Research article

Particulate matter source identification and triangulation using a low-cost sensor network in Nigeria

Johanna M Rehbein[1,2,3], Dimitrios Bousiotis[1], Olalekan AM Popoola[4], Arunik Baruah[5,6], Olusegun G Fawole[7], Oyediran K Owoade[8], Francis D Pope[1*]

[1]School of Geography, Earth and Environmental Sciences, University of Birmingham, Edgbaston, Birmingham, UK
[2]Now at School of Geography, Queen Mary University of London, London, UK
[3]Department of Geography, King's College London, Aldwych, London, UK
[4]Centre for Atmospheric Science, Yusuf Hamied Department of Chemistry, University of Cambridge, Cambridge, UK
[5]Dept. of Engineering 'Enzo Ferrari', University of Modena and Reggio Emilia, Modena, Italy
[6]University School for Advanced Studies IUSS Pavia, Pavia, Italy
[7]School of the Environment and Life Sciences, University of Portsmouth, UK
[8]Dept. of Physics and Engineering Physics, Obafemi Awolowo University, Ile-Ife, Nigeria
*Corresponding author: f.pope@bham.ac.uk

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Abstract

Knowledge of air pollution sources is crucial for air pollution mitigation and policy making. Due to multiple constraints, air quality monitoring is often limited in lower- and middle-income countries, where rapid urbanisation and industrialisation are causing the local population to be exposed to dangerous concentrations of pollutants. The use of low-cost sensor (LCS) networks offers a more affordable alternative and a stepping stone in monitoring and assessing the air quality where research-grade equipment is currently unavailable. The present study re-assesses a previously published dataset of particulate matter (PM) concentrations in Ile-Ife, Nigeria, for source identification using k-means clustering and triangulation of the sources. The method identified six clusters based on particle number concentration profiles, separating daytime and night-time conditions, as well as the periods when local or regional sources had the greatest effect on the local air quality. The highest concentrations of particulate matter in Ile-Ife were associated with stagnant conditions and at the sites closer to the industrial activities in the area, for which the PM concentrations were about 10 times higher than the daily average (mean ± standard deviation $PM_{2.5}$ 30.6 ± 40.7 µg m^{-3}, and PM_{10} 83.4 ± 259.2 µg m^{-3}). The methodology also provides information on the circumstances when cleaner conditions occur, and these were found during the daytime with higher wind speeds from the southwest (SW), when PM concentrations were significantly lower than the average at all sites ($PM_{2.5}$ 11.5 ± 4.7 µg m^{-3}, and PM_{10} 37.2 ± 26.0 µg m^{-3}), but still above the annual limits recommended by the World Health Organization (WHO). Additionally, the polluting effects of the urban background as well as from traffic were identified, and the atmospheric conditions which increased the importance of these sources were elucidated.

Keywords

Air Pollution, particulate matter, $PM_{2.5}$, source identification, low cost sensors

Introduction

Air pollution is the largest environmental health risk of the 21st century, causing an estimated 8.8 million premature deaths annually (Lelieveld et al., 2020; Prüss-Üstün et al., 2016; World Health Organization (WHO), 2015), with 90% of these deaths occurring in low- and middle-income countries (LMICs) (United Nations Environmental Programme (UNEP), 2021). Although air pollution is made of both gaseous and particulate matter (PM) pollution, PM is considered the major risk to public health (Cipriani et al., 2018; Rahul and Jain, 2014). As a result, advisory and regulatory daily and annual limits are set for its concentrations by the World Health Organization and local government bodies, such as the US EPA and the UK DEFRA (DEFRA, 2010; US EPA, 2022; WHO, 2021), with the WHO recommending annual $PM_{2.5}$ and PM_{10} limits of 5 µg m^{-3} and 15 µg m^{-3}, respectively.

Air pollution is typically more problematic in urban areas (Valavanidis et al., 2018), where multiple pollution sources

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exist. Highly populated neighbourhoods are frequently located near or within pollution hot spots, causing socioeconomic disparity among the population (Hajat et al., 2015). This is especially apparent in LMICs (WHO, 2016), which have seen the steepest increase in pollution concentrations worldwide (Landrigan et al., 2018), often associated with fast unregulated growth, underdeveloped infrastructure, and common usage of pollution-generating practices, such as the usage of solid fuels for cooking, heating, and energy generation, slash-and-burn methods to clear land, and open waste incineration (Guo et al., 2020; Gurjar et al., 2008; Sastry, 2002; Wiedinmyer et al., 2014; Yadama, 2013; Zhang et al., 2010).

The knowledge of air pollution sources is vital to understand the air quality trends at a given site as well as for policymaking and action to improve air quality. Traditionally, the data needed for this comes from expensive research-grade (RG) instruments. These instruments, while providing high-quality data, are rather expensive, thereby limiting the spatial resolution of any measuring network, resulting in increased spatial interpolation uncertainty (Kanaroglou et al., 2005). These monitoring systems are often scarce in LMICs, due to their costly nature and the expertise required, resulting in air quality management receiving low public and government attention, as well as partial knowledge of emission sources (Mir Alvarez et al., 2020), which would be needed to implement policies and management options successfully.

This discrepancy between knowledge and management options is visible in Nigeria, the most populous country in Africa, with an estimated 215 million inhabitants, projected to reach 400 million by 2050 (World Population Review, 2022a). In Nigeria, an estimated 205,753 deaths were attributable to total air pollution (including both ambient $PM_{2.5}$ and household air pollution) in 2023, with approximately 40% of these linked to ambient $PM_{2.5}$ exposure (Health Effects Institute, 2025).

Although the country has an abundance of legislative pieces, a National Air Quality Standard, and an agency to enforce it, air quality has not been placed as a priority on its agenda (Ladan, 2012), and consequently, installation and maintenance of monitoring equipment has been scarce, with most air quality assessment being carried out using remote sensing (Mir Alvarez et al., 2020). Recent studies on PM concentrations in Nigeria have highlighted the usefulness of low-cost sensor equipment for air quality assessment (Amegah, 2018; Awokola et al., 2020), ability to be used for educational purposes (Abulude et al., 2022), but also highlighted dangerously high PM concentrations in some cities, such as Opebi, with daily means of 69.3 μg m^{-3} and 107.4 μg m^{-3} for $PM_{2.5}$ and PM_{10}, respectively (Abulude et al., 2021), and Zaira, with a daily mean of 219.7 μg m^{-3} $PM_{2.5}$ and 452.0 μg m^{-3} PM_{10} (Aliyu and Botai, 2018). These studies emphasise the need to advance the understanding of pollutants' concentrations, their sources, and the implementation of monitoring systems in these countries.

In the past decade, the development of low-cost sensors (LCSs) measuring either gaseous pollutant or PM concentrations has intensified (Lewis et al., 2018; Penza, 2020). Although these sensors are cost-efficient and have been shown to perform well in most environmental conditions when compared to research-grade equipment (AQ-SPEC, 2022; Bousiotis et al., 2021a; Chatzidiakou et al., 2019; Li et al., 2020; Sousan et al., 2016), some limitations and shortcomings are associated with their usage. One common issue with LCSs is the overestimation of particle mass in the coarse PM size fraction ($PM_{2.5-10}$) in environments with high relative humidity (≥ 85%) (Crilley et al., 2018), due to the hygroscopic growth of particles (Chuang, 2003; Rovelli et al., 2016). The sensors therefore require consistent calibrations (De Vito et al., 2020; Kosmopoulos et al., 2020) as well as post-collection correction of PM size fraction concentrations (Crilley et al., 2018) in order to yield data comparable to RG instrument measurements. Nevertheless, these sensors have the potential to change the state of air pollution monitoring by increasing the spatial resolution of existing RG measuring networks (Shindler, 2021), or the implementation of low-cost measuring networks in areas where the use of RG equipment is unfeasible due to location (Whitty et al., 2022), cost (Pope et al., 2018), or required expertise to maintain equipment (Agbota et al., 2013).

