' need to protect intellectual property such as sensor algorithms) as this allows users to fully understand the data.

The reliability of sensor networks will need to be improved if they are to become more broadly accepted. This study experienced power and comms issues symptomatic of deployments elsewhere. Jiao et al. (2016) reported comms signal issues, Connolly et al. (2022) reported the loss of wireless connection and sensor breakages and malfunctions and Johnston et al. (2019) reported hardware bugs and reliability issues with comms technology. Environmental degradation is to be expected when deploying any sensor into a field environment but best practices should ensure that hardware is rugged and reliable for outdoor monitoring. Comms often presents issues as they can be a significant power drain on the device, which is a challenge with field deployments of sensors where mains power is not always accessible. Low Power Wide Area Networks (LPWANs) provide a novel opportunity here, as they are often power and economically efficient and can transmit small quantities of data over long-range distances (Mekki et al., 2019; Patel & Won, 2017; Song et al., 2017). With data coverage checks, this technology could be a solution to increasing the reliability of sensor networks.

Another challenge this project faced was accessing infrastructure to install sensors. Whilst in practice, installing self-contained sensors such as those in this study is simple, gaining permission for the University owned sensors to be placed in locations of interest was challenging and required navigating bureaucracy. This slowed down initial deployment, created a barrier for co-location studies and maintenance efforts and limited the locations available to us. This also limited the ability of the network to be wholly representative of the entire city, or even the specific interventions such as the CAZ that we initially planned to focus on. Best practice moving forward would involve strong collaborations between researchers, communities and the local agencies in control of infrastructure to reduce these limitations on installation.

4 | CONCLUSIONS

This study has shown clear benefits of IoT low-cost sensor networks; the networks were successful at monitoring at a regional level comparable to reference instrument concentrations and provided novel insight into location-specific analysis. This project presented a low-cost sensor dataset that was reflective of the real-world application of sensors, including deployment limitations and sensor downtimes that are common to environmental sampling. Whilst there are inevitable gaps in the data, spatial patterns and pollution episodes could be detected. Sensors performed well in both field co-locations and against a high-resolution model, especially when capturing spatial patterns. This paper has shown that with a relatively small network size ($\geq$5 low-cost sensors), estimates into regional urban background concentrations were within $\sim$10% of the regulatory measurements, suggesting that well-deployed low-cost sensors have good potential to meet novel monitoring guidelines (Secretary of State, 2023) which require an increase in sampling sites (i.e., not just indicative). However, for near-source (roadside) monitoring sites, the location and spatial scale of the sensors are very important to ensure the representativeness of the target area of the sampling and guidelines will need to be updated to emphasize the importance of sampling strategy and representation of sources alongside sensor quantities.

The network provides opportunities for users to understand exposures in places that would not normally have monitoring coverage for a fraction of the cost of a traditional monitoring campaign. Spatial analysis was able to draw limited conclusions about roadside concentrations, suggesting that roadside $PM_{2.5}$ concentrations between 2 major traffic routes can vary $\sim$4.5% although there is much room to expand this analysis with targeted monitoring aimed at capturing specific roadside sites. The network also presents an opportunity to support the optimization of high-resolution models for PM, as they provide a higher spatial resolution of observations to evaluate model performance.

To conclude, whilst the limitations of low-cost sensors are still prevalent, and there is still work to be done before they are widely accepted as a tool for regulatory monitoring, this work has highlighted both the potential of the approach and started to identify best practices for use. It has shown that the nested network approach, combining a range of low-cost devices with standard monitoring, helps increase confidence in the novel insights now being routinely collected by cities across the world. Fundamentally, it is evident that the densification of observations can now be achieved without excessively increasing spend on instrumentation, but for this to be effective, collaborative working across city stakeholders is required.

AUTHOR CONTRIBUTIONS

Nicole Cowell: Conceptualization (equal); data curation (lead); formal analysis (lead); investigation (lead); methodology (lead); project administration (equal); visualization (lead); writing – original draft (lead). **Clarissa Baldo:** Methodology (equal); validation (equal); writing – review and editing (equal). **Lee Chapman:** Conceptualization (equal); funding acquisition (equal); methodology (supporting); project administration (equal); resources (equal); supervision (equal); writing – review and editing (equal). **William Bloss:** Conceptualization (equal); funding acquisition (equal); supervision (equal); writing – review and editing (equal). **Jian Zhong:** Methodology (supporting); software (equal); visualization (equal); writing – review and editing (equal).

