Environmental Science: Atmospheres

ROYAL SOCIETY OF CHEMISTRY

PAPER

View Article Online
View Journal

Cite this: DOI: 10.1039/d5ea00096c

Particulate matter monitoring and source apportionment inside and outside schools in a Global South metropolis

Vitalis C. Nwokorie, Dimitris Bousiotis and Francis D. Pope *

Globally, particulate matter (PM) air pollution is a significant threat to public health. The city of Port Harcourt, Nigeria, is heavily impacted by PM pollution through both natural and anthropogenic sources, including desert dust, vehicular emissions and gas flaring from crude oil processing and refining. Children are especially vulnerable to air pollution, and since they spend a large proportion of their time at school, this microenvironment is critical for their total air pollution exposure. Using low-cost sensors, PM were monitored in three schools in Port Harcourt. The $PM_{2.5}$ and PM_{10} concentrations were, in almost all cases, significantly higher during the dry season compared to the rainy season, up to a factor of 3. Both $PM_{2.5}$ and PM_{10} concentrations were also found to be greater than the annual WHO recommendations throughout the campaign, often exceeding the 24 hour recommendations, in some cases more than 5 times, for both the dry and rainy seasons. Indoor PM_1, $PM_{2.5}$ and PM_{10} concentrations during the school day were significantly higher than outdoor concentrations highlighting the influence of indoor PM sources, in addition to the infiltration of outdoor sources. Source apportionment revealed consistent source patterns across both seasons, showing that outdoor emissions overwhelmingly dominated indoor air quality. Outdoor sources accounted for more than 95% of indoor $PM_{2.5}$ and for more than 60% of the indoor PM_{10}. The high PM level exposure during the dry season was significantly influenced by the Harmattan desert dust both inside and outside the schools. In the rainy season, local anthropogenic sources played a more significant role in the absence of the Harmattan effect. These results underscore the urgent need for targeted mitigation strategies within school environments and their surrounding communities to protect children's health and reduce the long-term burden of air pollution in Port Harcourt and other similar urban settings.

Received 14th August 2025
Accepted 1st December 2025

DOI: 10.1039/d5ea00096c

rsc.li/esatmospheres

Environmental significance

This study demonstrates the use of low-cost sensors combined with Low Cost Source Apportionment (LoCoSA) to disentangle indoor and outdoor particulate matter (PM) sources within Nigerian schools. By triangulating local and regional contributors, we reveal that indoor exposures often exceed outdoor levels, driven by resuspension and infiltration of desert dust, vehicular emissions, and gas flaring. The approach provides a scalable, cost-effective framework for identifying priority pollution sources in understudied environments. These insights enable targeted interventions to reduce children's exposure in schools and offer a transferable methodology for improving air quality management in rapidly urbanising cities across Africa and beyond.

1. Introduction

Indoor air quality is a critical issue in both the Global North and Global South, with associations between particulate matter (PM) pollution and premature mortality and morbidity established by many epidemiological studies.[1–3] Assessments have identified indoor air pollution as the ninth largest risk factor in the Global Burden of Disease.[4] Studies have linked prolonged exposure to high levels of PM to childhood cancer, increased respiratory symptoms, and impaired lung function.[5,6]

Exposure to PM pollution has also been linked to cognitive health in addition to physical health.[7] The 2021 WHO guidelines provide recommended 24-hour and annual limits for $PM_{2.5}$ and PM_{10}, which are particulate matter with diameters less than 2.5 and 10 μm, respectively.[8] The WHO 24-hour limits for $PM_{2.5}$ and PM_{10} are 15 μg m^{-3} and 45 μg m^{-3}, respectively, whilst the annual WHO limits for $PM_{2.5}$ and PM_{10} are 5 μg m^{-3} and 15 μg m^{-3}, respectively. The toxicity of PM increases with decreasing particle size,[9] hence there is a growing interest in particles in the PM_1 size fraction (particles with diameters less 1 μm). The detrimental effects of PM are also influenced by the chemical composition and hence the different sources of the PM.[10]

School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, B15 2TT, UK. E-mail: f.pope@bham.ac.uk

Children are particularly vulnerable to the effects of air pollution because of their higher respiratory rates, larger lung surface area relative to their body size, and incomplete respiratory system development, which allows pollutants to become more concentrated in their systems.[11,12] According to Perera,[13] children are more vulnerable to air pollution because of increased physical activity and underdeveloped cerebral, cardiovascular, pulmonary, and immune systems.

Researchers have linked prolonged exposure to air pollution to poor academic performance, in addition to the health implications.[13,14] Poor indoor air quality impacts students' cognitive function, development, comfort, concentration, and performance.[15] One study reported that children aged 7 to 10 attending schools exposed to high levels of traffic-related air pollution exhibited slower cognitive development compared to children attending less polluted schools.[16] Another study in Barcelona found that children aged 7 to 11 years exposed to air pollution at school had increased behavioural problems.[17] Research on air quality in 51 schools in Portugal found that high levels of indoor air pollution, resulting from poor ventilation, negatively impacted cognitive function and learning.[18]

Nigeria, which is Africa's leading economy, has a young and rapidly growing population. In Nigeria, schoolchildren generally spend 4–8 hours per day in severely congested urban classrooms, which are often located near important air pollution sources, exposing them to PM. Vehicle emissions have a significant influence upon air quality, and schools located near to highways have higher air pollutant levels with proven harmful health effects.[13,14,19,20] In Nigerian schools, outdoor pollution infiltration can significantly alter indoor PM concentrations. The rate and level of infiltration depend on factors such as building architecture, ventilation practices, climatic conditions, sources, particulate physiochemical characteristics, and size.[14]

Previous studies on indoor air quality typically focus on particle mass concentrations without identifying the main pollutant sources,[21–23] An important first step in reducing children's exposure to pollutants indoors at school is the development of more accurate methods to disentangle source contributions in the indoor environment. Understanding the indoor pollution sources allows for targeted mitigation measures to reduce air pollution. Recently, Rose *et al.* 2024 showed that sources of pollution within schools can be source apportioned into indoor and outdoor sources,[24] which should allow for more targeted mitigation.