LCSs measuring PM currently offer better quality data than gaseous LCSs when compared to RG instruments (Lewis et al., 2018). The number concentrations of particles in size bins from LCSs can offer valuable insights into pollution sources affecting any site, as PM sources in the atmosphere have unique particle number size distributions, which has yet to be exploited commonly. Pope et al. (2018) managed to separate and identify the effect of major sources of pollution in two cities in Kenya using LCS PM ratios. Popoola et al. (2018), using a network of LCSs, managed to separate local and non-local emissions at Heathrow Airport, UK. Yang et al. (2022) applied a non-negative matrix factorisation on normalised LCS data at an urban site in Atlanta, US, resulting in 4 distinct factors impacting the local air quality. Bousiotis et al. (2021a), using k-means clustering on both LCS and RG size bin data, managed to identify six distinct clusters at a background site in Birmingham, UK, and in a different study the sources associated with industrial activities (Bousiotis et al., 2023). Furthermore, using a two-step positive matrix factorisation (PMF) on size bin data, Bousiotis et al. (2022) identified four distinct sources of PM pollution using LCSs and confirmed their reliability using RG instruments in Birmingham, UK. Westervelt et al. (2023) also used a mixture of LCS to perform source apportionment in Kinshasa, DRC. These studies confirm that data from a single LCS or a LCS network can be used successfully for source differentiation using various methods. A recent review article by our group summarizes advances in low cost source apportionment (LoCoSA) of air pollution that has been achieved in the last years, Bousiotis et al. (2025).

However, to the author's knowledge, this is the first study which attempts to identify pollution sources by applying statistical methods to the particle size profiles derived from a broad network of LCSs, which allows both differentiation and triangulation of the sources of particles in a wide area. This would allow for the implementation of site-specific air pollution

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mitigation plans and policies. Therefore, the present study attempts to expand the existing knowledge by reanalysing a previously published dataset (Owoade et al., 2021) of a LCSs network in Ile-Ife, Nigeria, using the k-means clustering method, successfully trialled on both LCS (Bousiotis et al., 2021a) and RG data (Beddows et al., 2009; Dall'Osto et al., 2011, 2012; Sabaliauskas et al., 2013; Von Bismarck-Osten and Weber, 2014). Results will be visualised spatially to allow for source triangulation, and discussed considering previous studies in the region.

Materials and methods

Location of the study sites and material

Nigeria is located in West Africa and experiences two major seasons, wet and dry. The dry season occurs between November and March, with little precipitation, clear skies, and high air temperatures. The wet season occurs between April and October when dominant south-westerly winds from the Atlantic Ocean bring moderate temperatures and an abundance of rain to the country (Falaiye et al., 2013). Owoade et al. (2021) deployed five Alphasense OPC-N2 sensors in the northern part of Ile-Ife (Fig. 1), a growing city in southwestern Nigeria with an estimated 400,000 inhabitants (World Population Review, 2022b), between 8th June 2018 and 31st July 2018. Ile-Ife experiences an average of 191 mm and 223 mm of rain in June and July, respectively, with both months having an average of 16 rainy days (World Weather Online, 2022).

The Alphasense OPC-N2 sensor used in this study is an optical particle counter (OPC), which measures particle number concentrations in the size range between 0.38 and 17.4 µm, at rates up to about 10,000 particles s^{-1} (Crilley et al., 2018).

Table 1: *Description of monitoring sites, including data coverage per site (percent valid data points between 08/06/2018 and 31/07/2018. Table amended from Owoade et al. (2021).*

Code	Sites	Site Description	Data Coverage
P1	Teaching and Research Farm (OAUTRF)	Within the OAU farm, it is dedicated to agricultural activities including planting and rearing of animals.	76.7%
P2	Staff Quarters	Within OAU Staff Quarters, used as a residential area and near to the university waste dump site.	80.2%
P3	Fire Service Station	Within OAU campus area, near the university main road and near to a bus station	95.1%
P4	Modomo	Fast growing residential area, close to the main road and downwind of the iron and steel smelting factory.	74.7%
P5	Eleweran	Residential area further away from the iron smelter and major roads, but close to a main road.	62.3%

Information on the exact ranges of each size bin can be found in Table S1. The standard measurement frequency is 1 to 10 seconds, with a sample flow rate of 210 mL m^{-1}. The particles are counted, and their size is determined by laser light scattering of individual particles (Bousiotis et al., 2021a). As the OPC-N2 sensors for the original study by Owoade et al. (2021) were acquired prior to commercial release by Alphasense, the sensors only reported the number concentrations of particles, while later firmware also reported the PM mass concentrations, calculated using a standard particle density of 1.65 g cm^{-3}. The PM mass concentrations ($PM_{2.5}$ and PM_{10}) were calculated and corrected

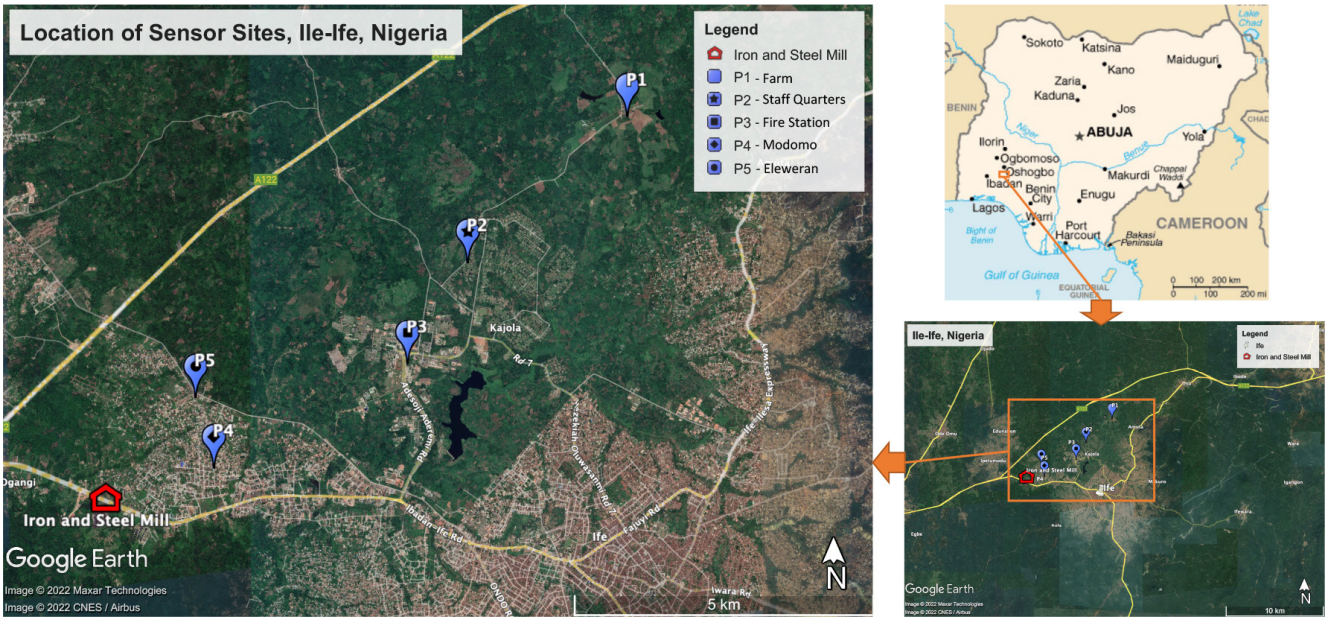


Figure 1: *Location of the monitoring sites (P1-5) in Ile-Ife, Nigeria. The Iron and Steel Mill is also highlighted since it is thought to be a major pollution source. Figure created using Google Earth Pro (2022).*

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for high relative humidity by the Department of Chemistry, University of Cambridge, UK, following the method suggested by Di Antonio et al. (2018).

Sensor locations in the original study were chosen based on open space, the absence of obstructions that would hinder the free circulation of air, as well as the relative distance to the iron and steel mill and the Ibadan-Ife Expressway in Ile-Ife, whose impact on air quality has previously been studied by Obioh et al. (2005), Owoade et al. (2012; 2013; 2015; 2016), and Ogundele et al. (2016). The sensors were mounted on a 6-meter pole, 3 meters above ground, and recorded the size bins used to calculate $PM_{2.5}$, PM_{10}, gaseous pollutants CO, NO_2, and O_3, as well as temperature (°C), relative humidity (%), wind speed (m s^{-1}), and wind direction (degrees). For the purpose of this study, only the PM number concentrations, corrected $PM_{2.5}$ and PM_{10}, and the meteorological data will be considered. For further information on the sensor design, corrections, and measurement of gases and meteorology, please see the original work published by Owoade et al. (2021).