ACKNOWLEDGEMENTS

The authors would like to thank Dr Siqi Hou for assisting in the co-location of sensors at Birmingham Air Quality Supersite at the University of Birmingham. We would like to thank colleagues at Birmingham City Council for collaborating on this project, sharing access to their Zephyr network and their support in the installation of our sensors on their infrastructure. We would also like to thank University Hospitals Birmingham, Birmingham Women's' and Children's Hospital, the Commonwealth Games, Birmingham City Council Redfern Depot and the University of Birmingham Estates team for hosting units.

FUNDING INFORMATION

This work was funded as part of the NERC RISE WM-Air project (NE/S003487/1), EPSRC UKCRIC Urban Observatories project (EP/P016782/1) and EPSRC IAA funding which helped support the translation. BAQS is supported through the NERC project OSCA (NE/T001976/1).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Nicole Cowell https://orcid.org/0000-0002-6270-0913

REFERENCES

Birmingham City Council. (2018) Consultation: a clean air zone for Birmingham. In: Brumbreathes (ed.).

Birmingham City Council. (2021a) #brumbreathes Charges and operation. Available from: https://www.brumbreathes.co.uk/info/25/welcome-2/45/charges-operation-1 [Accessed 4th November 2022].

Birmingham City Council. (2021b) Population and census: Overview. Available from: https://www.birmingham.gov.uk/info/20057/about_birmingham/1294/population_and_census [Accessed 4th November 2022].

Birmingham City Council. (2022) Clean Air Zone Six Month Report.

Bulot, F.M., Johnston, S.J., Basford, P.J., Easton, N.H., Apetroaie-Cristea, M., Foster, G.L. et al. (2019). Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Scientific Reports*, 9(1), 7497.

Bush, T., Papaioannou, N., Leach, F., Pope, F.D., Singh, A., Thomas, G.N. et al. (2022) Machine learning techniques to improve the field performance of low-cost air quality sensors. *Atmospheric Measurement Techniques*, 15, 3261–3278.

Cambridge Environmental Research Consultants Ltd. (2020) *ADMS-urban urban air quality management system user guide*, 5th edition. Cambridge, UK: Cambridge Environmental Research Consultants Limited.

Carslaw, D. (2019) The openair manual—open-source tools for analysing air pollution data. Manual for version 2.6-6 University of York.

Carslaw, D. & Ropkins, K. (2012) Openair—an R package for air quality data analysis. *Environmental Modelling & Software*, 27–28, 52–61.

Chang, Y.S., Lin, K.M., Tsai, Y.T., Zeng, Y.R. & Hung, C.X. Big data platform for air quality analysis and prediction. 2018 27th Wireless and Optical Communication Conference (WOCC), 30 April–1 May 2018, 2018. 1–3.

Connolly, R.E., Yu, Q., Wang, Z., Chen, Y.-H., Liu, J.Z., Collier-Oxandale, A. et al. (2022) Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale. *Science of the Total Environment*, 807, 150797.

Cowell, N., Chapman, L., Bloss, W., Srivastava, D., Bartington, S. & Singh, A. (2023) Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. *Environmental Science: Atmospheres*, 3, 65–84.

Cowell, N.H., Chapman, L., Bloss, W. & Pope, F. (2022) Field calibration and evaluation of an Internet of Things based particulate matter sensor. *Frontiers in Environmental Science*, 733, 798485.

Crilley, L.R., Shaw, M., Pound, R., Kramer, L.J., Price, R., Young, S. et al. (2018) Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. *Atmospheric Measurement Techniques*, 11, 709–720.

DEFRA. (2017) UK plan for tackling roadside nitrogen dioxide concentrations detailed plan. London, UK: Joint Air Quality Unit, Departments for Environment Food and Rural Affairs and Department for Transport.

DEFRA. (2023a) Automatic Urban and Rurual Network (AURN). Available from: https://uk-air.defra.gov.uk/networks/network-info?view=aurn [Accessed 17th March 2023].

DEFRA. (2023b) Site Information for Birmingham Ladywood (UKA00655). Available from: https://uk-air.defra.gov.uk/networks/site-info?site_id=BMLD [Accessed 17th March 2023].

