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Structuring an integrated air quality monitoring network in large urban areas – Discussing the purpose, criteria and deployment strategy

Said Munir[a,*], Martin Mayfield[a], Daniel Coca[b], Stephen A. Jubb[a]

[a] Department of Civil and Structural Engineering, The University of Sheffield, Sheffield, S1 3JD, UK
[b] Department of Automatic Control and Systems Engineering, The University of Sheffield, Sheffield, S1 3JD, UK

HIGHLIGHTS

- In this study an integrated air quality monitoring network is proposed.
- The methodology is supported by numerical, conceptual and GIS frameworks.
- Siting of air quality sites is based on social, economic and environmental indicators.
- Population, pollution and their spatial variability are main factors for site selection.
- The aim is to structure and AQMN following a formal approach.

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ABSTRACT

Air pollution in large urban areas has become a serious issue due to its negative impacts on human health, building materials, biodiversity and urban ecosystems in both developed and less-wealthy nations. In most large urban areas, especially in developed countries air quality monitoring networks (AQMN) have been established that provide air quality (AQ) data for various purposes, e.g., to monitor regulatory compliance and to assess the effectiveness of control strategies. However, the criteria of structuring the network are currently defined by single questions rather than attempting to create a network to serve multiple functions. Here we propose a methodology supported by numerical, conceptual and GIS frameworks for structuring AQMN using social, environmental and economic indicators as a case study in Sheffield, UK. The main factors used for air quality monitoring station (AQMS) selection are population-weighted pollution concentration (PWPC) and weighted spatial variability (WSV) incorporating population density (social indicator), pollution levels and spatial variability of air pollutant concentrations (environmental indicator). Total number of sensors is decided on the basis of budget (economic indicator), whereas the number of sensors deployed in each output area is proportional to WSV. The purpose of AQ monitoring and its role in determining the location of AQMS is analysed. Furthermore, the existing AQMN is analysed and an alternative proposed following a formal procedure. In contrast to traditional networks, which are structured based on a single AQ monitoring approach, the proposed AQMN has several layers of sensors: Reference sensors recommended by EU and DEFRA, low-cost sensors (LCS) (AQMesh and Envirowatch E-MOTEs) and IoT (Internet of Things) sensors. The core aim is to structure an integrated AQMN in urban areas, which will lead to the collection of AQ data with high spatiotemporal resolution. The use of LCS in the proposed network provides a cheaper option for setting up a purpose-designed network for greater spatial coverage, especially in low- and middle-income countries.

1. Introduction

Air pollution is one of the most serious current threats to health, killing 6.4 million people in 2015 worldwide both in developed and less-wealthy nations (Landrigan, 2017). Air pollution is causing various health problems including respiratory problems, cardiovascular diseases, lung cancer and asthma (WHO, 2013). Particulate matter and nitrogen dioxide (NO_2) pollution may cause premature deaths and hospital admissions for conditions such as cardiovascular problems, allergic reactions and lung cancer (Walters and Ayres, 2001). Air

* Corresponding author.
E-mail addresses: smunir2@sheffield.ac.uk (S. Munir), martin.mayfield@sheffield.ac.uk (M. Mayfield), d.coca@sheffield.ac.uk (D. Coca), steve.jubb@sheffield.ac.uk (S.A. Jubb).

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pollution is particularly harmful for children, people with existing health problems and the elderly (Khallaf, 2011). Furthermore, air pollution may reduce visibility, damage historical buildings and monuments, affect vegetation and reduce crop yield and quality (Khallaf, 2011; Ivaskova et al., 2015). Air pollution is considered more of a serious problem in large urban areas in both developed and less-wealthy nations (Brunt et al., 2016; DEFRA, 2015). This is due to the fact that urban areas possess greater numbers of emission sources and densely built-up areas including tall buildings and street canyons which hinder dispersion of locally emitted air pollutants (Wu et al., 2017). Urban areas have various emission sources, e.g., road traffic, point emissions and area emissions emitting high volume of both gaseous (e.g., NO, NO_2, CO, SO_2, and H_2S) and particle pollutants (e.g., PM_{10} and $PM_{2.5}$) (DEFRA, 2017). In addition, more people are exposed to air pollution due to high population density in urban areas.

To improve air quality (AQ), the first step is to improve air quality monitoring networks (AQMN) in large urban areas as the current networks are not dense enough for developing high resolution maps and highlighting local micro-level drivers of air pollution (Castell et al., 2017; Schneider et al., 2017). Urban areas exhibit much greater spatial variability in air pollution levels, which require a dense (ubiquitous) AQMN. Traditional and more accurate AQ monitoring instruments are expensive to purchase and maintain, therefore it is not practical to set up a dense network to capture local-scale spatial variability in air pollution concentrations (Castell et al., 2017; Schneider et al., 2017). Traditional AQMN are sparse having few sites widely spaced around a city therefore historically no or little attention has been paid to selecting monitoring sites by following a formal approach to provide spatial coverage and deploy AQ sensors in various environmental types (e.g., roadside, kerbside, urban and suburban background and green spaces). The current literature lacks a rigorous methodology for determining locations of AQMS (Hoek et al., 2008; Wu et al., 2017).

Assessment of the spatial representativeness of air quality monitoring station (AQMS) is an important subject and is linked to health risk assessment, population exposure to air pollution, the design of AQMN, AQ modelling and data assimilation (Kracht et al., 2017; Martin et al., 2015). The spatial representativeness of a monitoring site is related to the variability of pollutants concentrations around that site (Righini et al., 2014). However, scientific literature and European regulation lacks a clear definition and unified agreement for determining the spatial representativeness of an AQMS. Santiago et al. (2013) have reported that due to the complexity of urban meteorology and emissions distribution, AQ in urban areas cannot be assessed with confidence using only air pollutant measurements from a monitoring station. Air pollution levels estimated by street scale dispersion models and maps of population density and residence time can be used to get a more complete and precise view of the air pollution conditions. To analyse the spatial representativeness of urban AQMS and to complement their measured concentrations, Santiago et al. (2013) have developed a methodology using a set of computational fluid dynamics simulations based on Reynolds-Averaged Navier–Stokes equations (CFD-RANS) for different meteorological conditions in two urban areas Pamplona and Madrid in Spain. They defined the representativeness area of AQMS, as the area where concentrations were within an interval of ± 20% of the pollutant concentrations at the monitoring station. Righini et al. (2014) presented a methodology to assess spatial representativeness of an AQMS by analysing the spatial variation of emissions around it. Spatial variability of several air pollutants was carried out using a neighbourhood statistic function in a Geographic Information System (GIS). Low variability of emission around a site showed high spatial representativeness of that site and vice versa. To detect spatial representativeness of several urban background or rural background monitoring sites the methodology was applied in Northern and Central Italy.

There are two types of AQMN: routine networks and purpose-designed monitoring networks (Hoek et al., 2008). They both have their pros and cons. Routine monitoring networks are designed mainly for assessing AQ compliance with regulatory standards. An example of such a network is the Automatic Urban and Rural Network (AURN) in the UK. The AQ monitoring sites in the AURN are continuous sites and most of them have been running over a long period of time (ten years or more), however, the monitoring stations are sparse and not suitable for urban scale modelling and mapping. Purpose-designed monitoring networks are set up for a particular purpose, e.g., for developing a land-use regression (LUR) model or for developing urban scale air pollution maps. In these types of networks, the designers (researchers) have control over the selection of the types and number of monitoring sites required for the purpose, however they could be extremely expensive (Hoek et al., 2008) and unaffordable especially in low- and middle-income countries. Therefore, due to lack of funding many researchers have been using data from the routine (e.g., AURN) networks. More recently due to the introduction of low-cost sensors (LCS) (Schneider et al., 2017; Castell et al., 2017; Borrego et al., 2016; Lewis et al., 2016; Lebret et al., 2000; Goswami et al., 2002) several academic and research organisations have set up purpose-designed AQMN for urban scale modelling and exposure assessment. However, these studies have not followed formal procedures for allocating sites, which means performing the GIS calculation of various variables on the basis of which the sites are selected, e.g., population density, pollution concentrations and their spatial variability. In many studies sites are selected informally i.e. without the GIS calculation of various variables or on an ad hoc basis (favouring the placement of monitors in traffic hot spots or in areas deemed subjectively to be of interest). This is because using a formal procedure requires a significant amount of data on the required variables, which are normally not available.