This study investigates the air pollution situation within three schools in Port Harcourt, Nigeria. The objectives of the study are to: (1) assess the mass concentrations of PM_1, $PM_{2.5}$, and PM_{10} within the indoor and outdoor school microenvironments, (2) identify the air pollution factors and sources that contribute to variations in the PM_1, $PM_{2.5}$, and PM_{10} mass concentrations, and (3) to assess the differences between the dry and rainy seasons. The information from (1) and (2) will allow for the assessment of air pollutant control measures and the provision of practical recommendations to mitigate air pollution problems within schools in Port Harcourt and beyond.

2 Methods

2.1 Study area

Port Harcourt, the capital of Rivers State, is located on the southern part of Nigeria's southern Atlantic coastline, see Fig. 1. Port Harcourt experiences two main seasons: the dry and rainy seasons. It is the hub of oil and gas exploration and production in the Niger Delta region of Nigeria.[25] Hence, Port Harcourt is surrounded by gas flare stacks and oilfields. The study sites are surrounded by 28 oil fields and 15 gas flare flow stations within

Fig. 1 Map of the Amadiama community area of Port Harcourt showing the monitored schools and important pollution sources locations.

a 20-mile radius[26] (NOSDRA, 2024). The region also faces significant environmental stress due to its rapidly growing population,[27] with the 2020 population estimated as 5 198 716.[28] Port Harcourt is experiencing significantly increasing urbanisation caused by rural-urban migration.[25,29]

2.2 Sampling locations

The three schools in this study are in the Amadiama community (4°47′30″N 7°01′54″E) within the city of Port Harcourt. A primary school (PS), a junior secondary school (JS) and a senior secondary school (SS) were chosen for the study locations. The three schools are all naturally ventilated buildings and are therefore expected to have significant infiltration of outdoor air pollution to the indoor classrooms. The JS and SS schools consist of two storey buildings, whereas the PS is a single storey building. The locations of the schools are shown in Fig. 1. In each school, a single classroom was selected for sampling. Table 1 provides information about the monitoring campaigns in the three schools, and Table S1 provides information on potential pollution sources that are located close to the three study schools.

The monitoring campaign was conducted in two distinct periods to cover the dry and rainy seasons. The rainy season measurements were conducted in October 2020 and the dry season measurements were conducted in January 2021. The measurements took place at each school in each season. Sampling was conducted both inside and outside the selected classrooms during the measurement periods. Every attempt was made to concurrently measure both indoors and outdoors at all schools during both seasons, but due to a mechanical fault with one of the sensor boxes, this was not always possible (see Table 1 for operating periods).

In the rainy season, due to COVID restrictions, children at nursery school age were restricted from attending schools. This meant that the PS school was largely empty during this period and hence the study classroom was also empty of people except for when the researcher and teacher delegations attended.

For the indoor measurements within the classrooms, the monitors were placed opposite the blackboard in the middle of the class. The height of the measurements varied dependent on the room configuration, but always at a height between 1.5–2 m, at least 1 m from the wall and at least 2 m from the ceiling. For outdoor sampling the samplers were placed at the side of the building on the veranda or balcony near to the school playground area. The exact positioning of the outdoor sensors varied from school to school. The PS sensor was installed next to the school playground and the Amadiama creek which has a jetty that houses several fossil fuel powered water transport vehicles. The site is also exposed to sporadic open-air burning fumes in a condensed neighbourhood. Soot deposits coming from the creeks can be visually seen in the air, as well as deposits on the surfaces of PS desks as seen in the graphical abstract. The JS sensor was installed next to the school playground, which is very close (<10 m) to a major road and close to a fish packaging factory, which utilises a very large diesel-powered generator. Finally, the SS sensor was installed next to the SS playground, in the direction of the cement factory, the main road, and the creek. It is noted that smoke from artisan crude oil "kpo-fire" production,[30] was observed from the SS outside location.

2.3 Monitoring instruments and calibrations. The PM mass concentration – in the PM_1, $PM_{2.5}$ and PM_{10} size fractions – were monitored using two Alphasense OPC-N2 optical particle counter (OPC) sensors (Alphasense Ltd, UK), taking a similar approach to Pope *et al.*.[31] The OPC-N2 provides PM size information in 17 size bins (0.38–20 μm), which is converted to PM_1, $PM_{2.5}$ and PM_{10} mass concentrations assuming a density of 1.65 μg m^{-3} and particle sphericity. PM mass concentrations were collected at a time resolution of 10 s, which was then averaged to 1 hour for assessing the PM mass concentrations. For the source apportionment work, the data was averaged to 10 minutes. The mass concentrations were calibrated for UK conditions by the manufacturer. It was further calibrated through comparison with the reference OPC instrument (GRIMM portable aerosol sampler model 1.108) at the University of Birmingham, UK. However, it was not possible to further calibrate the sensors for Nigerian conditions due to the lack of regulatory sites to compare against in Port Harcourt or surrounding areas. Furthermore, while low-cost sensors of the same type tend to show consistent variability in their reported PM concentrations, they may present differences in absolute values due to uniformity or ageing factors.[32] To ensure consistency between the different OPCs, they were collocated to confirm they were collecting similar readings. The effects of RH on the performance of OPC-N2 have previously been evaluated.[33,34] At high relative humidity (RH > 85%), the OPC-N2 often gives unrealistically high PM values because of particle hygroscopicity, in which hygroscopic particles take up atmospheric water thereby increasing their mass. Nearby RH data was obtained from a meteorological station, which highlighted that the RH during the study periods was always less than 85%.