Data processing

The raw data sets of the number concentrations, meteorological variables per sensor and calibrated PM data were supplied by the Department of Chemistry, University of Cambridge, UK (Owoade et al., 2021). Both supplied data sets contained data in 1-minute intervals. All available 1-minute data was merged and averaged over 30 minutes. Cases with incomplete particle count or PM data were removed, as well as cases with faulty size bin data. This resulted in 9969 valid cases used for the remainder of this study. A PM_{Ratio} was calculated by dividing the $PM_{2.5}$ concentrations by PM_{10}. Descriptions of sensor location sites and total valid coverage are given in Table 1 (detailed list of days with missing data is found in Table S2). The data was processed and visualised using Microsoft Excel and the OpenAir package for R (Carslaw and Ropkins, 2012).

k -means clustering

For the identification of the sources and conditions affecting the study area, the k-means clustering technique was used. k-means is a centroid-based clustering method that has been successfully used on a variety of datasets (Caron et al., 2019), including in particle source differentiation studies (Beddows et al., 2015; Brines et al., 2015; Giorio et al., 2015; Von Bismarck-Osten and Weber, 2014; Wegner et al., 2012). The technique was found to produce clusters with the highest similarity between their elements and the highest separation against other clusters formed (Hennig, 2007; Kaushik and Mathur, 2014) and has been found to perform better compared to other clustering techniques (Beddows et al., 2009; Salimi et al., 2014).

The k-means algorithm was applied to the normalised 30-minute particle count data across the 16 size bins, with each available data point being treated independently. As such, each observation was assigned to a single cluster, representing the dominating particle count size distribution during each 30-minute period at each site.

To determine the optimal number of clusters, two statistical tests were used in the present study, as suggested by Beddows et al. (2009); the Dunn Index, which provides a measure of the ratio of the minimum and maximum cluster separation, and the Silhouette width, which describes the similarity of spectra within each cluster (Bousiotis et al., 2021a). Both methods estimate values across a range of cluster solutions, identifying the most appropriate number of clusters where both metrics are maximised. As these statistical tests do not have physical meaning and are only used as a guideline, different cluster solutions can be chosen in source identification studies, depending on knowledge of the study site and expected sources, as well as comparison of meteorological variables and PM concentrations between clusters.

Source triangulation

Source triangulation is a method intermittently used in source apportionment studies as a standalone method (Kosmopoulos et al., 2022; Byrne et al., 2023) or to aid more common approaches, such as PMF analyses. It visualises pollutant concentrations, and their associated wind directions and speeds spatially, between a sensor network, usually around a known point source, such as a steel plant (Amodio et al., 2013) or industrial district (Yadav and Turner, 2014). Using this methodology, the effect of a point, line or an area source can be quantified according to different wind conditions by comparing the measurements from the different stations. This methodology is useful because it can help identify not only the effect of a source on multiple sites, but it can also provide important information about its dispersion in the local atmosphere. This method will be used in the current study to help differentiate the sources and elucidate the variability of the effect of different sources of pollution in the greater area.

Results

General conditions and temporal variation of the clusters

During the study period, Ile-Ife experienced predominant winds from SW, with a mean wind speed of 0.86 ± 0.43 m s^{-1}, which are common conditions during the wet season in South-West Nigeria (Falaiye et al., 2013). The mean temperature was 24.7 ± 3.5°C, and the mean relative humidity was 77.1 ± 14.9%. During this period, mean $PM_{2.5}$ and PM_{10} concentrations were 30.6 ± 40.7 µg m^{-3} and 83.4 ± 259.2 µg m^{-3} respectively, exceeding current guideline values published by the WHO (WHO, 2021). An in-depth assessment of meteorological values and PM concentrations per site for the period used in the present study can be found in Table S3. Average particle size distribution profiles per site can be found in Fig. S1. The most polluted sites in the area are P1 and P4, being closer to the main industrial activities in the area, the agricultural and steel milling accordingly.

Before choosing the optimal number of clusters, the statistical tests suggested in the literature were applied. For the combined dataset used, the Dunn metric peaked at a 5 and 7 cluster solution, while the Silhouette peaked at a 5 and 8 cluster solution.

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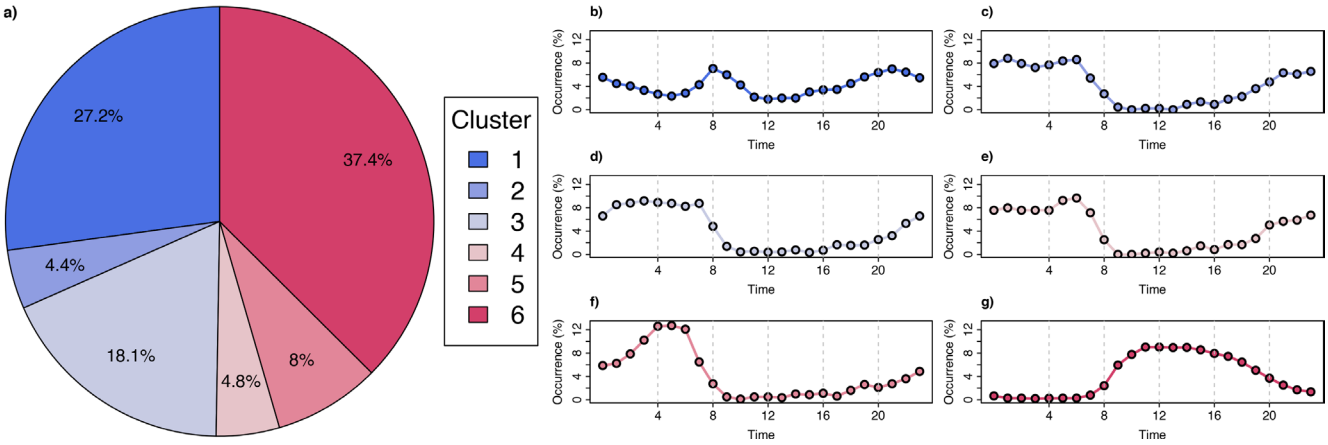


Figure 2: *Frequency (a) and normalised diurnal variation of the 6 clusters across all sites (b – g).*

Nevertheless, while these solutions were tested, a 6-cluster solution was chosen as the most appropriate for this analysis, providing the greatest number of interpretable clusters with atmospheric relevance, as the best statistical solution may not always be the most appropriate for the analysis of atmospheric data. Thus, given the spatial coverage of the sensor sites, the resulting particle source profiles, and the general conditions of both meteorological and PM concentrations between the clusters, this solution was found to provide the most consistent and meaningful results. The particle size profiles of the six clusters can be found in Fig. S2.

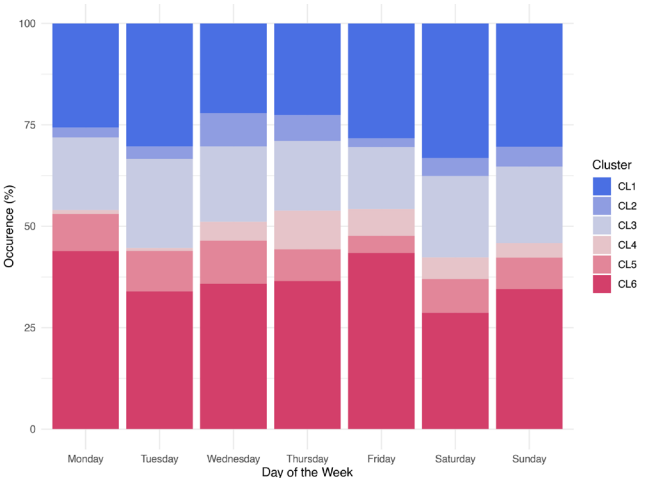


Figure 3: *Weekday variation of cluster frequency throughout the study period.*

Figure 2, showing the frequency and diurnal variation of the clusters, reveals that the three dominant groups, CL1, CL3, and CL6, appear to have a distinct diurnal variation coinciding with rush hour (CL1), night-time (CL3) and daytime (CL6). The other 3 clusters (CL2, CL4, and CL5) are most likely associated with specific air pollution events and sources, most common during the night and early morning hours. The weekday variations between the clusters for the entire study period are given in Fig. 3 (and per week in Fig. S3).

When considering the weekday variation of the clusters for the entire study period (Fig. S3a), the night-time source (CL3) shows the least variability between the days, followed by a specific early-morning source (CL5). Although CL6 is more common during workdays (Monday to Friday), CL1 does not follow the same trend and is instead most common on Tuesdays and Saturdays. Both remaining clusters, CL2 and CL4, are more frequent towards the end of the week (Wednesday to Sunday). Although the more frequent clusters generally follow this trend when considering the week-by-week counts (Fig. S3 b to j), CL2, CL4, and CL5 are more sporadic, indicating their association with specific conditions or sources. It should also be noted that some differences in weekday occurrences and counts could be caused by the individual start and end dates of the sensors, with sensors at P4 and P5 commencing data capture from 15 June 2018 and 26 June 2018, respectively, compared to the other four locations which commenced slightly earlier on 8 June 2018.