In this study, we intend to structure an AQMN in Sheffield utilising population-weighted air pollution concentration (PWPC) and weighted spatial variation (WSV), which incorporate population density (social indicator), pollution concentrations and spatial variability of pollution concentrations (environmental indicator). Furthermore, a conceptual model is presented which in addition to PWPC and WSV considers the opinions of experts having local experience and understanding of the purpose of AQ monitoring. This study proposes an integrated air quality monitoring network (IAQMN) in Sheffield using a multipurpose and more robust approach aimed at providing maximum value from a network of sensors by adopting an integrated approach which draws on multiple data sources and techniques to inform decision making. The procedure proposed in this study is based on numerical equations using data of population density, pollution concentrations and their spatial variability. The approach can be applied anywhere and shouldn't be susceptible to failure due to changes in location or time. The proposed network integrates various layers of AQ monitoring techniques including reference sensors which are the most accurate and are recommended by EU and DEFRA for AQ monitoring, LCS (AQMesh and Envirowatch E-MOTEs), and very low-cost IoT (Internet of Things) sensors. These sensors will be deployed as fixed stations in various layers and mounted on vehicles (mobile monitoring). The aim of the proposed AQ network is to collect AQ data of high spatiotemporal resolution to be used in local-scale high resolution mapping and modelling as a case study in Sheffield. This case study will provide a great example of a purpose-designed monitoring network using mostly LCS, especially for low- and middle-income countries where such networks don't exist due to the high purchase and maintenance cost of reference AQ instruments.

2. Methodology

This paper proposes an IAQMN in urban areas using the city of Sheffield as a case study. The aim is to structure a multipurpose robust and systematic approach based on formal procedure utilising numerical, GIS and conceptual modelling techniques. In the proposed network AQMS are mainly selected on the basis of PWPC and WSV of air pollutant concentrations. PWPC accounts for population density and air pollution concentrations, whereas WSV is the factor of spatial gradients of air pollutant concentrations. In this way, the site selection criteria integrate population density, pollution concentrations and spatial variability of both population and pollution levels. Furthermore, a conceptual model is provided, which in addition to PWPC and WSV focuses on the purpose of the monitoring network, opinion of experts with local experience and financial resources (budget of the project) to determine the number of monitoring sites and to select their locations. The total number of sensors is decided on the basis of project budget, whereas the number of sensors in each output area is a factor of WSV. Once the sensors are deployed and data collected, we will analyse the data to assess spatial representativeness of the sites, which can help us decide how many sensors are redundant and how many more sensors are required in areas where spatial variability of air pollution has not been captured.

Air quality management areas (AQMA) are declared mainly on the basis of NO_2 and PM_{10} levels, which are the cause of primary concern in the urban areas of Sheffield and therefore the project focuses on these two pollutants. However, the measurements of other pollutants (e.g., O_3, CO and SO_2) and meteorological parameters (e.g., wind speed and direction, relative humidity and temperature) will be used to analyse the chemistry and dispersion of air pollutants, which will further help to determine the main drivers of air pollution in Sheffield. In this project the network is designed according to the spatial variability of NO_2. Each pollutant has different spatial variability, therefore a network designed based on the spatial variability of another pollutant (e.g., PM_{10}) will have different characteristics.

In this project the intention is to make use of several layers of AQ sensors including both static (fixed) and mobile monitoring to provide AQ data for high spatial and temporal resolution AQ maps. AQ sensors are installed in vehicles, known as MOBIle Urban Sensing (MOBIUS) vehicle. The monitoring only takes place when the vehicle is stationary. The vehicle is driven to the intended location, parked safely and then the monitoring equipment is turned on. AQ monitoring is not carried out when vehicle is in motion. These layers are shown in Fig. 1 and their main features are given in Table 1. The types of AQ sensors employed include reference sensors, LCS and IoT sensors. IoT sensors are miniature electronic devices that are comprised of sensors, microprocessors and communication integrated circuits that are able to detect changes in the environment. IoT sensors are generally much cheaper, lighter and smaller than the LCS. Generally, their prices are a few tens of pounds for a single pollutant sensor. The quality of data collected by IoT sensors is inferior to the LCS and reference sensors. LCS are more compact, portable and use less power when compared to reference instruments. However, they are larger in size and have much better accuracy than IoT sensors. LCS range in price from a couple of thousand to several thousand pounds (for a relatively sophisticated multi-pollutant and meteorological sensor with communication capabilities). Reference sensors are expensive, both to purchase and maintain, and bulky but are the most accurate units, recommended for use by EU and UK government bodies for AQ monitoring and comply with standards such as MCERTS in the UK. A single unit costs in the region of twenty thousand pounds to monitor a single gas or gaseous species or particle pollutants. IoT, LCS and reference sensors all employ different techniques of air pollutant measurement, which include optical particle counters, light scattering, metal oxide semiconductor sensors, electrochemical sensors, nondispersive infrared sensors, ultraviolet fluorescence, chemiluminescence, infrared photometry and photo-ionisation detection sensors. For more detail see Borrego et al. (2016) and Mead et al. (2013). The LCS used in this project are either Envirowatch E-MOTEs or AQMesh pods. Envirowatch E-MOTEs are deployed either in a local mesh (deployed in a cluster, providing data via ZigBee, within a certain area for high resolution monitoring, no more than 100 m from each other, with a gateway providing uplink capability) or independent (distributed sensors that can be deployed at any distance from each other and can be used for both high and low resolution monitoring, using longer distance communications systems such as GPRS or Wi-Fi providing internet access). AQMesh sensors are independent and can be deployed at both high and low spatial resolution. In this case each sensor independently sends data to a cloud server using GPRS. LCS offer great potential for AQ monitoring in low- and middle-income countries.

The new generation of sensors such as E-MOTEs and AQMesh pods have the capability to mitigate the effect of climatic factors such as temperature and relative humidity on AQ data collection. The innovation is the addition of a fourth electrode, which is embedded in the sensor electrolyte allowing the reaction from environmental effects to be measured without the effects from the target gas. Furthermore, mathematical algorithms are developed for individual sensor types to compensate for environmental effects and cross-gas interference to provide the best possible precision and accuracy of measurement.

All sensors are pre-calibrated by the manufacturers and, subsequently returned for sensor replacement and recalibration periodically as specified by the manufacturer. In-the-field local calibration of sensors is required in certain circumstances including: (a) following a sensor-pack change the new sensor should be calibrated; and (b) following a large step change in environmental conditions, e.g., a change in average temperature of 10 degrees Celsius or more, relative to when it was originally calibrated. During this project, the sensors will be calibrated locally in two ways: (i) Co-location with reference sensors, and (ii) Using MOBIUS.

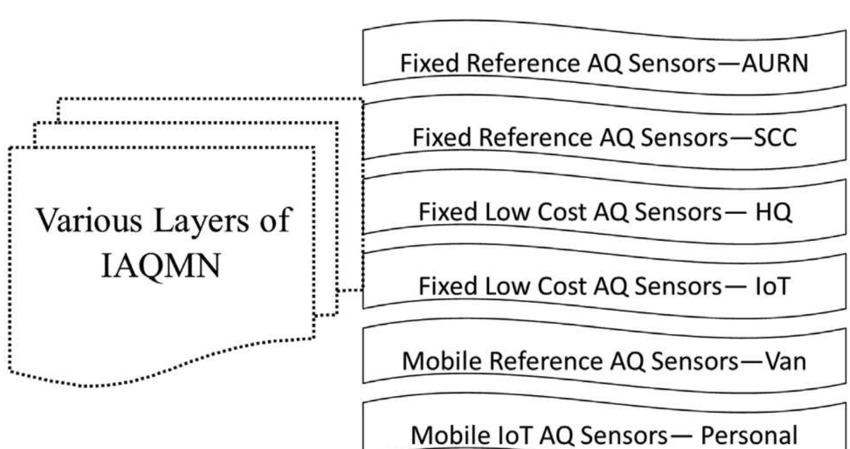

Fig. 1. Various layers of AQMS. In the diagram AURN stands for automatic urban and rural network, SCC for Sheffield City Council, HQ for High Quality (e.g., AQMesh and Envirowatch E-MOTEs), IoT for Internet of Things, Van – sensors mounted on a vehicle (MOBIUS), and Personal – sensors carried by people.

Table 1
Summarising the features of various types of monitoring techniques.

Sensor type	Temporality (resolution)	Spatiality (resolution)	Quality
Reference sensors - AURN	Medium (hourly), long term	Low (fixed)	High
Reference sensors - SCC	Medium (hourly), long term	Low (fixed)	High
LCS	High (minute), long term	High (fixed)	Medium
IoT	High (minute), long term	High (fixed)	Low
Mobile Ref. sensors	High (variable), short term	Variable (determinate)	High
Mobile IoT sensors	High (minute), short term	Variable (indeterminate)	Low

Several LCS will be deployed next to reference AQMS including at Devonshire Green and Siemens Close Tinsley. At these sites one E-MOTE and one AQMesh pod will be deployed next to the reference AQMS. The sensors will be placed immediately adjacent or no further than 2 m apart from the reference sensors. This will help correct slopes and offset (intercept) values of the LCS to improve the accuracy of results by comparing data over a period of several months. The manufacturer recommends co-location of sensors with reference sensors for several days or weeks, however, in this project LCS will be co-located for a year with reference sensors and the calibration will be across the seasons (Winter – Nov, Dec, Jan; Spring – Feb, Mar, Apr; Summer – May, June, July; and Autumn – Aug, Sep, Oct), which can help determine the effect of various meteorological parameters on the performance of these sensors. During the calibration LCS measurements are regressed versus reference (Ref) measurements, where LCS data are taken as independent (x-axis) and Ref as dependent (y-axis) variable. Regression model is run and values of slope and intercepts are calculated using the measured LCS and Ref concentrations as shown in equations (1) and (2).

$$\text{Ref} = \text{intercept} + (\text{slope x LCS}) \tag{1}$$

$$\text{NO2\_Ref} = a + (b \text{ x } NO_2\text{\_LCS}) \tag{2}$$

The values of slope and intercept are then applied to the whole dataset of LCS.