Department of Environmental Food and Rural Affairs. (2023) Site Environment Types. Available from: https://uk-air.defra.gov.uk/networks/site-types [Accessed 11th January 2023].

DIGIMAP. (2019) Digimap. Available from: https://digimap.edina.ac.uk/ [Accessed 28th May 2019].

Earthsense. (2019) Zephyr® Sensors Send Alerts to Divert Traffic From Pollution Hotspots in Coventry. Available from: https://www.earthsense.co.uk/post/zephyr-sensors-send-alerts-to-divert-traffic-from-pollution-hotspots-in-coventry [Accessed 17th March 2023].

Earthsense. (2022a) EarthSense's Zephyr® Air Quality Monitor Meets MCERTS Performance Standards. Available from: https://www.earthsense.co.uk/post/zephyr-meets-indicative-mcerts [Accessed 25th November 2022].

Earthsense. (2022b) Zephyr Air Quality Monitor Specification Sheet.

Feng, S., Gao, D., Liao, F., Zhou, F. & Wang, X. (2016) The health effects of ambient PM2.5 and potential mechanisms. *Ecotoxicology and Environmental Safety*, 128, 67–74.

Fishbain, B., Lerner, U., Castell, N., Cole-Hunter, T., Popoola, O., Broday, D.M. et al. (2017) An evaluation tool kit of air quality micro-sensing units. *Science of the Total Environment*, 575, 639–648.

GOV.UK. (2022) Guidance: Clean Air Zones. Available from: https://www.gov.uk/guidance/driving-in-a-clean-air-zone#cities-with-clean-air-zones [Accessed 10th November 2022].

Hagan, D.H. & Kroll, J.H. (2020) Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. *Atmospheric Measurement Techniques*, 13, 6343–6355.

Harrison, R.M., Allan, J., Carruthers, D., Heal, M.R., Lewis, A.C., Marner, B. et al. (2021) Non-exhaust vehicle emissions of particulate matter and VOC from road traffic: a review. *Atmospheric Environment*, 262, 118592.

Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D. et al. (2016) Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. *Atmospheric Measurement Techniques*, 9, 5281–5292.

Johnston, S.J., Basford, P.J., Bulot, F.M., Apetroaie-Cristea, M., Easton, N.H., Davenport, C. et al. (2019) City scale particulate matter monitoring using LoRaWAN based air quality IoT devices. *Sensors*, 19, 209.

Kosmidis, E., Syropoulou, P., Tekes, S., Schneider, P., Spyromitros-Xioufis, E., Riga, M. et al. (2018) hackAIR: towards raising awareness about air quality in Europe by developing a collective online platform. *ISPRS International Journal of Geo-Information*, 7, 187.

Kuula, J., Mäkelä, T., Aurela, M., Teinilä, K., Varjonen, S., González, Ó. et al. (2020) Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors. *Atmospheric Measurement Techniques*, 13, 2413–2423.

Lu, F., Xu, D., Cheng, Y., Dong, S., Guo, C., Jiang, X. et al. (2015) Systematic review and meta-analysis of the adverse health effects of ambient PM2. 5 and PM10 pollution in the Chinese population. *Environmental Research*, 136, 196–204.

Lu, Y., Giuliano, G. & Habre, R. (2021) Estimating hourly PM2.5 concentrations at the neighborhood scale using a low-cost air sensor network: a Los Angeles case study. *Environmental Research*, 195, 110653.

Luo, L., Zhang, Y., Pearson, B., Ling, Z., Yu, H. & Fu, X. (2018) On the security and data integrity of low-cost sensor networks for air quality monitoring. *Sensors*, 18, 4451.

Ma, L., Graham, D.J. & Stettler, M.E. (2021) Has the ultra low emission zone in London improved air quality? *Environmental Research Letters*, 16, 124001.

Magi, B.I., Cupini, C., Francis, J., Green, M. & Hauser, C. (2020) Evaluation of PM2.5 measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor. *Aerosol Science and Technology*, 54, 147–159.

Mahajan, S., Gabrys, J. & Armitage, J. (2021) AirKit: a citizen-sensing toolkit for monitoring air quality. *Sensors*, 21, 4044.