Table 1 Characteristics and sampling period of monitored schools[a]

School	Age grade	Rainy season sampling period	Dry season sampling period	Floor	Approximate classroom volume (m^3)
Primary school (PS)	5–11	26/10/2020–30/10/2020*	11/01/2021–15/01/2021**	Ground	120
Junior secondary school (JS)	11–14	19/10/2020–23/10/2020*	18/01/2021–22/01/2021*	First	130
Senior secondary school (SS)	14–17	19/10/2020–23/10/2020*	18/01/2021–22/01/2021*	First	130

[a] Classroom occupancy status: occupied = *, unoccupied = **.

2.4. Positive matrix factorisation (PMF) and estimation of PM concentrations

Positive matrix factorisation (PMF) is a multivariate method developed by Paatero *et al.*.[35,36] While it can be used in multiple scenarios, in atmospheric sciences it has been extensively used and considered as one of the best approaches for the apportionment of air pollution sources using data from both reference grade[37,38] or low-cost sensors.[39–41] The method describes the relations between the variables considered, using the least-squares technique.[42] In atmospheric applications, these variables are chemical species or PM concentrations, which are inputted in the model along with their uncertainties (as provided by the manufacturer of the sensor used). The model forms a number of groups (factors), according to the user's input PMF being a descriptive model, does not have an objective criterion for the optimal number of factors[35] and the similarity of the variation of the variables inputted. The outputs consist of a matrix of the factors (F), which represents the average concentration of the given variables for each factor (source) formed and a matrix of contributions (G), which represent the relative contribution of each factor for each timestep of the initial dataset. For the specific analysis, two separate analyses were conducted due to the significant differences between the periods. One for the dry period using the indoor and outdoor dataset available, and one for the rainy period using the combined indoor and outdoor dataset from the three schools.

For the estimation of the PM concentrations, the elements of the (F) matrix were multiplied with the elements of the (G) matrix, a methodology successfully applied in previous studies.[39,40] As the (G) matrix is normalised (by the model) to 1, its variation provides a metric of the contribution of the given factor on each timestep of the dataset, thus providing of the partial effect of the factor on the atmospheric conditions at the given time period (*e.g.* if the G contribution of a factor at a given time is 2, this means that the specific source associated with the factor was contributing twice its average contribution at that time. If the contribution was 0.5, then the specific source was contributing half its average contribution *etc.*). By multiplying this contribution with the average conditions provided by the (F) matrix an estimation of the PM contributed by each factor was acquired on the specific timestep.

It should be noted that PM_{10} concentration sometimes appear lower than the $PM_{2.5}$ concentration. While this is physically impossible, mathematically this result is valid, as the model does not consider the nature and relationships between the independent variables. When trying to decipher the result this translates as a minimum effect of the specific factor on the coarse mode ($PM_{2.5–10}$). Thus, it can be considered that the PM_{10} contribution of the specific factors is similar to its $PM_{2.5}$ contribution.

2.5. Statistical analysis

All statistical analysis was performed in R (version 4.4, 2024-02-29), using the RStudio GUI (version 2023.03.0386). The normality of the data was tested using Shapiro–Wilk test ($\alpha = 0.05$), then depending on the normality of the data, or not, hypothesis tests were performed with two-sample *t*-test or Mann–Whitney test for two samples. Graphical processing of the data was performed with the following packages within R: ggplot2 and Openair.[43]

3. Results and discussion

3.1 Particulate matter monitoring

Data was collected for all three schools (PS, JS, SS) in both the dry and rainy seasons. Indoor and outdoor data was collected at all sites during the rainy season. During the dry season, indoor data was collected for all schools, but outdoor data was only collected for JS. The time series data for all available monitor data is shown in Fig. S1–S3. The battery size available for the sensors dictated how long monitoring lasted for. To ensure the school present period (08:00–16:00) was monitored, this time period was prioritized. Example time series for the JS in the dry season for all three monitored PM size fractions, for both indoor and outdoor monitoring, is shown in Fig. 2.

The mean and median mass concentrations for the observed PM, in all the monitored size fractions, for PS, JS and SS, for both seasons, both inside and outside, are provided in Table 2. The descriptive statistics are only calculated for data collected within the school period (08:00–16:00) to be able to assess the effect of the school day upon student's air pollution exposure.

The acquired PM data allows for multiple comparisons of air pollution within the three Port Harcourt study schools. The PM_1, $PM_{2.5}$ and PM_{10} mass concentrations can be compared between seasons, between schools, and finally between indoor and outdoor measurements. The following observations are taken for the measurements collected during school hours (08:00–16:00). In Fig. 3, the boxplots visualise the distributions and differences between indoor and outdoor mass concentrations of PM_1, $PM_{2.5}$ and PM_{10} within the different schools and seasons, during school hours (08:00–16:00).

During the school present period, the greatest mean PM_1, $PM_{2.5}$ and PM_{10} concentrations were observed inside the SS during the dry season with values of 38.1, 58.5 and 261.0 $\mu g\ m^{-3}$, respectively. Comparing the different schools between the same seasons, JS and SS have similar concentrations in the PM_1 and $PM_{2.5}$ size fractions, whereas the PM_{10} mass concentrations are more variable. The PS has the lowest PM concentrations among all the schools. The JS and SS sites are closer together (approximately 100 m apart) than the PS which is approximately 700 m from the other schools. Hence the similarity in JS and SS PM_1 and $PM_{2.5}$ mass concentrations and their difference to the PS mass concentrations makes sense. PM_{10} is typically associated with sources with local effects, so the greater variability in PM_{10} between the different schools is understood. Larger particles are primarily generated by mechanical processes such as construction activities, road dust, and natural sources like sea spray and desert dust. This finding is in accordance with Monn[44] study who reported that the spatial variability for $PM_{2.5}$ is generally smaller compared to PM_{10}. Furthermore, PM_1 is expected to be more regional and less spatially variable in particularly in the peak hours of the day.[45] The primary reason for this uniformity in fine particles is their ability to stay suspended in the air for long periods and be transported over large areas by wind.