MOBIUS will be used for calibrating LCS around the city in different locations and different seasons. It will be parked for a minimum period of five hours adjacent to the sensors (preferably no more than two metres apart, but as close as practically possible). In situations where the vehicle cannot reach the vicinity of the sensor, it will be removed from its mount and temporarily affixed to MOBIUS for the period of calibration. Installation of the sensors is relatively easy and quick so if necessary this can be accomplished within a matter of minutes. The calibration time period is limited by the auxiliary battery/inverter sets (a total of 2.8 kWh) carried on MOBIUS which power the reference analysers. In some cases, where mains power is available (e.g., sensors deployed at the university campus) the period of colocation can be extended to 24 h to cover the whole diurnal cycle. Calibration will be carried out at least once in each season (Winter – Nov, Dec, Jan; Spring – Feb, Mar, Apr; Summer – May, June, July; and Autumn – Aug, Sep, Oct). After obtaining the concentrations of the LCS and MOBIUS, the values of intercept and slopes will be calculated and applied as shown in equations (1) and (2). The main features we want to see in a sensor network are temporal resolution (time), spatial resolution (space) and quality of the data (Fig. 2). Reference sensors provide high quality data with reasonable time resolution (hourly), however, their spatial resolution is low due to their large size, power requirements and high price. We have only 3 AURN sites and 6 Sheffield City Council (SCC) sites in the whole city of Sheffield, so spatial resolution is low. In contrast, LCS both AQMesh and Envirowatch E-MOTEs, can provide high resolution spatial and temporal data but at relatively lower quality. LCS can provide real-time minute-by-minute data and a high-density network can be set up due to their low price and maintenance cost. Both reference and LCS can provide long-term data (e.g., over a year or longer). On the other hand, mobile networks can utilise both reference sensors and LCS to provide high resolution temporal and spatial data, however they normally provide short term data (e.g., the vehicle can be parked on a specific location for a limited period of time, usually up to five hours) and their spatial resolution is variable. Mobile networks can provide high or low spatial resolution data depending on the need. Furthermore, using MOBIUS we have to monitor roads or streets one by one. This temporal differences (gaps) render the data incomparable with each other due to the fact that AQ levels vary during different hours of the day, days of the week or seasons of the year mainly due to differences in meteorological conditions (e.g., temperature, solar radiation, wind speed and direction) and boundary layer characteristics which affect pollutant dispersion. Therefore, MOBIUS will be mainly used for calibration or for short term monitoring purposes.

As shown in Fig. 2, in the three-dimensional (3-D) time-space and quality box we want to achieve point (P) ideally, which indicates high quality data with high spatiotemporal resolution. However, this is not always practical due to various reasons, mainly financial budget. Therefore, we need to compromise either on quality, spatial or temporal resolution. The dimension that will be subject to compromise is dependent on the reason for monitoring and the intended purpose of the output data. For example, if we want to determine a long term temporal trend over a ten-year period, there is no need for high temporal resolution (e.g., minute-by-minute or hourly data), daily or even monthly data will suffice. Also, we might not need a dense network of AQ sensors, a small number deployed in urban background, suburban background or rural locations will suffice. In contrast, if the purpose is to investigate how road traffic-flow affects AQ, we will need high temporal resolution, e.g., minute-by-minute data, because in this instance anything with less frequency will be too coarse. Furthermore, in monitoring the effect of traffic on AQ, if the purpose is to see the pattern in air pollution levels, we might not need very accurate readings, so the quality (accuracy) of the readings might not be of a great concern. On the other hand, for urban-scale modelling and mapping, high-resolution spatial data collected by a dense AQMN will be required. Therefore, it can be said that the type of sensors, type of monitoring sites, quality of data, density of monitoring network and temporal resolution are dependent on the purpose of monitoring programme.

2.1. Population-weighted pollution concentration (PWPC)

Human exposure to air pollution is a function of population density (residents/km^2) and pollution levels. Therefore, both social (population) and environmental (air pollution) indicators should be considered in structuring an AQMN. Population data are normally more readily available than pollution data, e.g., population data can be obtained from a recent census or local council. In contrast, detailed pollution data of various air pollutants are generally not available, especially in countries with less well developed infrastructure. Therefore, in the absence of air pollution data, as an alternative air pollution emissions or modelling estimations of air pollutants can be used. For example, Righini et al. (2014) have used air pollutant emissions data to optimise AQMN in Italy. It is worth mentioning that air pollutant emissions and concentrations are not the same and the same amount of emissions may result in different concentrations due to differences in meteorological

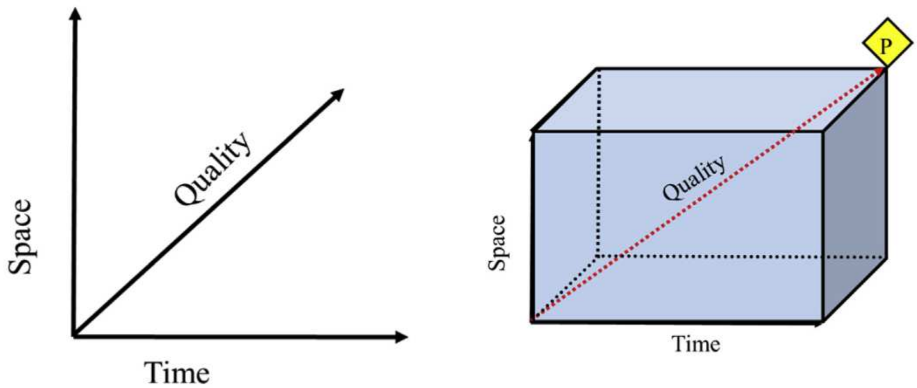

Fig. 2. Three-dimensional (3-D) box, where x-axis is represented by time (temporal resolution of collected data), y-axis by space (spatial resolution of the collected data) and z-axis by quality (quality of the collected data). Ideally, we want to achieve high spatial and temporal resolution with high quality data (represented by point 'P'), however this may not be always possible.

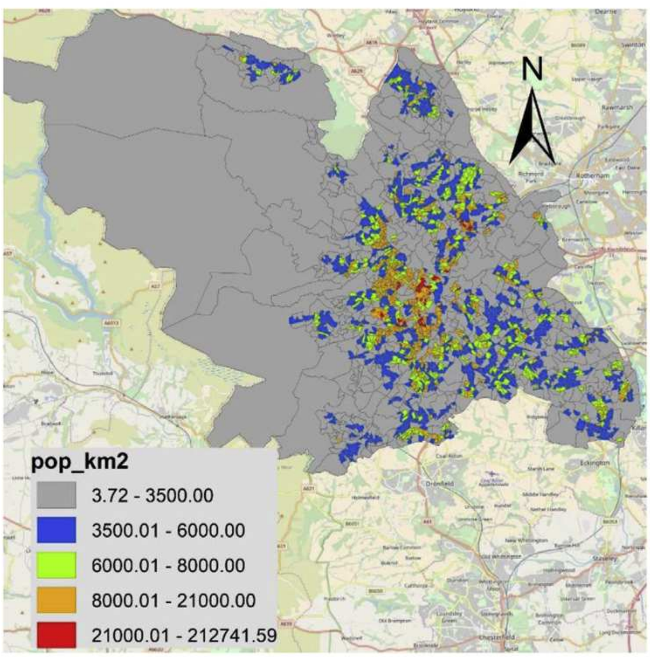

Fig. 3. Population density (residents/km^2) map of Sheffield (2016).