Description of the clusters

The mean and standard deviation of the variables for each cluster is given in Table S4. $PM_{2.5}$ and PM_{10} and the PM_{Ratio} ($PM_{2.5}$/ PM_{10}) concentrations per cluster are visualised in figure 4. Windroses portraying the wind conditions per cluster can be found in Figure S4.

CL1 is the second most frequent group (27.2% of total data), peaking during the morning rush hour (8 am) and in the evening between 8 and 10 PM. Its meteorological conditions are similar to the average, while both the concentrations of $PM_{2.5}$ (16.9 ± 8.3 µg m^{-3}) and PM_{10} (48.5 ± 31.2 µg m^{-3}) are lower than the average (Figure 4; Table S3). This cluster has a mean PM_{Ratio} of 0.37± 0.11, which is lower than the average ratio at the study sites (0.41). Fan et al. (2021) classified the PM_{Ratio} values at an urban site in China and considered that ratios below 0.40 are most likely associated with dominant sources of dust rather than combustion sources. This cluster is dominated by winds from the SSW and displays the second fastest average wind speed with a mean of 0.81 ± 0.35 m s^{-1}.

CL2 is the most polluted cluster, with mean $PM_{2.5}$ and PM_{10} concentrations of 134.6 ± 80.2 µg m^{-3} and 389.7 ± 941.4 µg m^{-3}, respectively. It is the least frequent cluster with a 4.4% occurrence. This group is associated with slightly cooler than

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average temperatures, higher relative humidity, and slower average wind speeds. It has the second highest PM_{Ratio} (0.56 ± 0.20), indicating a probable anthropogenic influence. It occurs mostly between 9 PM and 6 AM (Fig. 2) which explains the meteorological conditions found, and its particle size profile has distinct peaks at 0.43 µm, 0.77 µm, and 1.54 µm to 2.45 µm (Fig. S2).

CL3 is the third most frequent group (18.1%) and occurs predominantly at night between 11 PM and 7 AM (Fig. 2). Looking at the meteorological conditions for this cluster, the temperature and wind speed are lower than the average (22.2 ± 1.7°C and 0.64 ± 0.32 m s^{-1}, respectively), relative humidity is higher (86.7 ± 6.0%), while the wind direction is similar to the general trend during the campaign. The $PM_{2.5}$ and PM_{10} concentrations are comparable the average for the study (32.4 ± 19.5 and 82.4 ± 81.3), with concentrations of 32.4 ± 19.5 µg m^{-3} and 82.4 ± 81.3 µg m^{-3} respectively, and a PM_{Ratio} of 0.42 ± 0.15.

CL4 is the second most polluted cluster, with mean $PM_{2.5}$ and PM_{10} concentrations of 98.0 ± 63.5 µg m^{-3} and 220.4 ± 530.5 µg m^{-3} respectively. It has similar frequency with CL2 (4.8%), and its diurnal variation also follows a similar trend with that cluster, peaking between 5 and 6 AM, being more frequent at night-time than during the day. It is associated with cooler than average temperatures and the highest relative humidity of all clusters (93.2 ± 2.6%), which is expected according to its diurnal variation. While there are not significant differences between the wind profile for this cluster and the average conditions, it is the cluster with the highest frequency of northeastern winds (Fig. S4d) though with lower than the average wind speeds (0.56 ± 0.32 m s^{-1}). This cluster also has the highest PM_{Ratio} (0.64 ± 0.19) of all the clusters, indicating a strong anthropogenic influence.

CL5 is the third smallest group (8%), and the third most polluted cluster with mean $PM_{2.5}$ and PM_{10} concentrations of 61.6 ± 38.1 µg m^{-3} and 151.7 ± 275.3 µg m^{-3} respectively. The temperature during the occurrence of this cluster is slightly cooler than the average (22.1 ± 1.3°C), has a higher relative humidity (88.1 ± 3.2%), slower winds, but similar wind directions compared to the average for the campaign. It peaks significantly between 4 and 6 AM, and its particle size profile peaks in the smallest size fraction (0.43 µm) and at 1.54 µm. Despite its relatively low frequency, this cluster was present throughout the sampling period (Fig. S3).

CL6 is the most frequent cluster (37.4%). This is the only cluster with strong daytime association, peaking between 9 AM and 7 PM. It is the second least polluted cluster, with mean $PM_{2.5}$ and PM_{10} concentrations of 11.5 ± 4.7 µg m^{-3} and 37.2 ± 26.0 µg m^{-3} respectively. The average temperature and wind speed are higher than the network average (27.4 ± 3.2°C and 1.14 ± 0.41 m s^{-1}, respectively), while it has the lowest RH of the clusters (65.1 ± 13.9%). This group has a low mean PM_{Ratio} of 0.35 ± 0.11 and is therefore likely to be affected by natural sources. Specifically, it is likely that this cluster also includes the effect of secondary aerosol formation occurring at this time of the day under less polluted conditions, as it is common in areas with increased solar radiation (Bousiotis et al., 2021b).

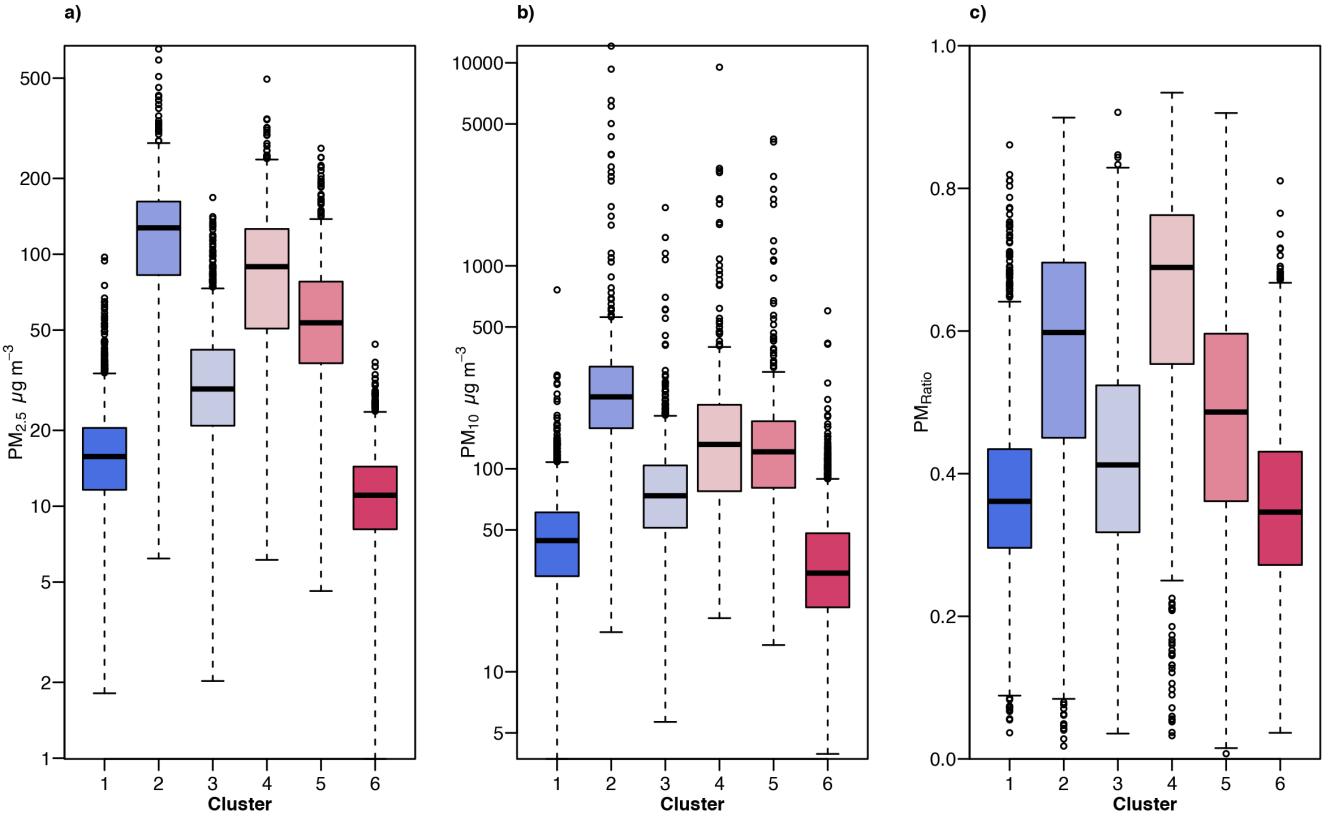


Figure 4: *Variability of $PM_{2.5}$ and PM_{10} concentrations per cluster (a and b) and PM_{Ratio} (c). Due to the high variability in the $PM_{2.5}$ and PM_{10} values, the PM values are plotted using a log(1p) transformation.*

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Source triangulation and cluster characterisation

Spatial variation of the clusters using source triangulation

To further aid the differentiation and identification of sources and conditions the clusters represent, the percentage occurrences of the clusters per site are given in Figure 5.