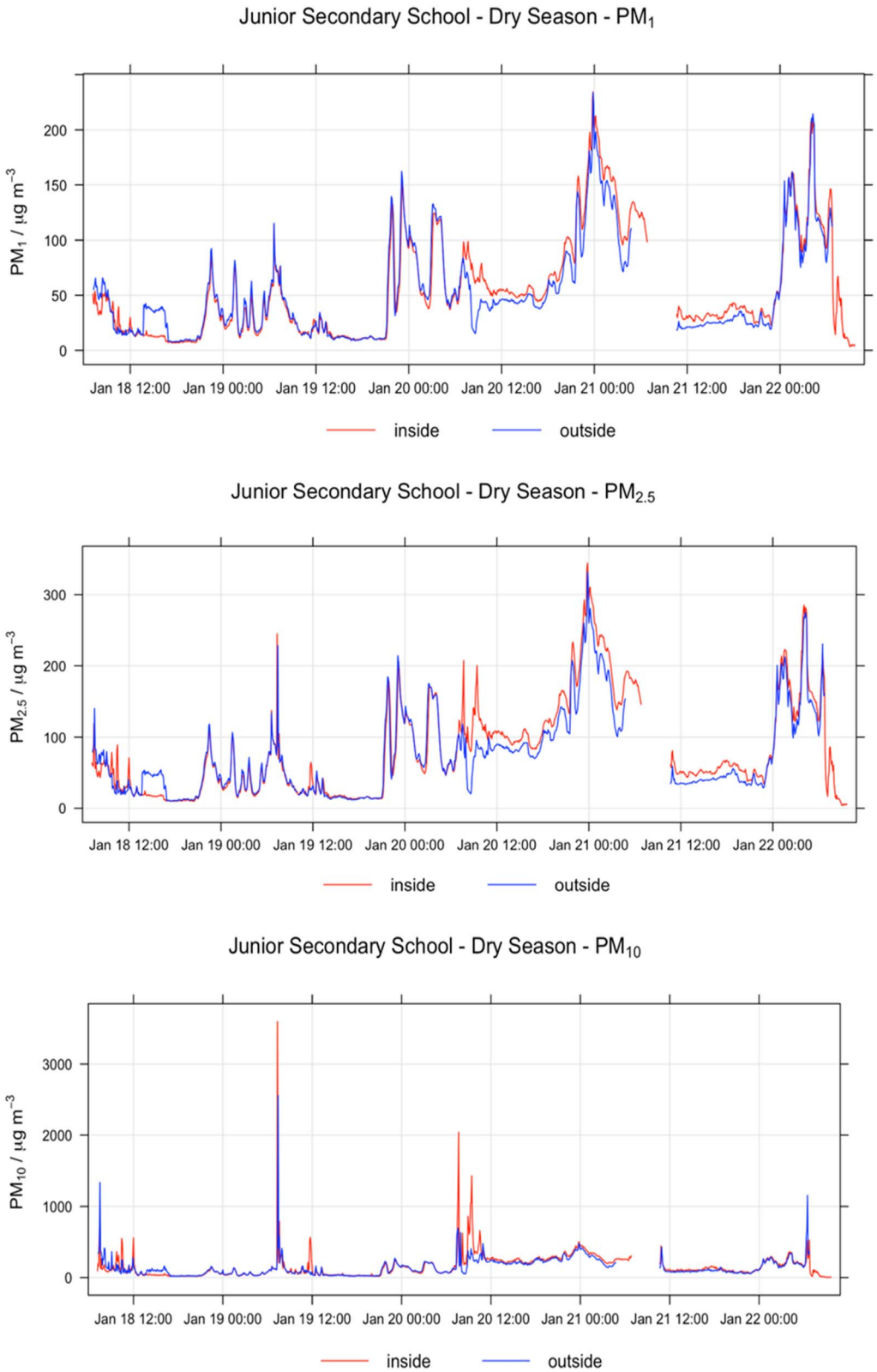

Fig. 2 Trends in PM_1, $PM_{2.5}$ and PM_{10} mass concentrations in the junior secondary school (JS) in the dry season, both inside and outside the school.

Comparing the inside and outside measurements, within a given school and season, various trends can be observed. For this comparison there are four cases that can be investigated, JS in both the dry and wet season, and PS and SS in the dry season. In general, the PM mass concentrations, in the PM_1, $PM_{2.5}$ and PM_{10} mass fractions, are larger when measured indoors

Table 2 The mean and median averages for PM_1, $PM_{2.5}$ and PM_{10} mass concentrations measured during the school period (08:00–16:00) for the different sampling campaigns both inside and outside the three studied schools. No data is available is available for outside measurements at the PS and SS during the dry season due to a fault with a sensor

			PM_1 ($\mu g\ m^{-3}$)		$PM_{2.5}$ ($\mu g\ m^{-3}$)		PM_{10} ($\mu g\ m^{-3}$)	
School	Season	Location	Mean	Median	Mean	Median	Mean	Median
PS	Dry	Inside	21.7	14.4	28.4	19.0	70.3	55.3
PS	Dry	Outside	No data	No data	No data	No data	No data	No data
PS	Rainy	Inside	7.3	4.7	10.0	6.2	24.2	8.4
PS	Rainy	Outside	13.2	6.9	16.1	9.0	20.9	12.9
JS	Dry	Inside	31.5	28.5	53.0	47.1	156.1	104.5
JS	Dry	Outside	30.4	25.3	45.0	37.9	114.2	84.1
JS	Rainy	Inside	10.5	7.9	24.4	14.7	238.8	96.8
JS	Rainy	Outside	7.7	5.8	12.7	9.2	63.1	34.5
SS	Dry	Inside	38.1	28.7	58.5	44.6	261.0	126.1
SS	Dry	Outside	No data	No data	No data	No data	No data	No data
SS	Rainy	Inside	8.2	6.8	14.4	10.5	79.5	35.3
SS	Rainy	Outside	5.0	4.5	8.0	6.9	35.6	24.3