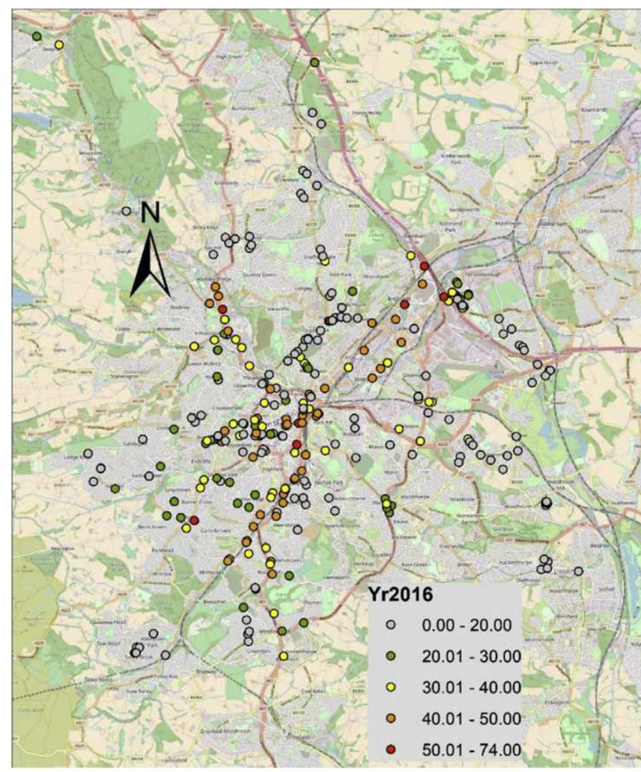

Fig. 4. Locations and annual average NO_2 concentrations (μg/m^3) of NO_2 diffusion tubes in Sheffield (2016).

conditions and atmospheric boundary layer height. However, generally emissions of primary pollutants are accepted as a reasonable estimates of pollutant concentrations (Righini et al., 2014). In this study we used population density maps of 2016 to show population density of Sheffield (Fig. 3). In these maps bright green (6000–8000 residents/km^2) represents average population (7000 ± 1000), as the average population of Sheffield is about 7000 residents/km^2. Orange and red show areas where population is greater than average, in some case more than double and treble. Areas of high population density are mostly shown in the city centre where people live in multi-storey buildings. Locations of primary and secondary schools were used to represent areas of more vulnerable people (children are more vulnerable and are more likely to be adversely affected if exposed to high levels of air pollution). Schools represent urban and suburban background environmental types. NO_2 diffusion tube locations and annual concentrations (μg/m^3) are shown in Fig. 4. NO_2 diffusion tubes data are available in Sheffield for the last several years providing reasonable spatial coverage. Therefore, these maps were used to determine spatial variability of NO_2 in the City. In Fig. 4, orange and red dots show locations where NO_2 levels exceeded annual AQ limits (40 μg/m^3) (Air quality objectives, 2015).

NO_2 concentration is shown in the form of points, whereas population density is shown in the form of polygons, therefore, firstly NO_2 concentration was converted into the same format. In case there were more than 1 point in a polygon, their average NO_2 concentrations were calculated for the polygon. Output areas (polygons) are the lowest geographical levels that are created for Census data. Output areas are built from clusters of adjacent unit postcodes. They are designed to be similar in terms of cultural and demographic characteristics with relatively similar populations for statistical purposes. Output areas do not mix urban and rural areas and should be consisted either entirely of urban postcodes or rural postcodes. An output area should have minimum size of 40 resident households and 100 resident people, however its recommended size is 125 households (Office for National Statistics, 2018).

Averaging NO_2 concentrations across the polygon may introduce a degree of error, especially if the polygon is large and heterogeneous in terms of air pollutant concentrations. However, heterogeneity of air pollutants is minimised by the fact that an output area doesn't mix urban and rural areas. Any polygon without data was excluded from the analysis, which means the polygon was not coloured. Unshaded polygons mean there were no data of NO_2.

To calculate population-weighted pollution concentrations (PWPC), firstly normalised population density (NPD) of each cell was obtained

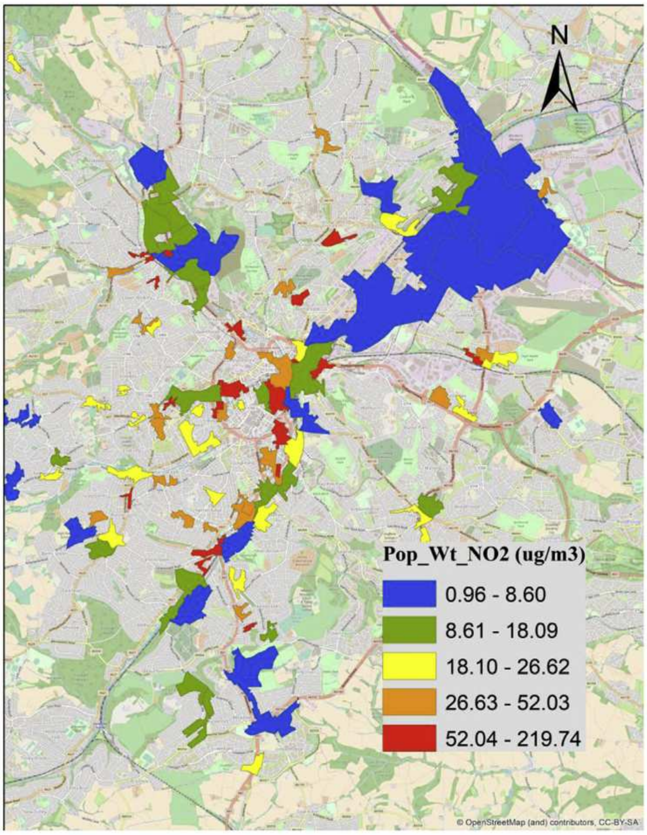

Fig. 5. Population-weighted NO_2 concentrations (PWPC) ($\mu g/m^3$) Sheffield, 2016.

by dividing population density (PD) of each cell by average PD (mean-PD) of all polygons, following the approach used by Carslaw (2015) in the 'openair-manual' (equation (3)). In the second step NPD was multiplied by pollution concentration (PC) of each cell (equation (4)) to get PWPC, which is an important indication of people exposure to air pollution. PWPC was mapped using ArcGIS version10.4.1 as shown in Fig. 5.

$$NPD_i = (PD_i/\text{mean-PD}) \tag{3}$$

$$PWPC_i = NPD_i * PC_i \tag{4}$$

In Fig. 5, red shows the highest PWPC, whereas blue indicates the lowest PWPC. The number of sensors to be deployed will depend on the budget of the project (economic criteria). The areas with higher PWPC should get priority in deploying AQ sensors. However, it is important to quantify spatial variability of NO_2 concentrations to determine how many sensors will be deployed in each polygon. More sensors should be deployed in the area with greater spatial variability and vice versa, which is discussed in the next section (2.2).

2.2. Spatial variability of NO_2 concentrations ($\mu g/m^3$)

In the previous section PWPC (Fig. 5) was analysed, which highlights those areas where more people are exposed to NO_2 concentrations. However, to decide where more sensors should be deployed we need to determine spatial variability of NO_2. Areas experiencing high concentrations of PWPC and greater spatial variability require more sensors in contrast to those areas where PWPC is low and are spatially homogenous in terms of pollution concentrations. Therefore, in this section first we quantify spatial variability (SV) of NO_2 concentrations.

SV of NO_2 concentrations ($\mu g/m^3$) are shown in Fig. 6, which are calculated and mapped in ArcGIS 10.4.1. Standard deviation (STD)

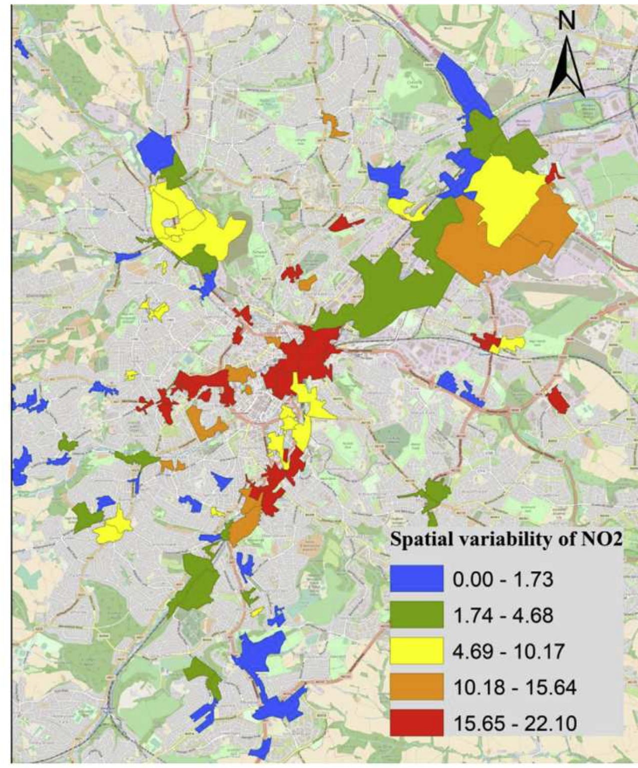

Fig. 6. Showing spatial variability of NO_2 concentrations($\mu g/m_3$).

determines how NO_2 concentration is dispersed within a given area. To determine SV, we calculated STD of NO_2 concentrations within each 400 m^2 area, having at least 3 observations using equation (5).

$$STDi = \sqrt{1/n \sum_{i=1}^{n} (xi - \mu)^2} \sqrt{1/\, \mathrm{n} \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{xi} - \mu)^2} \tag{5}$$

In equation (5), x is NO_2 concentrations, μ is the mean concentrations and n is the number of data points. STDi are mapped in Fig. 6, where red shows more spatial variability of NO_2 concentrations. To provide a quantitative assessment as to how many sensors should be deployed in each area, in this study we propose an approach, which integrates PWPC (Fig. 5) with SV (Fig. 6), thus accounting for population density, pollution concentrations and SV. The resultant variable is termed weighted spatial variability (WSV), which is the product of PWPC and normalised standard deviation (NSTD) as shown in equation (6).

$$WSVi = PWPCi * NSTDi \tag{6}$$

Finally, the number of sensors in each cell (n_i) is determined by solving equation (7) using the WSVi value within each cell and sum of the WSV_i of all cells.

$$n_i = (WSV_i \,/\, \Sigma(WSV_i)) * N_t \tag{7}$$

Where N_t is the total number of sensors to be deployed, which is decided on the basis of economic criteria (budget).