CL1 is more frequent at the northern sites P1 and P2, which are both located within the university campus, followed by site P5 (residential), with a reduced but still significant frequency (> 20%) at sites P3 and P4. CL2 is almost exclusively present at sites P1 and P4, where it represents around 10% of all readings there. The frequency of the occurrence of CL3 is similar between sites, with the lowest found at P5. Interestingly, the spatial distribution of CL4 is almost the mirror opposite of CL2, and almost exclusively occurs at sites P2, P3, and P5. Cluster 5 occurs predominantly at sites P1 and P4, and finally CL6 occurs more often at sites P3 and P5, while being least frequent at site P1 (Fig. 5).

Although the spatial distribution of the clusters between the sites confirms the likelihood of clusters being representative of background sources or specific pollution events, it also highlights the variability of cluster occurrence between sites and thus requires further investigation to confidently distinguish the sources and conditions. Polarplots of $PM_{2.5}$ and PM_{10} per site for clusters 1, 3, 5, and 6 are presented in Fig. 6, while additional PolarAnnuli plots for these clusters can be found in Fig. S5. Due to the diurnal, meteorological, and PM concentration similarities of clusters 2 and 4 (Table S4(b) and (d)), while presenting opposite spatial distributions between sites (Figure 5), these two clusters will be compared as a case study.

Cluster characterisation

Cluster 1 – Traffic/commuting

The first cluster describes daytime conditions and is affected by emissions associated with commuting activities, as concentrations correlate well with the expected diurnal variation and the presence of roads. However, rather than representing concentrations of exhaust emissions alone, which the OPC is not able to capture due to their size being below the measuring threshold of the sensor, it is likely inclusive of all emissions occurring from road activity, such as resuspended dust from the unpaved roads found in Ile-Ife, as well as vehicle emissions. Particulate matter is generally higher at sites either experiencing high volumes of traffic (sites P3, P4, and P5), or at site P1, where traffic would be expected to be lower, but the roads are unpaved, resulting in a higher load of resuspended dust (Table S3).

Specifically, site P3, the fire service station, which is close to major roads and a roundabout leading to the university grounds, is the most polluted site in this cluster (Table S4). This is reflected in the pattern visible in Figures 6a and e, with higher concentrations of $PM_{2.5}$ and PM_{10} associated with wind directions pointing to roads and thus where traffic emissions are increased at the sites. This is true for both local roads close to the sites, as well as the presence of major roads further away, with e.g. site P5 experiencing high PM_{10} concentrations during stronger winds from NW, where the Ibadan-Ilesha Expressway is located.

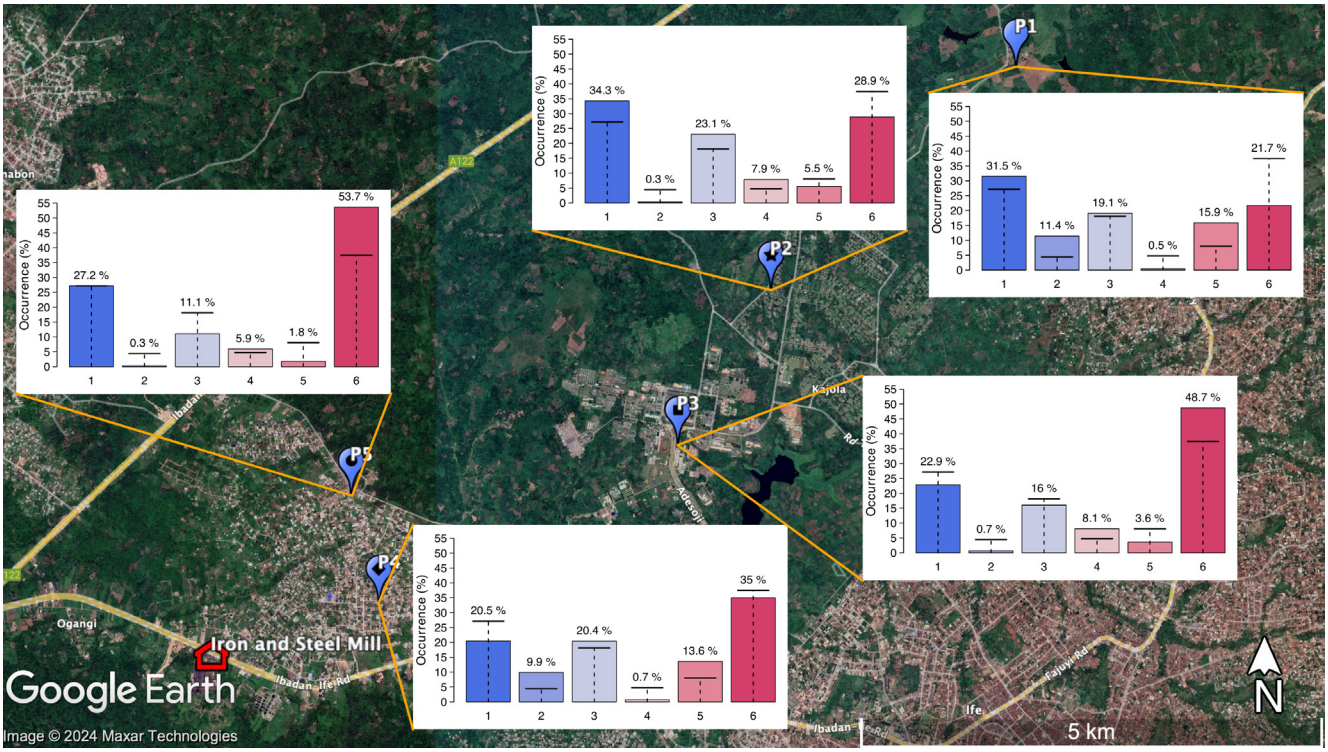


Figure 5: *Percentage of cluster occurrence per site, with reference to sensor/site locations. All counts per site = 100%. Whiskers refer to the mean distribution of clusters across all sites.*

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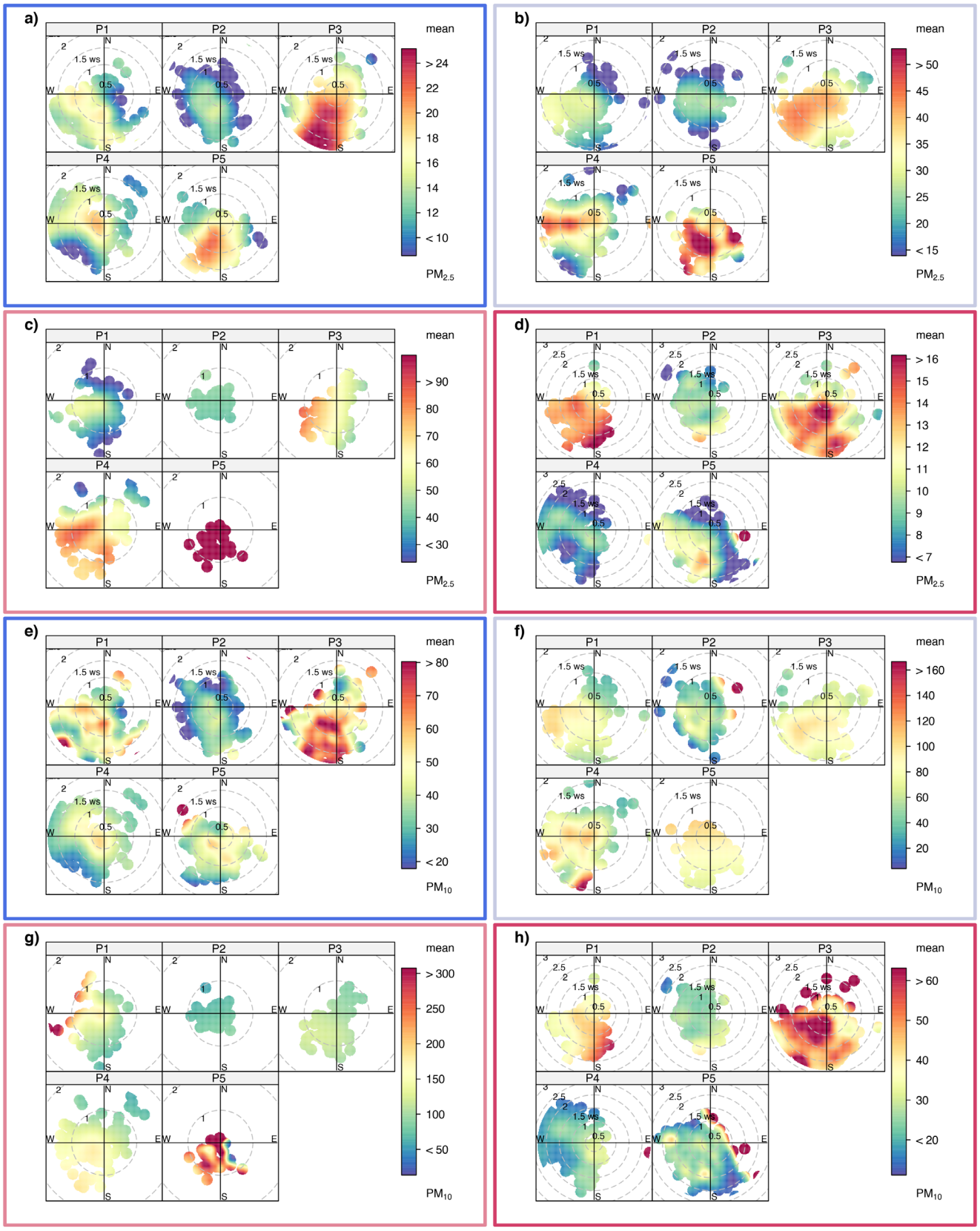