Table 3 Average estimated contribution of the four dry season factors to the dry season PM mass fractions in the PM_1, $PM_{2.5}$ and PM_{10} size fractions. *It is noted that PM_{10} mass concentrations are less than $PM_{2.5}$ mass concentrations for F3, which is physically unrealistic. This result is discussed further in the methodology

	PM_1 ($\mu g\ m^{-3}$)	$PM_{2.5}$ ($\mu g\ m^{-3}$)	PM_{10} ($\mu g\ m^{-3}$)	Inside contribution	Outside contribution
F1	0.000	0.019	7.72	1.10	0.89
F2	9.97	24.8	62.1	1.08	0.92
F3	43.2	51.2*	47.0*	1.06	0.94
F4	0.727	2.42	34.2	0.97	1.03

compared to outdoors. The only exception to this is for the PS in the rainy season. Interestingly, this period was during a COVID related lockdown within the school, when the PS was empty even during school hours. Some large peaks can be observed within the indoor measurement on the 28th of October 2020, see Fig. S3, which coincide with an official visit by the school team to meet the research team.

As can be seen in Fig. 2, 3 and S1–S3, the indoor and outdoor measurements are well correlated, suggesting that much of the indoor air pollution is caused by the infiltration of outdoor air pollution into the classrooms. However, the greater PM mass concentrations observed within the indoor environments, when the school was in session, highlights that within Port Harcourt schools there are significant indoor sources of PM, in all size fractions, often associated with the presence of the children themselves. The pollution source related to the presence of the children is most likely the resuspension of dust since there were no combustion sources present within the school rooms themselves.[24] The differences between indoor and outdoor monitoring were largest in the PM_{10} size fraction, followed by the $PM_{2.5}$ size fraction then the PM_1 size fraction. This variation in different PM size fractions further suggests that the additional indoor source is dust resuspension, which typically involves larger particles. The highest peaks in PM_{10} were typically observed during changes in teaching sessions when students entered or left the classroom. These periods are characterised by greater student movement and hence energy to resuspend dust within the classrooms.

In general, the average PM concentrations inside the classrooms were higher in the dry season compared to the rainy season. This is expected as the dry season has greater amounts of dust because of the Harmattan winds. In addition, the stronger winds can influence the incoming concentrations of sea salt from ocean spray as well as the smoke from the nearby artisanal flaring.

The measured mean averages for indoor and outdoor mass concentrations of $PM_{2.5}$ and PM_{10} concentrations, during the school hours, were always greater than the WHO annual recommendation, for both the rainy and dry seasons. It is emphasised that for each school, measurements were only made for two weeks, with one measurement week in the dry season and one in the rainy season. Hence the campaign data does not provide a true annual average. However, with both the dry and rainy season campaigns being greater than the annual WHO recommendations, it is likely that the students will be consistently exposed to PM mass concentrations greater than the WHO annual recommendation. Where measurements exist in the dry season (inside for PS, JS and SS; and outside only for JS), all measurements exceed the WHO daily 24 h recommendations for both the $PM_{2.5}$ and PM_{10} size fractions. In the rainy season the WHO daily 24 h recommendation were also exceeded for JS indoor, PS outdoor and JS outdoor measurements in the