The main points considered for site allocation are summarised in Fig. 7, including population density, pollution levels and pollution spatial variability. Furthermore, the purpose of the AQ monitoring programme and the opinion of experts having experience of the local area are two important factors in siting the AQMS. They inform where exactly the sensors will be deployed in each polygon. Therefore, it is important to analyse the purpose of the AQ monitoring, discussed in next section (2.3).

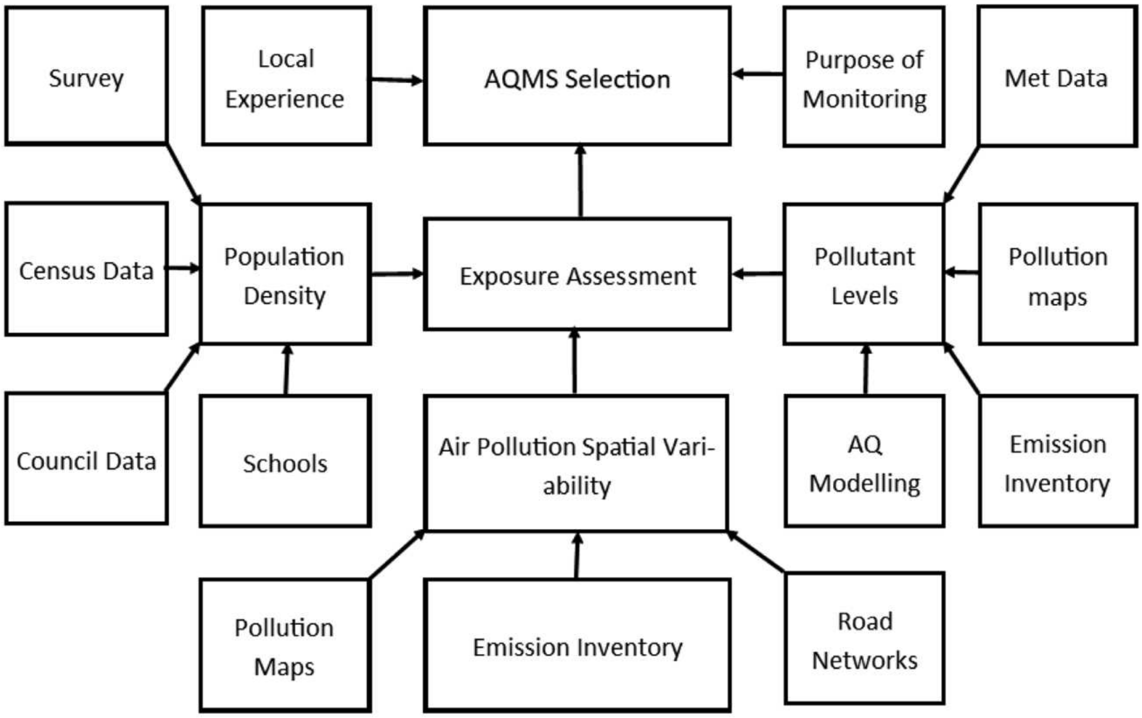

Fig. 7. Criteria for the selection of AQMS (ESCAPE, 2010; LAQM.TG, 2009; Kanaroglou et al., 2005). Also, see Fig. 8 for the description of 'the purpose of monitoring'.

2.3. Purpose of AQ monitoring and its role in site selection

The primary criterion among those that are most important for selecting the locations of AQMS is the purpose of the AQ monitoring programme. Therefore, it is important to briefly describe the main purposes of AQ monitoring and what role they play in determining sites for AQMS deployment. AQ monitoring may be carried out due to the following reasons:

(i) AQ review and assessment (regulatory compliance) (Kanaroglou et al., 2005; ESCAPE, 2010; LAQM.TG16, 2016; LAQM.TG09, 2009): AQ review and assessment involves monitoring current levels of air pollution and modelling how it might change in the near future. The main aim of the review and assessment is to ensure that national AQ objectives are achieved. The purpose of these objectives is to protect human health and environment from the negative impacts of air pollution. Probably the most important reason for AQ monitoring is to assess human exposure to air pollution. This determines the areas where people are exposed to high levels of air pollution. The monitoring programme should take into account air pollution and demographical characteristics of the region under consideration and consider worst-case public exposure both in terms of pollution levels and population density.

(ii) AQ modelling (Raffuse et al., 2007; LAQM.TG16, 2016): AQ monitoring is also carried out to assess the outcome of dispersion modelling studies. In these types of monitoring programmes sensors should be deployed close to the emission sources. For example, if the purpose is to assess the performance of a dispersion model developed for a particular road, the AQ sensors should be deployed at the roadside of that particular road, even if there is

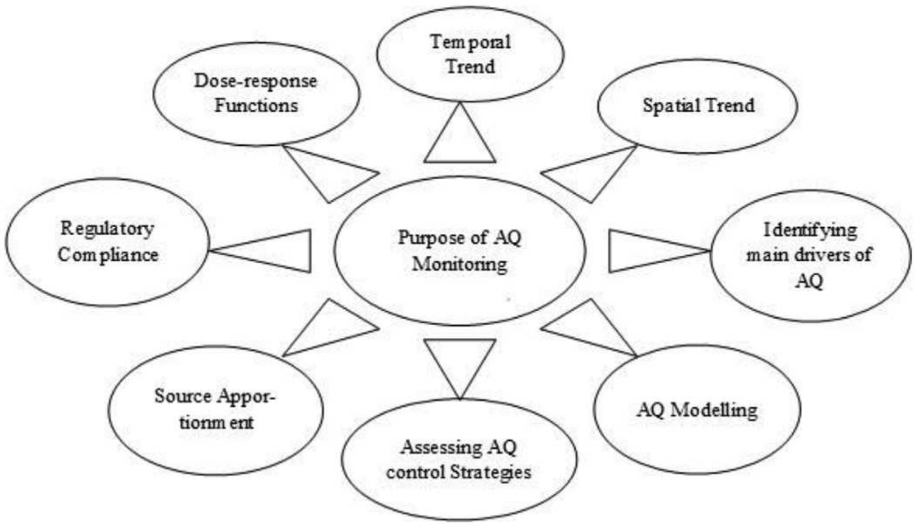

Fig. 8. The main purposes of AQ monitoring (ESCAPE, 2010; LAQM.TG09, 2009; Raffuse et al., 2007).

no exposure. In additional to dispersion modelling, AQ data collected by the monitoring programmes are used in various AQ statistical, photochemical, mathematical, forecasting and land-use regression models. These are employed in various investigations into AQ related projects and multi-disciplinary projects like transportation models, climate models and other urban system models. In this case AQ sensors should be deployed where the other variables (e.g., weather parameters) are also monitored.

(iii) Temporal trends (Raffuse et al., 2007): Sometimes AQ is monitored to determine how air pollutant levels have changed over a specific period of time, over the last ten years, for instance. In this case monitoring should be carried out at a background site, away from local sources, e.g., an urban background or suburban background site. However, if the purpose is to assess the temporal trend near a particular emission source, then sensors should be deployed as close as possible to that source. Furthermore, monitoring data can be used to determine diurnal, weekly and annual cycles of air pollutants, however for this purpose high resolution temporal concentration measurements are required, such as at intervals of one minute, 15 min or hourly.

(iv) Source apportionment (Raffuse et al., 2007): AQ monitoring programmes are also launched to determine various sources of air pollutant emissions. In this case AQ sensors should be deployed in different types of environments including roadside (where both heavy and intermediate traffic loads are encountered), next to point sources, urban background, suburban background and rural sites. Sensors next to local sources determine the contribution of local sources, whereas background and rural sites help determine the contribution of urban level and regional level emission sources.