Figure 6: *Wind variation of $PM_{2.5}$ and PM_{10} concentrations subset by cluster number and measurement location (for CL1, CL3, CL5 and CL6), pointing the direction of their dominant sources for each cluster and site. (a) map of study area and measurement locations. Polarplots of $PM_{2.5}$ and PM_{10} by site (P1-P5) for CL1 (a, e), CL3 (b, f), CL5 (c, g), and CL6 (d, h).*

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Both $PM_{2.5}$ and PM_{10} concentrations are generally higher from the late evening to early morning hours (8 pm to 6 am), with site P3 showcasing higher concentrations during the day (Fig. S5a and b). Interestingly, site P3 experiences higher $PM_{2.5}$ concentrations during the evening hours from all wind directions apart from NW compared to PM_{10}, which is mainly occurs during winds from SW, S, and SE at night.

Cluster 3 – Clean night-time conditions

As visible in Fig. 2d and its frequency, this cluster is strongly associated with common night-time conditions and is present throughout the whole sampling period with prevailing winds from the South-West (Fig. S4c), and least frequent at the residential site P5, Eleweran. (Table S4c).

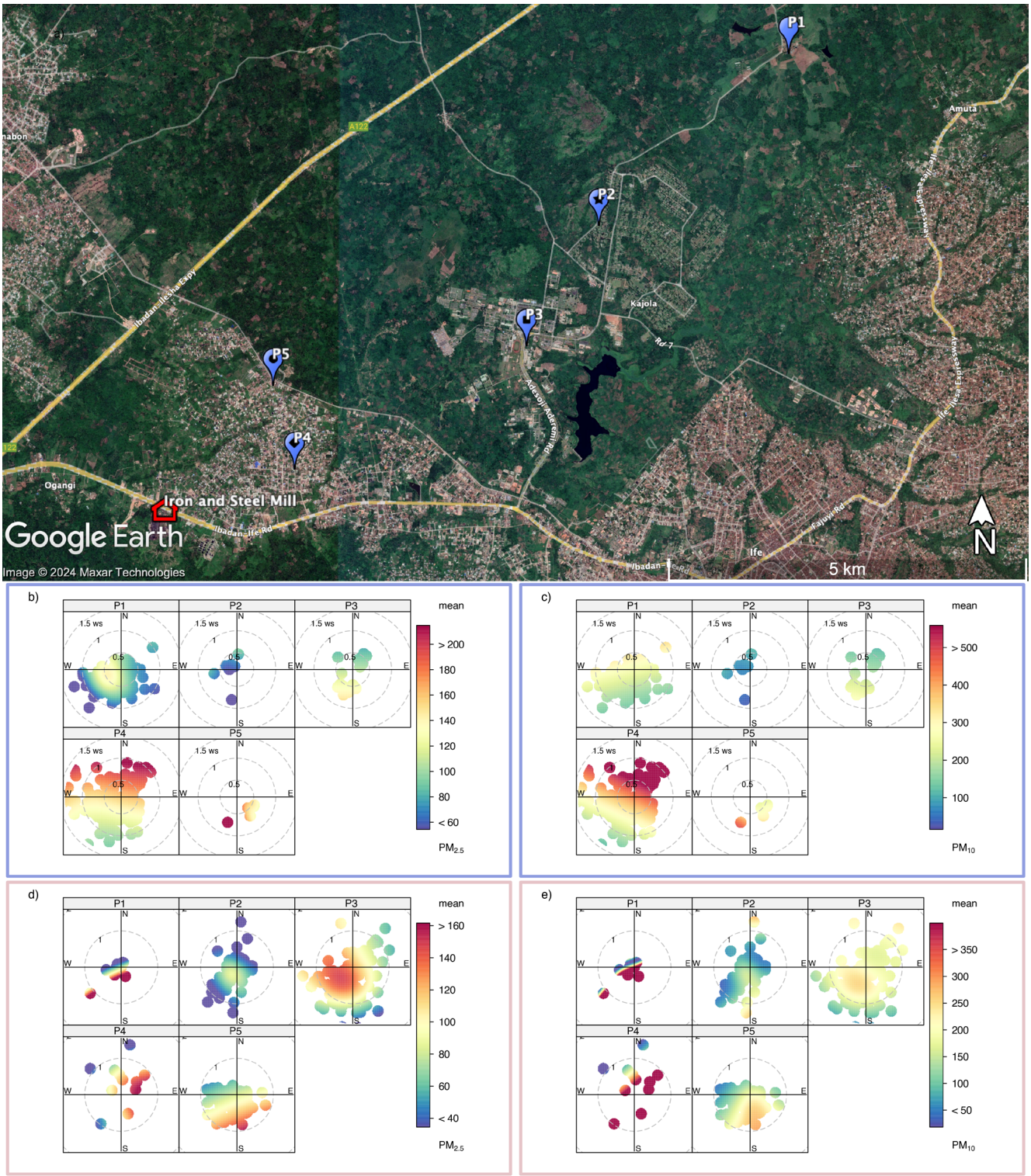


Figure 7: *Wind variation of $PM_{2.5}$ and PM_{10} concentrations subset by cluster number (for CL2 and CL4) and measurement location. a) is the reference map of Ile-Ife; b) and c) shows polar plots of $PM_{2.5}$ and PM_{10} for CL2 per site and d) and e) polar plots of $PM_{2.5}$ and PM_{10} for CL4 per site.*

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In this group, $PM_{2.5}$ concentrations are generally lower at sites P1 and P2 compared to the other sites (Table S4c). At site P1, higher $PM_{2.5}$ values are primarily associated with a south-westerly wind direction, similar to PM_{10}. Site P2 experiences higher $PM_{2.5}$ concentrations largely from the western section, with some high PM_{10} concentrations coming from the southwest and northeast during weak to medium winds. At site P3, high concentrations of $PM_{2.5}$ and PM_{10} are associated with weak and medium-high winds from the southwest sector. Higher $PM_{2.5}$ concentrations are strongly associated with westerly winds at site P4, while high PM_{10} concentrations are also associated with strong southerly winds. Site P5, despite having the least number of readings of all the sites for this cluster, shows a clear pattern of high $PM_{2.5}$ and PM_{10} concentrations close to the sensor location (low wind speeds), potentially indicating the influence of local sources (Fig. 6b and f).

Cluster 3 has higher $PM_{2.5}$ and PM_{10} concentrations during the night and early morning, as reflected by the diurnal variation in Figure 2d, and polar annulus (Fig. S5c and d), with sites P3 and P5 being the most polluted. There is a visible influence of higher $PM_{2.5}$ concentrations from multiple wind directions at the sites, with solely site P1 experiencing consistent higher concentrations from SW during the morning hours only. PM_{10} concentrations of this cluster are impacted by high concentrations at site P3 during the day, and in the early morning from NE at site P5.