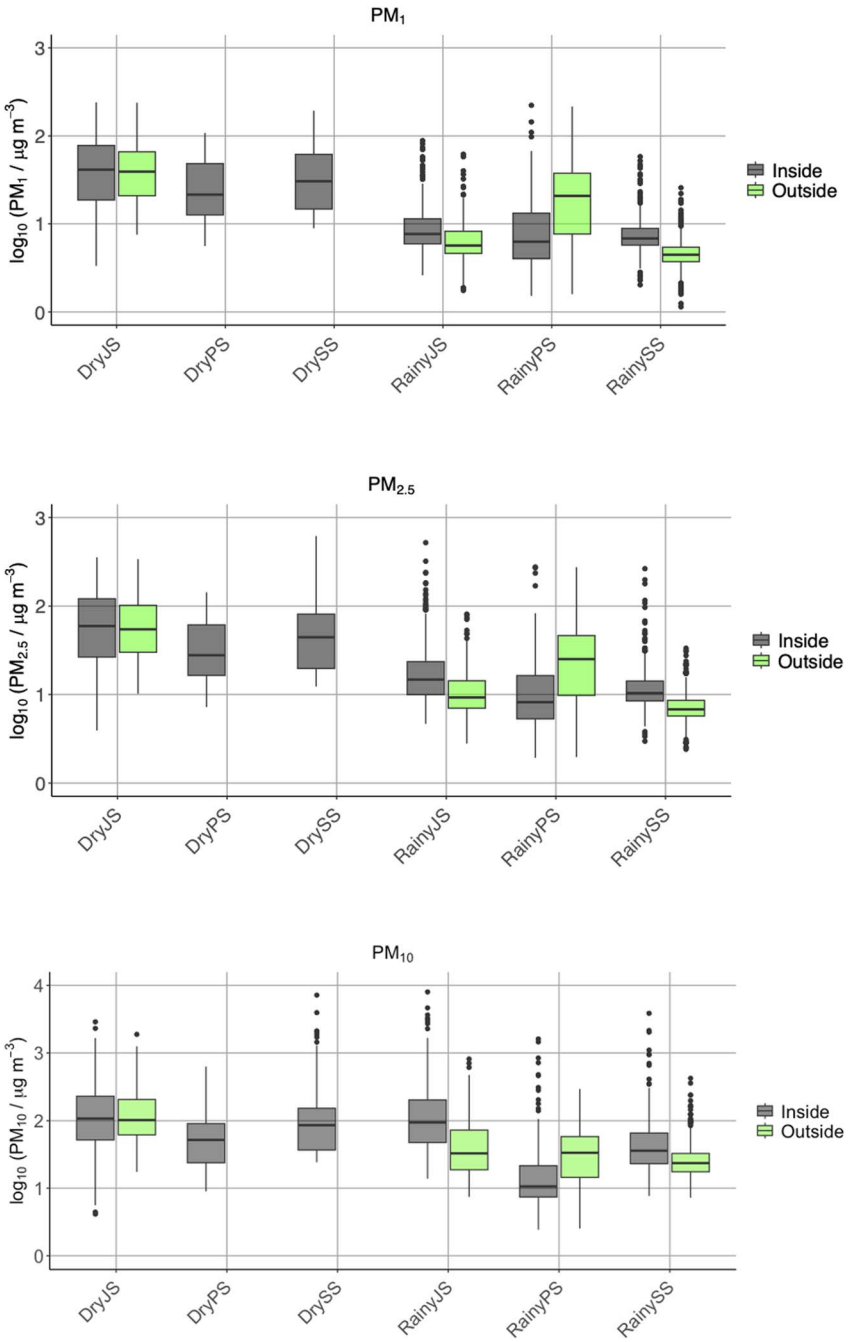

Fig. 3 Boxplots of the (top panel) PM_1, (middle panel) $PM_{2.5}$ and (bottom panel) PM_{10} mass concentrations observed during the PS, JS and SS field campaigns in both dry and rainy seasons, during school hours (08:00–16:00). Within the boxplot, the median is represented by the middle line, the interquartile range (IQR) by the box, the whiskers represent 1.5 * IQR, and the dots represent the outliers that lie outside 1.5 * IQR.

$PM_{2.5}$ size fraction. In the PM_{10} size fraction, the JS indoor, SS indoor and JS outdoor exceeded the WHO daily 24 h limits.

3.2 Particulate matter source apportionment

The average mass concentration of PM_{10}, $PM_{2.5}$ and PM_1 varied from school to school depending on the proximity to the outdoor sources, indoor sources, season and meteorological parameters. Furthermore, pollutants can migrate from outdoors to indoors and indoor air sources can exacerbate indoor air pollution.[24]

The source apportionment analysis was performed using PMF on the datasets which had both indoor and outdoor data available, to identify the sources that affected the indoor environment within the classrooms. For the dry season, the analysis was done only for the SS which was the only school with both indoor and outdoor data. The analyses were performed over all time periods, and not just the school hours investigate in Section 3.1, since this provided more information to the PMF algorithm. As there are great differences on the conditions between the two seasons (dry and rainy), the two periods were

considered separately. In both the dry and rainy season cases, a 4-factor solution was chosen, as it best described the conditions found.

The factors formed from both analyses can be classified into two groups. Firstly, the local factors, which include sources of PM from the school (classrooms and surrounding area) and are characterised by a distinct diurnal and weekly variation that follow expected school-based activities. Secondly, the regional factors associated with sources of PM from the greater area. These regional sources present a more balanced contribution within the day, a common characteristic of regional sources,[46] with a slight but distinct increase during the night hours, typical for regional outdoor sources. The nighttime increase is associated with a reduced boundary layer height (BLH). For the dry season, factors 1 and 4 represent local sources, and for the rainy season it is factors 3 and 4.

The profiles of the four factors, for both the dry and rainy seasons, are provided in Fig. 4. The diurnal profiles of the four dry factors and the four rainy factors are shown in Fig. 5. The dry season factor profiles can be described as follows:

- Dry factor 1 has a unique particle diameter peak at 700 nm and 1200 nm and 7000 nm.