(v) Spatial coverage (Raffuse et al., 2007): AQ monitoring can help determine spatial trend in air pollution levels. Urban areas demonstrate high spatial variability in air pollution levels due to changes in emission sources and tall buildings which affect air pollutant dispersion processes. Therefore, urban areas in comparison to suburban or rural areas would require more sensors to capture variability in air pollution levels. Sensors should be deployed in different environmental conditions, including next to busy roads, point sources, open streets, street canyons, market places and residential areas. For air pollution mapping at an urban level, a dense network of sensors is required. The density of sensor should be high where air pollution levels are more variable and vice versa (Kanaroglou et al., 2005).

(vi) Identifying the main drivers of AQ: AQ monitoring is sometimes carried out to investigate the effects of various factors on AQ conditions such as various land-use strategies, climate and meteorology, boundary layer height, and topographical and geographical characteristics. If this is the case, then AQ sensors should be deployed in various environment types such as urban background, suburban background, and traffic sites including various altitudes and land-use types.

(vii) Dose-response relationship (Munn, 1981): If an air pollution monitoring programme is used to collect air pollutant data which will be used to establish a dose-response relationship for investigating the effects of air pollution on human health, vegetation, soiling and corrosion of different materials, and economic effect, then AQ sensors should be deployed next to the location where the investigation is taking place.

(viii) Assessing AQ control strategies: Air pollution monitoring is needed for assessing the effectiveness of control strategies, e.g., if an air pollution management and control strategy is implemented in a specific area, then AQ data are required to cover the period just before and after the implementation of the strategy to assess how effective the strategy has been.

These are the main purposes of AQ monitoring, however by no means this list is exhaustive. The purposes of AQ monitoring are summarised in Fig. 8.

The opinion of experts having experience of the local area is a valuable asset in identifying suitable sites for the deployment of AQ sensors. To utilise this, several meetings were arranged with the AQ group and transport team at SCC and researchers from various departments of the University of Sheffield. They had extensive experience of the city and helped identify areas where air pollution has been or is likely to be a problem, where emissions have declined or increased, or where air pollutants emissions are going to change in the near future, e.g. Abbeydale and London Rd, Meadowhall, City Centre and so on. To fully utilise this resource an Air Quality Sensors Network (AQSN) workshop was organised, which was attended by air pollution and environmental science experts from different departments of the University of Sheffield and SCC. Their suggestions were sought on sensor deployment and utilised wherever possible and applicable.

3. Results and discussion

In this study following the WSV model and purpose of monitoring, AQ sensors will be deployed in a variety of locations including urban background, suburban background and roadside sites. Some AQMS will be located in the main city centre and others in the suburbs of the city to represent different types of environments. Roadside sites will include both highly and intermediately trafficked roads. Also, both open streets and street canyons will be monitored to analyse the effect of tall buildings on air pollutants dispersion. Urban and suburban monitoring sites will monitor the urban level emission, whereas roadside sites will monitor more local emissions from the traffic. Several sensors will be deployed next to existing reference sites including both AURN and SCC sites for calibration purposes.

Here firstly the existing AQMN is described (section 3.1), followed by the proposed AQMN (section 3.2).

3.1. Existing AQMN

3.1.1. Reference sensors (static)

Reference sensors are the most accurate type and are recommended by the EU and UK DEFRA for monitoring AQ. However, reference instruments are expensive to purchase and maintain and require skilled staff for deployment and calibration. Due to their high purchase and maintenance costs DEFRA and SCC have a sparse network of these sensors in Sheffield. These networks are mainly set up for the purpose of regulatory compliance (in the UK commonly known as review and assessment), mostly providing hourly concentration of various air pollutants over a long period of time (Table 1). There are three AURN sites in Sheffield run by DEFRA and six under SCC control. These continuous AQMS are shown in Table 2 giving their names, site types, pollutants measured and other details, whereas their locations are shown in Fig. 9.

3.1.2. Low-cost sensors

An AQMN of LCS in Sheffield is shown in Fig. 10. In this network the city is divided into three parts: (I) The University of Sheffield Campus; (II) Sheffield City Centre; and (III) Other parts of the city, which include Meadowhall Shopping Centre, Brightside & Attercliffe, Abbeydale and London Roads, southwest of the city, north and northwest of the city, e.g., Penistone Road - A61 and Barnsley Road - A6135, and east and southeast of Sheffield, e.g., Sheffield Parkway.

The University of Sheffield Campus has two meshes (clusters) of sensors, each made of nine (9) E-mote sensors. One is deployed along Broad Lane, Portobello Lane and between them (Fig. 10, middle-panel) and second mesh along A57 (Brook Hill and Western Bank) near Sheffield Children Hospital, Royal Hallamshire Hospital and Sheffield Student Union (Fig. 10, middle-panel). The intention is to capture more micro-level factors causing changes in air pollution concentrations. In addition to multi-storey student accommodation, University students

Table 2
Automatic AQMS in sheffield (SCC, 2016).

Site name	Site type	Easting (X)	Northing (Y)	Pollutant monitored	Monitoring Technique	Distance to road (m)	AURN/SCC
Firvale School (GH1)	Urban BG	436990	390218	NO_2, PM_{10}	CL, TEOM	10	**SCC**
Tinsley Infant School (GH2)	Urban Industrial	440077	390794	NO_2, PM_{10},, $PM_{2.5}$	CL, TEOM	90 (M1)	**SCC**
Lowfield School (GH3)	Roadside	435181	385366	NO_2, PM_{10}, SO_2	CL, TEOM, UV Fluores.	10	**SCC**
Wicker (GH4)	Urban BG	435959	388021	NO_2, PM_{10}, O_3	CL, TEOM, UV abs.	50	**SCC**
King Ecgbert School (GH5)	Urban BG	430977	380760	NO_2, PM_{10}, O_3	CL, TEOM, UV abs.	100	**SCC**
Waingate (RM1)	Roadside	435750	387647	NO_2, PM_{10}	CL, TEOM	3	**SCC**
Tinsley (SHE)	Urban Industrial	440215	390598	NO_2	CL	120 (M1)	AURN
Devonshire Green (SHDG)	Urban Centre	435158	386885	NO_2, O_3, PM_{10}, $PM_{2.5}$	CL, TEOM, UV abs.	20	AURN
Barnsley Road (SHBR)	Urban Traffic	436276	389930	NO, NO_2, NOx	CL	3	AURN

Table abbreviations are as follows: CL - Chemiluminescence, BG - Background, SCC - Sheffield City Council and AURN - Automatic Urban and Rural Network.

are present in this area much of the time. Further details of the sensor locations are provided. The western side of the A57 also has many pedestrians due to university students and patients attending the hospitals (who may be sensitive receptors). Several major and minor roads further contribute to the number of emission sources.

Ten (10) Envirowatch E-MOTE sensors are deployed around the city centre (Fig. 10, lower-panel), covering the busiest area around the train and bus stations, Arundel Gate, Pond Street, Sheaf Street, Sheffield Hallam University and Town Hall. This area experiences high levels of air pollution and WSV due to several busy roads and transport hubs and is surrounded by tall buildings creating dispersion barriers. This area is extensively covered to obtain high spatial resolution readings in order to identify the main drivers of air pollution. The sensor on Arundel Gate between Genting Casino and Hallam Business School is especially deployed to study the street canyon effect. One sensor next to Devonshire Green AQMS, which is part of the UK AURN, is deployed for calibration purposes.

Independent LCS are deployed in the rest of the city in various areas including Meadowhall (2 independent sensors), Brightside & Attercliffe (2 independent E-MOTEs), Abbeydale and London Roads (2 independent AQMesh pods), Southwest of City (2 independent AQ Mesh pods), North and northwest of Sheffield, e.g., Penistone Road (A61) and Barnsley Road (A6135) (3 Independent AQMesh pods), and East and southeast of Sheffield, e.g., Sheffield Parkway (2 independent sensors) (Fig. 10).

Meadowhall is a very busy shopping centre with large parking areas which remain busy throughout the day and evening. Furthermore, Meadowhall is about to undergo major development in the coming years, therefore AQ monitoring in this area can determine how air pollutant levels will alter once the plans are completed. The Tinsley area is adjacent to a large road network interchange, where several busy roads intersect and access the Motorway (M1), A631 and A6178.

Fig. 9. Continuous Air Quality Monitoring Stations (AQMS) in Sheffield comprising of 3 AURN (DEFRA) and 6 SCC sites.