This cluster displays patterns of PM_{Ratio} that are similar to the overall mean of all readings, displaying the absence of a predominant local anthropogenic source associated with it, with site P5 having a higher PM_{Ratio} than the other sites (Table S4c). Site P1 is predominantly associated with a low PM_{Ratio}, indicating a higher fraction of PM_{10} to $PM_{2.5}$, possibly affected by local sources.

CL3 was present throughout the study period and was found primarily between 11 PM and 7 AM. Although $PM_{2.5}$ concentrations showed patterns associated with the activities at the iron and steel mill located south-west of the sites, PM_{10} concentrations did not and instead seemed to be associated with long-range sources. Therefore, it is suggested that this group is affected by regional sources in the greater area of Ile-Ife, which at night, in the smaller fraction of PM, is impacted to a reduced extent by the steel mill compared to the more polluted conditions found for other clusters, while its PM concentrations are also exacerbated by the reduced boundary layer height (BLH) during night hours.

Cluster 5 – Urban background

Cluster 5 is most frequent at sites P1 and P4, located at the northern and southern ends of the study area accordingly, followed by site P2. High $PM_{2.5}$ concentrations of this group are generally associated with slower winds, while high PM_{10} is more common during stronger winds at the sites (Fig. 6c and g). At P1, higher $PM_{2.5}$ is most common during westerly winds, while PM_{10} is also present during stronger north-westerly winds. Sites P3 and P4 showcase similar PM patterns, with $PM_{2.5}$ and PM_{10} being associated with all windspeeds from the SW sector. At site P5 this is the most polluted group for both PM size fractions, with high concentrations being associated with slow to medium winds. This result though may be biased from the small number of occurrences, which are mainly on the 26th and 27th of June, on which the same cluster is observed at all 3 southern sites (P3, P4 and P5).

This group generally experiences higher PM concentrations during the early morning hours and at night at the sites from a south-westerly direction (Figures S5e and f), with some exceptions, e.g. P3 with high $PM_{2.5}$ from NE at night, and P5 with a high PM_{10} reading from NWW at around 4 AM. The PM_{Ratio} varies between sites (Table S4), with P5 having the highest ratio (0.65).

The fifth cluster showed a diurnal pattern of an early morning source (4 to 6 AM) and was the third most polluted cluster. Due to the low number of readings for some sites, no clear pattern of origin between the sites was visible in the data. Instead, it is postulated that this cluster represents windblown dust from the surrounding area, including the main part of the city to the east, exacerbated by anthropogenic movement, due to the presence of unpaved roads as well as open fields surrounding the measuring sites. Soil was also the most frequent source found in the $PM_{2.5}$ size fraction by Owoade et al. (2016), representing 44% of the total $PM_{2.5}$ mass found in Ile-Ife during their study.

Cluster 6 – Daytime/clean conditions

Cluster 6 is most frequent at P5 and P3 and is strongly associated (~ 75% of counts) with winds from the south-western sector (Fig. S4f). $PM_{2.5}$ and PM_{10} concentrations of this cluster are highest at P1 and P3 (Fig. 6d and h). At P1, higher $PM_{2.5}$ and PM_{10} values are associated with strong southerly winds, as well as from a SWW direction. At P3, high $PM_{2.5}$ concentrations are common during winds from the southerly half, with winds from the southwest being most uniformly polluted, similar to the PM_{10} concentrations. However, this site also experiences a number of high PM_{10} and $PM_{2.5}$ readings during weak to medium winds from the northern sector. Site P2 mainly shows higher PM concentrations during winds from the southern sector, whereas P4 experiences its main pollution from the western direction, a variation that seems to be affected by the position of the two sites. At P5, higher $PM_{2.5}$ concentrations are associated with winds from the west to south, while some higher concentrations are also recorded during easterly winds.

This group, despite being mainly present during the day, is also associated with high $PM_{2.5}$ and PM_{10} concentrations during the late morning hours (4 to 10 AM) at most sites (Fig. S5g and h), with $PM_{2.5}$ concentrations remaining high only at P5 and P1 during the day. Site P3 experiences high PM_{10} concentrations during the day, mainly in a south-westerly, north-westerly, as well as a north-easterly direction. The PM_{Ratio} varies between the sites (Table S4), with site P3 displaying the lowest PM_{Ratio}.

The sixth cluster is the only pure daytime cluster and is hypothesised to be representative of general urban activity during the day, without a distinct effect of sources like traffic or

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other daytime activities, showcasing the conditions for which PM pollution is at its lowest for all sites. Furthermore, as the formation of secondary aerosol is common during these hours, the possibility this cluster describes such conditions should be considered. This could be further elucidated with additional data for the chemical composition of the particles, which unfortunately was not available for this study.

Case studies of clusters 2 and 4

As mentioned previously, due to the low occurrence of these clusters, similar diurnal profiles and mean of variables but opposite site occurrence, these clusters have been studied further, allowing for better interpretation of the clustering result, and thus the source differentiation. Polar plots for CL2 and CL4 for all the sites of the study can be found in Fig. 7.

Cluster 2 – Industrial polluted

Cluster 2 occurs almost exclusively at P1 and P4 (Table S4), which are the sites closer to industrial activities in the area (agriculture and steel milling and processing, respectively). It includes the period of an extreme $PM_{2.5}$ and PM_{10} event that occurred on the 8th of July 2018 in the early morning hours (3 AM to 8 AM), where PM_{10} was consistently high (peaked at 12,085.9 µg m^{-3} at P4, and 4,328.8 µg m^{-3} at P1). During this period, $PM_{2.5}$ was also consistently high, with concentrations peaking at 652.1 µg m^{-3} and 206.2 µg m^{-3} at P4 and P1, respectively. Although this cluster occurs more often in July (21 days) than in June (12 days), overall data points are almost equal between the months.

At P1, the university farm, higher $PM_{2.5}$ concentrations are usually associated with slow to medium winds from the westerly direction, while at P4, high $PM_{2.5}$ and PM_{10} concentrations are dominant from the northern sector, indicating a potential point source to the northeast of the sensor (Fig. 7b and c). However, it should be noted though that the average wind speed for the periods with northern winds coincides with almost stagnant conditions (with wind speeds averaging at 0.36 m s^{-1}). This along with the few occurrences of this cluster with northern winds at the specific site are possibly biasing the direction of the source.

As mentioned previously, this cluster exhibits a high PM_{Ratio} associated with anthropogenic sources, and this is reflected at all sites (Table S4). The cluster occurrence over time (Fig. 2) points that while having few readings, it is present on multiple days, generally indicating its association with a frequent, point source, such as power generation, the effect of agricultural activities or the steel mill depending on the site.

Cluster 4 – Residential polluted

Cluster 4 resembles the mirror opposite of CL2, and is more frequent at sites P2, P3, and P5. However, similarly to CL2, this cluster is also dominated by the high pollution event occurring on the 8th of July between 3 to 8 AM, with PM_{10} concentrations peaking at 9,514.2 µg m^{-3} at site P4. Yet, one of the highest PM_{10} readings of this cluster (2,943.5 µg m^{-3}) occurred at site P5 on the 28th of July at 3:00 AM, while site P3 read 82.4 µg m^{-3} PM_{10}, during SWW winds, which was included in CL3. This indicates that the effect of this cluster is possibly localised to each site.

At site P1, higher $PM_{2.5}$ and PM_{10} concentrations are associated with a southerly wind direction, similar to site P5 (Fig. 7d and e). Site P2 experiences higher $PM_{2.5}$ during slow winds from all wind directions, while stronger winds are associated with lower $PM_{2.5}$ but higher PM_{10} values. At site P3, higher $PM_{2.5}$ concentrations are associated with all wind directions. The highest $PM_{2.5}$ and PM_{10} readings were found at site P4, associated with winds from the eastern sector.

To an extent, CL2 and CL4 seem to be interconnected between the sites and present the effect of the sources located at sites P1 and P4 (CL2) and their effect on the other three sites (CL4). While this is not the norm in all cases, the simultaneous occurrence between the source sites and the receptor sites is rather high, reaching up to > 60% of simultaneous occurrences for specific couples (Table 2). This effect is higher when the source is the site next to the steel mill, which has a greater percentage of simultaneous occurrences with the CL4 on the other three sites compared to that with P1. This is expected as the wind profile is mainly SW, putting most sites downwind to that source (as mentioned earlier, CL4 is the only cluster with an additional prominent NE wind portion (Figure S4), which when occurring it puts all the sites downwind to the main northern source of PM). Interestingly, this effect appeared increasing moving to the northern sites which can be explained probably by the local topography as well as by the northern sites being affected by both industrial sources. This is due to a combination of the general wind conditions (on one side) and proximity to the northern source (on the other side). Furthermore, a significant percentage of simultaneous occurrences of CL2 on the source sites was also found. While this cluster was more frequent at the northern P1 site, it was significantly more common for the conditions at P1 to be affected (or just occur at the same time) by the P4 (as it located downwind in most cases) than the opposite. The low similarity found when P1 was the source of CL2 points that, while there are similarities on the emissions from these two sites, they should be considered as two different sources and not as one being the effect of the other (in simple words the steel mill emissions greatly affect the particle composition in P1, while the opposite is not true).