Malings, C., Tanzer, R., Hauryliuk, A., Kumar, S.P.N., Zimmerman, N., Kara, L.B. et al. (2019) Development of a general calibration model and long-term performance evaluation of low-cost sensors for air pollutant gas monitoring. *Atmospheric Measurement Techniques*, 12, 903–920.

Mekki, K., Bajic, E., Chaxel, F. & Meyer, F. (2019) A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT Express*, 5, 1–7.

Molina Rueda, E., Carter, E., L'orange, C., Quinn, C. & Volckens, J. (2023) Size-resolved field performance of low-cost sensors for particulate matter air pollution. *Environmental Science & Technology Letters*, 10, 247–253.

Morawska, L., Thai, P.K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A. et al. (2018) Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: how far have they gone? *Environment International*, 116, 286–299.

Mousavi, A. & Wu, J. (2021) Indoor-generated PM2.5During COVID-19 shutdowns across California: application of the PurpleAir indoor–outdoor low-cost sensor network. *Environmental Science & Technology*, 55, 5648–5656.

NAEI. (2019) Data. Available from: http://naei.beis.gov.uk/data [Accessed 18th July 2019].

Ouimette, J.R., Malm, W.C., Schichtel, B.A., Sheridan, P.J., Andrews, E., Ogren, J.A. et al. (2022) Evaluating the PurpleAir monitor as an aerosol light scattering instrument. *Atmospheric Measurement Techniques*, 15, 655–676.

Patel, D. & Won, M. (2017) Experimental study on low power wide area networks (LPWAN) for mobile internet of things. In: *2017 IEEE 85th vehicular technology conference (VTC spring)*. Sydney, Australia: IEEE, pp. 1–5.

SAMHE Project. (2022) *SAMHE*. Available from: https://samhe.org.uk/ [Accessed 17th March 2023].

Sayahi, T., Butterfield, A. & Kelly, K. (2019) Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. *Environmental Pollution*, 245, 932–940.

Secretary of State. (2023) The environmental targets (fine particulate matter) (England) regulations 2023 In: England, E. P. (ed.).

Song, Y., Lin, J., Tang, M. & Dong, S. (2017) An internet of energy things based on wireless LPWAN. *Engineering*, 3, 460–466.

South Coast AQMD. (2023) Aeroqual AQY Sensor Network. Available from: http://www.aqmd.gov/aq-spec/special-projects/aeroqual-aqy-deployments [Accessed 17th March 2023].

Topping, D., Bannan, T., Coe, H., Evans, J., Jay, C.E., Murabito, E. et al. (2021) Digital twins of urban air quality: opportunities and challenges. *Frontiers in Sustainable Cities*, 141.

Transport for London. (2022) ULES:Where and when. Available from: https://tfl.gov.uk/modes/driving/ultra-low-emission-zone/ulez-where-and-when [Accessed 10th November 2022].

Williams, H., Bartington, S., Pope, F. & Landeg-Cox, C. (2022) Low emission (clean air) zones-policy briefing note produced by the TRANSITION clean air network. TRANSITION Clean Air Network Policy Briefing Notes.

Yong, Z. & Haoxin, Z. (2016) Digital universal particle concentration sensor PMS5003 data manual. PLANTOWER.

Zhang, J., Marto, J.P. & Schwab, J.J. (2018) Exploring the applicability and limitations of selected optical scattering instruments for PM mass measurement. *Atmospheric Measurement Techniques*, 11, 2995–3005.

Zhong, J., Hood, C., Johnson, K., Stocker, J., Handley, J., Wolstencroft, M. et al. (2021) Using task farming to optimise a street-scale resolution air quality model of the west midlands (UK). *Atmosphere*, 12, 983.

Zusman, M., Schumacher, C.S., Gassett, A.J., Spalt, E.W., Austin, E., Larson, T.V. et al. (2020) Calibration of low-cost particulate matter sensors: model development for a multi-city epidemiological study. *Environment International*, 134, 105329.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Cowell, N., Baldo, C., Chapman, L., Bloss, W., & Zhong, J. (2024). What can we learn from nested IoT low-cost sensor networks for air quality? A case study of $PM_{2.5}$ in Birmingham, UK. *Meteorological Applications*, *31*(4), e2220. https://doi.org/10.1002/met.2220