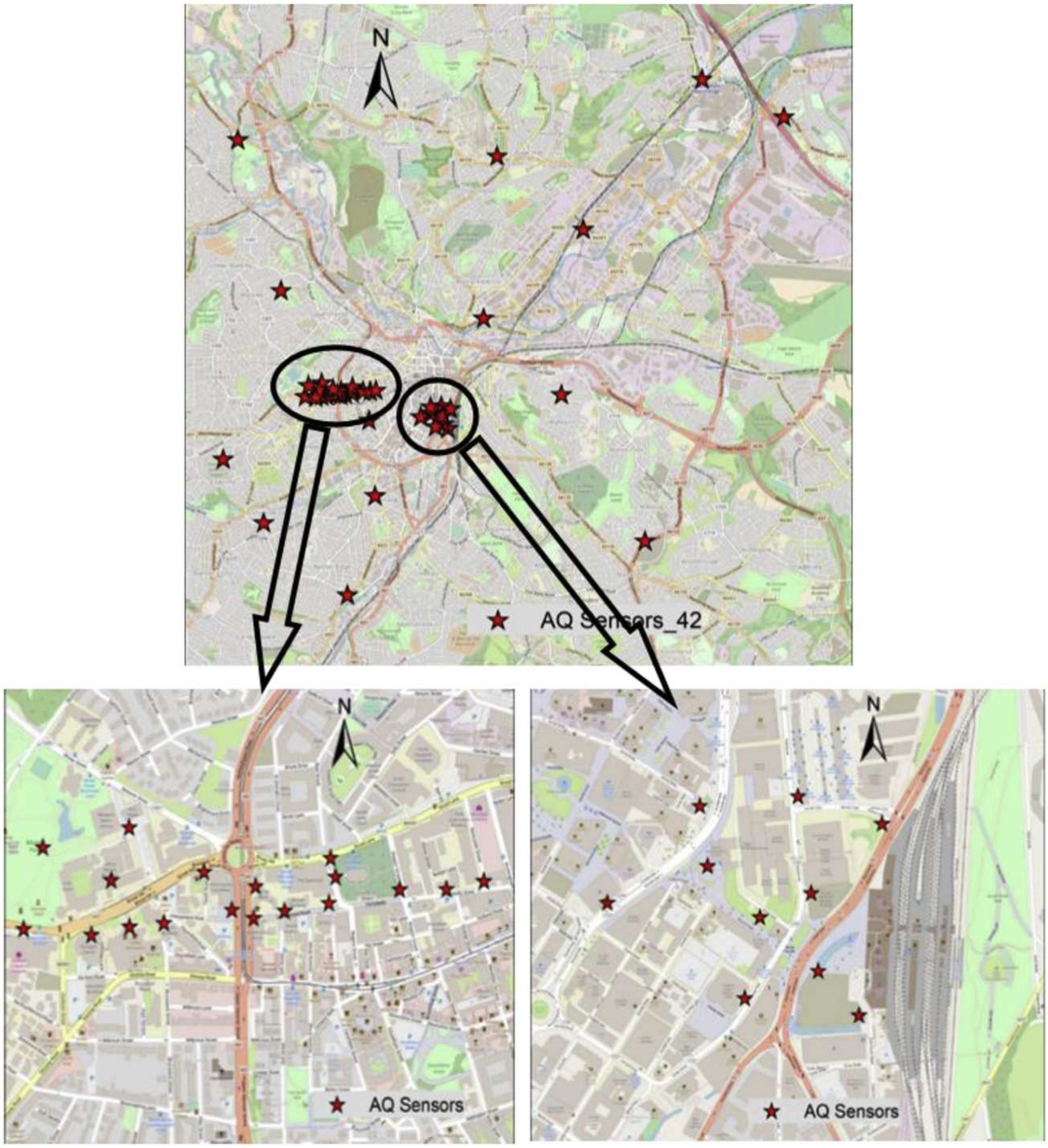

Fig. 10. EnviroWatch E-MOTE & AQMesh pod sensors (total 42 sensors) deployed around Sheffield (upper-panel). University of Sheffield Campus (lower-left panel) and City Centre (lower-right panel) are magnified to show their details.

In Tinsley a two continuous AQMS are also deployed. Sensors are deployed on Siemens Close, Meadowhall Way and the Meadowhall Interchange. Brightside and Attercliffe areas are also very busy in terms of traffic flow carrying most of the traffic from Sheffield City Centre, bus station, train station and universities to the M1 and Meadowhall Shopping Centre. These roads (A6178 and A6109) are therefore heavily trafficked and highly polluted. For these reasons, sensors are deployed on Savile Street (adjacent to Tesco Extra) and Brightside Lane. Sensors are also deployed in the Abbeydale and London road area, with high population density and pollution levels along these busy main roads. Proposals are in hand to retrofit buses to reduce emissions of NO_2 and PM that should be observed by monitoring these corridors. Furthermore, southwest and north-and-northwest of the city are highly populated and polluted areas where several hospitals and schools are located give rise to possibility of exposure of people who may be more vulnerable to high levels of air pollutants. In the North of City sensors are deployed at the Northern General Hospital, Hills Borough Primary School, and St Marys CoE Primary School. In the west sensors are deployed at Endcliffe Crescent and Cowlishaw Road, and in the east two AQ sensors are deployed at Prince of Wales Road and Maltravers Road.

3.2. Proposed AQMN

According to the methodology described in section 2.2, the whole city was mapped based on the value of WSV which incorporates PD, pollution levels and SV of air pollution. The number of sensors in each polygon was proportional to the value of WSV, which means more sensors should be deployed in polygons which show greater WSV value using equation (7). Firstly, an AQMN (Fig. 11) is proposed for nine reference instruments deployed by both SCC and DEFRA in Sheffield City (discussed in 3.1.1, Fig. 9). Fig. 11 (upper-panel) shows the proposed locations of nine AQMS. Comparing this to Fig. 9, we can clearly see that the proposed network allocates more sensors around the city centre, where pollution levels are higher and more people are exposed

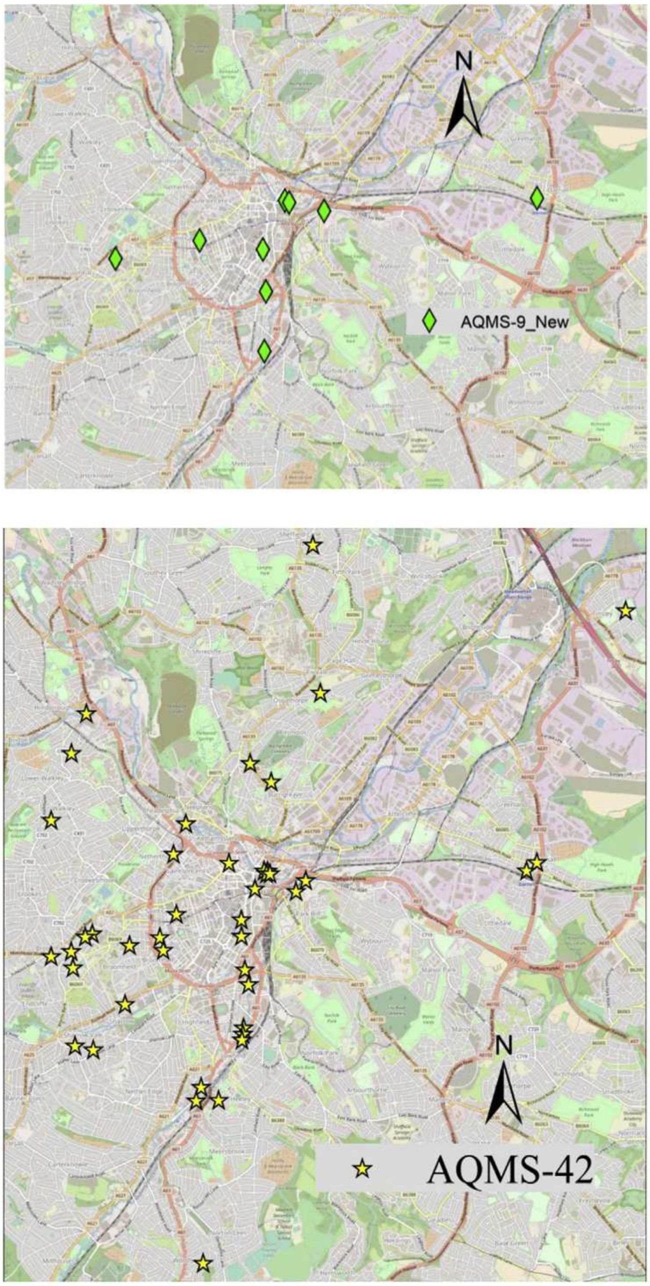

Fig. 11. Proposed AQ sensor locations based on WSV in Sheffield, where upper-panel shows locations of reference sensors and lower-panel shows locations of LCS.

to air pollution. Also, near the city centre air pollution levels demonstrate much greater SV probably due to tall buildings and numerous emission sources including many major and minor roads. Six sensors are sited in the city centre including two sensors along Blonk Street and one each along Sheffield Parkway, Arundel Gate, Shoreham Street leading to Sheaf Street and the University of Sheffield along Portobello. Three sensors are allocated outside the city, one each along Whitham Road, Queens Road and Staniforth Road (Fig. 11, upper-panel).