Clusters 2 and 4 were difficult to interpret due to their remarkably similar characteristics while being primarily present at opposite sites. Due to the similarities in the particle size profiles, high PM concentrations, meteorological variables, as well as the high pollution event on the 8th of July being present in both groups, it was postulated that this was representative of either local sources for each site which were exacerbated by both the meteorological conditions and low BLH or the effect of the industrial sources in the greater area (or the combination of both). When attempting solutions with more clusters, these two clusters were separated into smaller groups by all attempted solutions, i.e. using solutions of up to 9 clusters on the dataset. Apart from the local sources for each site, due to power-generation to support energy needs, and open burning

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Table 2: *Simultaneous occurrence of CL2 and CL4 across the sites. The table shows the occurrence of CL4 at sites P2, P3 and P5 when CL2 occurs at P1 and P4 (considering P1 and P4 as source sites). The two last columns indicate the simultaneous occurrence of CL2 on P1 and P4 (for either site).*

Source \ Receptor	P2 (CL4)	P3 (CL4)	P5 (CL4)	P1 (CL2)	P4 (CL2)
P1 (CL2)	37.8%	30.3%	28.7%		36.9%
P4 (CL2)	62.0%	47.3%	33.3%	60.3%	

and waste management being common practice in Nigeria (Mir Alvarez et al., 2020), it is hypothesised that CL2 is also affected by local power generation at sites P1 and P4, while CL4 is associated with both power-generation and biomass burning, given the close location of the university dump ground to site P2. CL4 is presumed to also include long-range particles of combustion from the main part of Ile-Ife, which lies south-east of the sites thus, a more generic characterisation was chosen.

Discussion

Overview of the results

Source identification and apportionment methodologies are extremely useful tools for air quality assessment. The k-means clustering methodology used in the present study identifies the sets of sources and conditions that affect air quality in an area. In this study, a combined dataset of 5 sites in Ile-Ife, Nigeria was analysed. These sites, while presenting great variability on the conditions found, all have very high average PM concentrations, exceeding the present and previous suggested concentrations from the WHO by a large margin. While source apportionment, attempted earlier by Owoade et al. (2016) quantified the effect of the sources in the area, the present study takes a different route. In this case, the focus is not on the exact effect of each source in the area, but rather the combined effect of the sources and conditions and how they affect the local air quality on each site. The combined dataset identified 6 different sets of the effect of sources, meteorological conditions, spatial and temporal variations, which result in different air quality levels in the area. With the applied analysis, the effect of the different sources of pollution, grouped in background, residential, traffic related, and industrial, were analysed in combination with the atmospheric conditions, and the expected outcome of each set was quantified. It was found that during the daytime, due to the higher mixing resulting from the increased BLH, the average PM concentrations were significantly lower than the average conditions. The main source affecting daytime PM concentrations was traffic, the effect of which was found throughout the study area and increased at sites that were near busy roads. The greatest source variations were found during the night. The methodology identified the conditions for which the PM concentrations were kept relatively low. However, the localised effects of the industrial, agricultural, biomass burning and residential sources were found to have significant effects on the local air quality, depending on site location. These peaks mostly occurred during the night times with very low wind speeds (reducing their dispersion) at all sites and had a tremendous effect on the PM concentrations increasing them by up to 5 times on average, thus having a detrimental effect on the local air quality. A significant increase was also found from the effect of the Urban Background, mainly associated with emissions from the south and east sides where the main part of the city is located, though the increase from this effect was more frequent and a lot lower. For the specific site, as conditions are rather polluted, only a fraction of the data set (about 37%) was found to comply with only the daily suggested concentrations from the WHO (which should not be exceeded for more than a few days per year, making this area stand way above the safe limits). These conditions occurred mostly during the daytime with stronger than average winds.

The methodology was successful in pinpointing the combined effect of conditions and sources upon local air quality. The triangulation of the measurements, helped in identifying the sources with the greatest effect for each site. It also highlighted the effect the major sources have on the air quality at all the sites across the studied area, and the expected conditions when these sources have their stronger emissions. Furthermore, the sites that presented the greatest effect from the local sources of pollution, as well as the temporal variation this has were identified, providing insight on the extent of the effect these sources have both on its range and intensity.

Limitations and recommendations

While the k-means clustering was successful in separating the size particle profiles, the triangulation based on the particulate matter concentrations of the clusters added clarity to the sources and provided insight on their spatial effect according to different diurnal and meteorological conditions. Owoade et al. (2016), using polycarbonate filters, separated sources found in Ile-Ife around the steel mill, with particles in the fine fraction ($PM_{2.5}$) and coarse fraction originating mainly from soil and biomass burning, and to a lesser extent from scrap processing, and vehicular emissions. The k-means cannot provide such information, though it correctly attributed that the majority of the PM variation at that site is due to background sources, while traffic, the agricultural activity and the mill were responsible for the extreme peaks.

Apart from the useful insight on the factors affecting the air quality in the area, this study highlights some important limitations of the methodology. While the use of low-cost sensors allows for air quality monitoring in places where expensive research-grade equipment is not available. It is highlighted that the OPC sensors used in this study are unable to observe particles smaller than 0.38 µm in diameter. Thus, sources with high variation below this limit were not separated. Better separation of smaller particles could provide a fuller picture of sources.

Finally, although the original study by Owoade et al. (2021) was a preliminary study on air quality in Ile-Ife, the steel mill was identified as the most critical point source in the area. Given the prevailing winds in this area coming from the south-west during the rainy season, it would have been advantageous to have

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placed sensors upwind of the mill, enabling the clear separation of particulate matter concentrations arising from this source. Furthermore, a longer study period including the dry season could have been beneficial, as well as the inclusion of daily rainfall, aiding the quantification of the washout effect (Guo et al., 2016) and other meteorological impacts on particulate matter concentrations.

Conclusions

Given the recent trends of deteriorating air quality and the associated health impacts in LMICs, investigating the sources associated with air quality is of utmost importance, as it allows for site specific management and mitigation options to be put into place. This study set out to reanalyse a previously published dataset of particle number concentrations, meteorological variables, and $PM_{2.5}$ and PM_{10} concentrations taken in Ile-Ife, Nigeria, between the 8th of June 2018 and the 31st of July 2018, for air pollution source differentiation. It did so by exposing the particle number size spectra of five Alphasense OPC-N2 sensors to k-means clustering and using triangulation to aid the source identification.

The key findings highlighted a clear separation of activities affecting air quality during the day and night, with night-time conditions and activities and therefore sources to be most impactful on the air quality in Ile-Ife. The effects of traffic, industrial activities, and residential emissions were identified as contributing the most to the variation of PM concentrations and need to be addressed to reduce the exposure of the local population to harmful concentrations of air pollutants. Previous studies identified the local iron and steel mill to be the main point source in this region. The current analysis shows that its effect is more dominant during the night hours, potentially increasing the PM concentrations to an average of more than 10 times above the PM_{10} hourly limits suggested by the WHO for specific atmospheric conditions. This was more prominent in stagnant conditions, which were more common during the night and at the sites closer to these activities. Furthermore, this study highlighted the effect traffic has on the PM concentrations, which was found to be increased compared to other similar studies, due to increased resuspension from unpaved roads. The triangulation process proposed in this study not only points to the effect specific activities have in the local atmosphere, but also shows the range of these effects on the greater area. Furthermore, as the methodology presented here separates not only sources but the effect of atmospheric conditions on them as well, it provided the expected air quality for the different scenarios that occurred during the measuring period. Therefore, results from similar analyses can be used for air quality management, urban planning and raise of public awareness on the conditions which improve or deteriorate the local air quality.

This study demonstrates the suitability of a low-cost sensor network to be implemented in regions where the attainment and maintenance of research grade equipment is not affordable or suitable, as well as the capability of the k-means clustering method to differentiate between activities and conditions impacting the local air quality, when using multiple sensors.

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Supplementary material

Supplementary material can be accessed at https://cleanairjournal.org.za/index.php/caj/en/article/view/24186

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