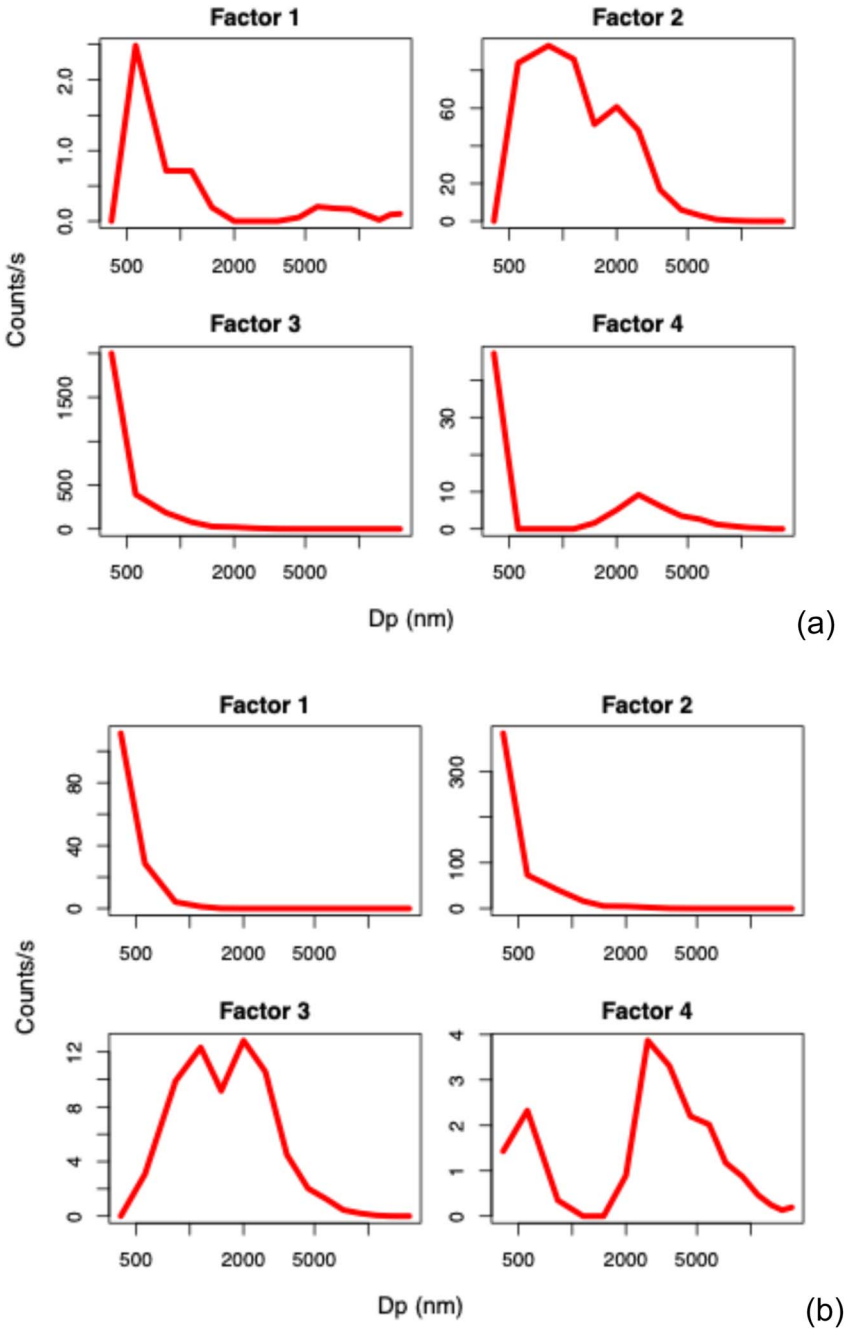

Fig. 4 Particle number concentration profiles of the factors from the PMF analysis in the (a) dry season and (b) rainy season. The plots provide the average particle count per second of the factors for each particle size bin.

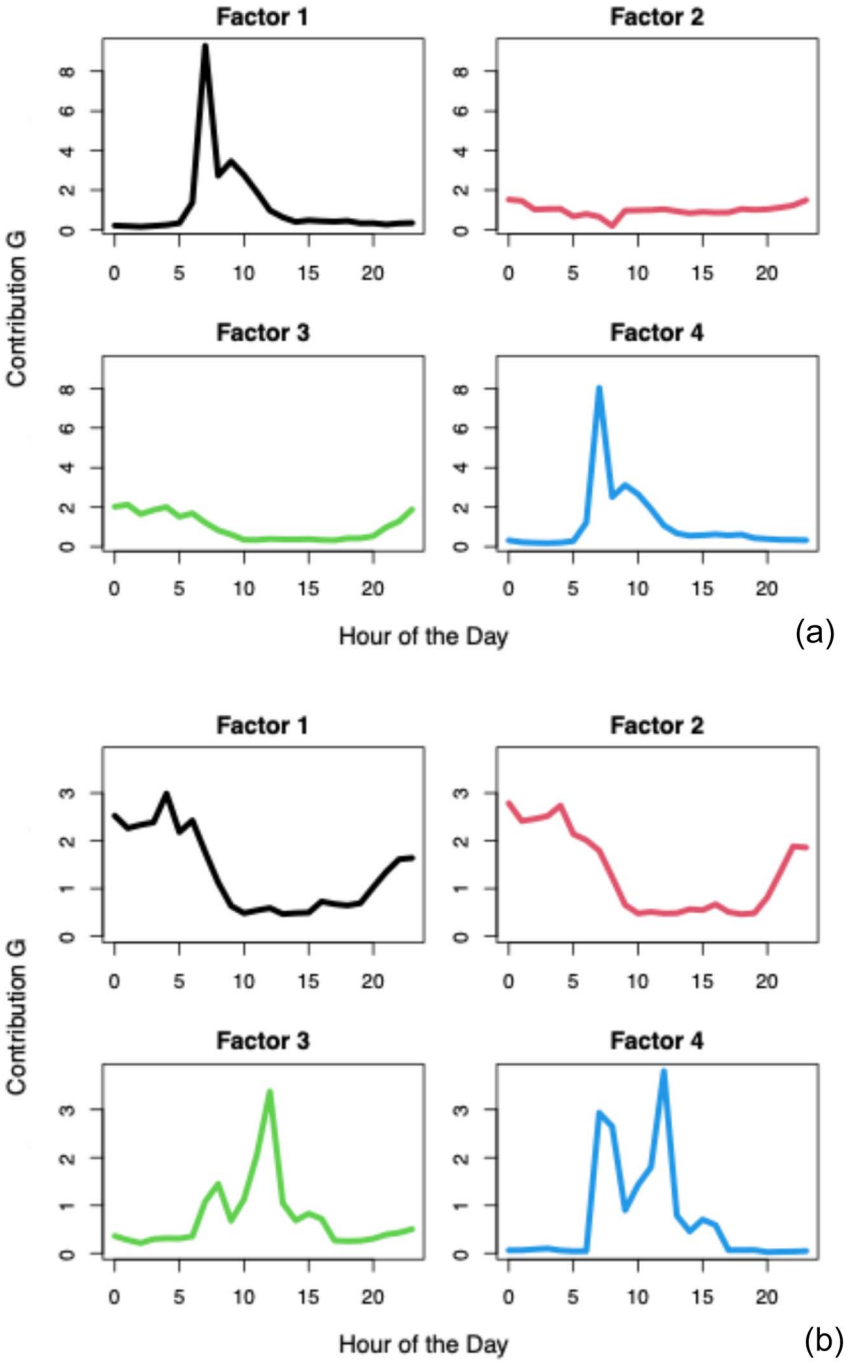

Fig. 5 Diurnal variation of the PM factor contributions from the PMF analysis in the (a) dry season and (b) rainy season. G contribution points the proportional intensity of the given factor normalised to 1 (*i.e.* a contribution of 2 means that the specific factor contributed double than average).