Fig. 11 (lower-panel) shows the locations of forty-two (42) LCS. The proposed network provides better spatial coverage, focusing more on the city centre and surrounding area where WSV values were higher. Seven sensors are allocated on the southern side of the city along Queens Road and Chesterfield Road. Two sensors to the east near the junction of Staniforth Road and Prince of Wales Road, and one near Tinsley roundabout. Four sensors are allocated in the north of city along

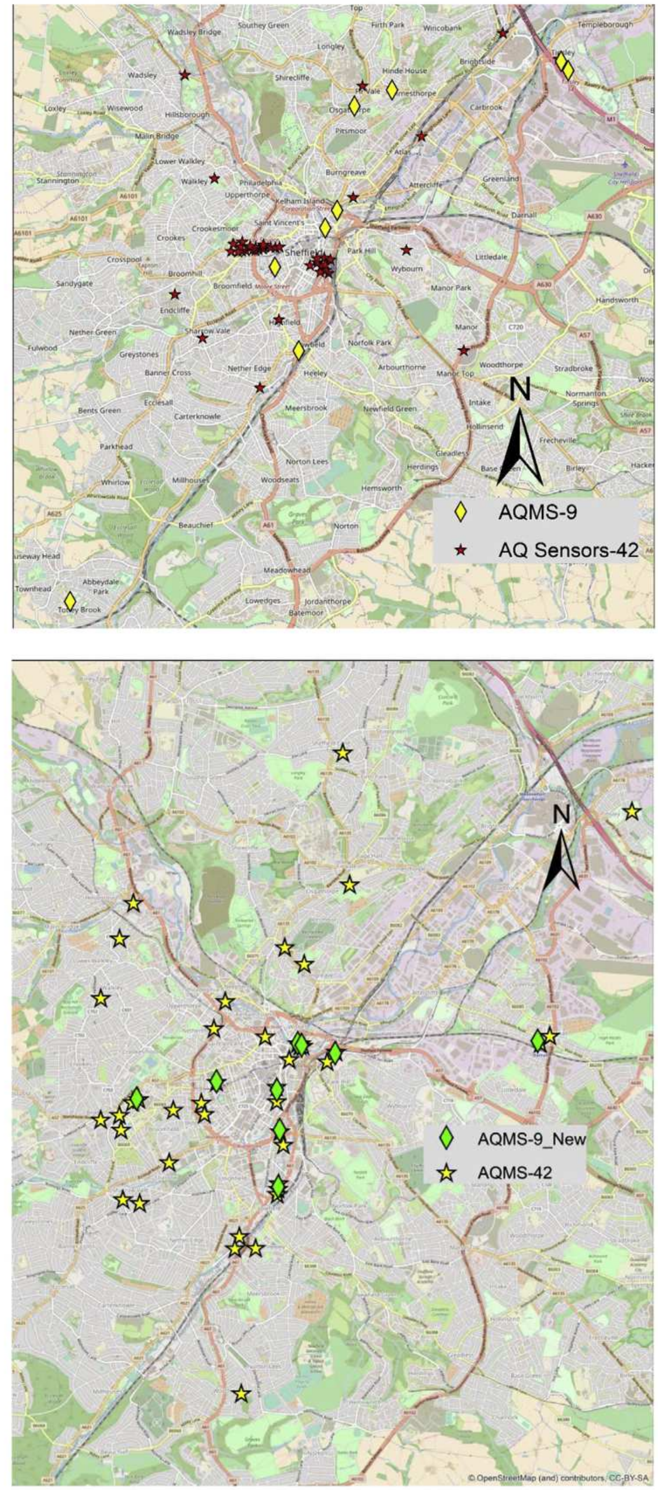

Fig. 12. AQMN with forty-two (42) LCS and nine (9) continuous AQMS, where the lower-panel shows the proposed network whereas the upper-panel shows the present locations in Sheffield.

Barnsley Road and five along Penistone Road and Walkley Road. Nine sensors are sited on the western side along Whitham Road and Ecclesall Road. Fifteen sensors are sited in the city centre: St Mary's Road (2), Arundel Gate (2), Sheffield Parkway (2), Blonk Street (4), Haymarket (1), Corporation Street (1), Mapping Street (1), Headford Gardens (1) and Gell Street (1).

The total number of sensors are decided on the basis of financial resources (budget of the project), whereas the number of sensors in each polygon are based on exposure (population and pollution levels) and its SV. Sometimes AQ sensors are deployed for a particular reason, to determine the background level of ground level O_3, for instance. In this case the AQMS should be deployed in a rural background area. Therefore, based on the purpose of monitoring, AQ monitoring authority may deploy a sensor in a specific place against the recommendation of this network. Furthermore, once the general locations and number of sensors are decided using the methodology suggested in this manuscript, the final location for each sensor within the polygon will be decided based on the purpose of the monitoring using the opinion of experts having experience of the local areas.

The final map of LCS and reference sensors is shown in Fig. 12, where the lower-panel shows the proposed locations according to WSV and the upper-panel shows the existing locations of AQMS in Sheffield. These two maps have been put together to facilitate their comparison.

In addition to reference sensors and LCS (AQMesh and EnviroWatch E-MOTEs), IoT sensors will be deployed in different parts of the city, however, how many is not yet known. IoT sensors will be deployed mostly next to AQMesh, E-MOTEs and reference sensors so that their performance can be compared. In addition, IoT sensors will be deployed to cover gaps between high quality sensors. MOBIUS will be used to take readings between static sensors. The data points are tagged with location and time utilising an on-board GPS. MONIUS will be used for AQ monitoring in places where the deployment of fixed sensors is not possible due to limiting factors, e.g., lack of power supply, insufficient space or unsafe location for fixed monitoring stations. MOBIUS is helpful to collect data between various fixed monitoring stations, to highlight hot spots and provide much better spatial coverage, however they are mainly suitable for short term monitoring and sensors calibration. In this way using different types of sensors, an IAQMN will provide high spatiotemporal resolution maps in Sheffield.

The proposed network is more spatially representative than the previous network because it is structured based on WSV. Air pollutant concentrations measured by the proposed network will capture spatial variability of air pollution in locations not captured before and will highlight hotspots of air pollution where more people are exposed to high levels of air pollutants. This proposed network provides a great example for local authorities and DEFRA for structuring an IAQMN. Future work includes collection of AQ data from the proposed network, integrating the data collected by various sensors, and developing a land-use regression model.

4. Conclusions

With new developments in AQ monitoring technology including the availability and popularity of LCS, more and more people are setting up purpose-designed AQMN for various purposes, e.g., to produce high resolution AQ maps, to assess human exposure to air pollution, and to review regulatory compliance of air pollutant levels. In this study we proposed an IAQMN based on population density, pollution concentrations and WSV. This is further supported by a conceptual model which analyses the purpose of AQ monitoring and discusses how the purpose is linked with sensors deployments. This study proposes an IAQMN utilising several layers of AQ monitoring approaches including both fixed and mobile techniques employing reference, LCS, and IoT sensors. The aim is to achieve AQ data of high spatiotemporal resolution, however, in many cases there is a compromise made on one or more dimensions due to various constraints, e.g., financial constraints. As a case study, an IAQMN has been proposed in Sheffield, which will monitor AQ levels on roadsides, urban background, suburban background, hospitals, schools and universities. Forty-two (42) LCS along with nine (9) reference sensors will be deployed. The network will be further supported by mobile monitoring using both reference and LCS. The data obtained from various layers of the network will be fused together to be used for developing spatiotemporal high resolution maps and LUR model in Sheffield. This study provides a practical example as to how various types of AQ monitoring sensors can be integrated into one monitoring network in large urban areas to capture local level spatiotemporal variability in air pollution concentrations, especially in low- and middle-income countries where AQMNs either do not exist or are sparse. LCS will be of particular importance in those countries for setting up purpose-designed AQMNs.

Declaration of interests

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

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Glossary

AQ: Air quality
AQMA: Air quality management area(s)
AQMN: Air quality monitoring network(s)
AQMS: Air quality monitoring station(s)
AURN: Automatic Urban and Rural Network
DEFRA: Department for the Environment, Food and Rural Affairs (UK)
GIS: Geographic information system
GPRS: Global packet radio service
IAQMN: Integrated air quality monitoring network
LUR: Land use regression
NPD: Normalised population density
PD: Population density
PWPC: Population-weighted pollution concentration
SCC: Sheffield City Council
SV: Spatial variability
VOC: Volatile organic compound
WSV: Weighted spatial variability