- Dry factor 2 has a distinct particle diameter bimodal peak at about 700 nm and 2000 nm.

- Dry factor 3 presents no significant peaks in the measured range of the OPC but does show a steady increasing trend with particle diameters below 600 nm.

- Dry factor 4 shows particle diameter peaking at about 3000 nm but however does also show a steady increasing trend with particle diameters below 600 nm.

For the rainy season, the factor profiles can be described as follows:

- Rainy factor 1 presents no significant peaks in the measured range of the OPC but does show a steady increasing trend with particle diameters below 1 μm.

- Rainy factor 2 has a similar profile with the first one, with increased particle concentrations at the lowest end.

- Rainy factor 3 shows bimodal peaking at about 1 and 2 μm.

- Rainy factor 4 also shows two distinct peaks at about 500 nm and at about 3 μm.

The PM contributions to the different factors for the dry and rainy seasons are found in Table 3 and 4, respectively. For both

Table 4 Average estimated contributions of PM level (μg m^{-3}) of identified factors in the rainy season. *It is noted that PM_{10} mass concentrations are less than $PM_{2.5}$ mass concentrations for F2, which is physically unrealistic. This result is discussed further in the methodology

	PM_1 (μg m^{-3})	$PM_{2.5}$ (μg m^{-3})	PM_{10} (μg m^{-3})	Inside contribution	Outside contribution
F1	10.5	12.8	15.7	0.72	1.32
F2	2.29	2.52*	0.001*	1.02	0.98
F3	0.408	2.99	16.5	1.34	0.62
F4	0.019	0.607	31.8	1.55	0.39

Table 5 Estimated PM contributions from the indoor and outdoor sources within the class for the dry and rainy seasons

	PM_1 (μg m^{-3})	$PM_{2.5}$ (μg m^{-3})	PM_{10} (μg m^{-3})	$PM_{2.5}/PM_{10}$
Dry season local	0.711	2.38	43.6	0.05
Dry season regional	56.5	81.1	117	0.69
Rainy season local	0.752	2.50	42.0	0.06
Rainy season regional	49.7	70.9	102	0.70

the dry and rainy seasons, Table 5 provides the estimated contributions of local and regional sources to the PM mass concentrations in the different size fractions, as well as the $PM_{2.5}/PM_{10}$ ratios.

For the dry season, the local sources had an estimated average contribution to the indoor PM_{10} of 43.6 μg m^{-3}, with a $PM_{2.5}:PM_{10}$ ratio of approximately 0.05. This is expected as indoor activities typically affect the larger sized PM, mainly in the coarse (PM_{10}–$PM_{2.5}$) size fraction, due mostly to resuspension of PM, as found in previous studies.[39,47] The contribution of the regional sources to the classroom was mainly found in the $PM_{2.5}$ size fraction, reaching an average of 81.1 μg m^{-3} with a $PM_{2.5}:PM_{10}$ ratio up to 0.69. This increased ratio is almost identical to that found outside the classrooms, which was at 0.70, pointing to a possible effect from sources associated with anthropogenic activity.

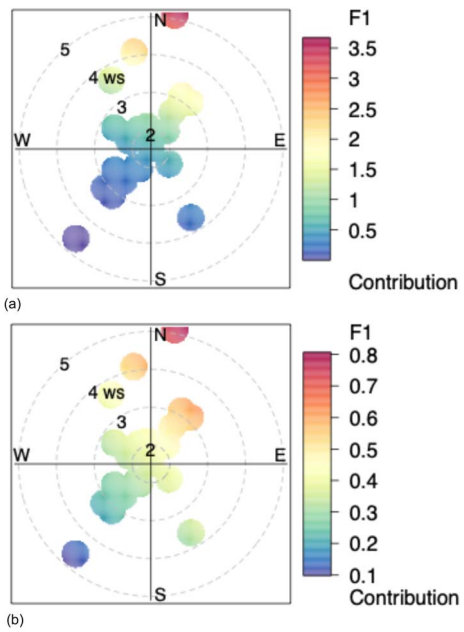

Fig. 6 Polar plots of the G contribution of the regional factors for the dry season. Panel (a) shows factor 2 and panel (b) shows factor 3.

Further analysis was performed to identify the sources of the regional factors during the dry season. The variation of the contribution of the factors with different wind conditions for the regional factors found in Fig. 6 points to a clear connection between high pollution events with strong N-NE winds. Strong NE winds are expected during the dry season in Nigeria, and are associated with the Harmattan season, which bring large amounts of Saharan dust into the city of Port Harcourt. The large effect of the Harmattan winds will overshadow the effect of additional sources of PM, which due to the limited dataset were not distinguished but should be considered. For example, the different profile of the regional F3 (mainly PM_1) along with significant contributions on stagnant conditions, probably points to anthropogenic sources of pollution. Thus, among the two regional factors, F2 is probably directly associated to the effect of the Harmattan winds, presenting a greatly elevated contribution on coarse particles with strong northern winds, while the third factor is probably associated with other regional sources (though still affected by the effect of the Harmattan) as pointed by its more balanced contributions with the different wind speeds. For the second factor, about 40% of the PM_{10} was fine particles, a PM ratio which agrees with previous studies for Saharan dust,[48] while the third factor has a more pronounced fine particle component. Nevertheless, as pointed by the source apportionment analysis, these regional factors greatly contribute to the elevation of PM in all size fractions, increasing $PM_{2.5}$ mass concentrations more than 4 times, and PM_{10} mass concentrations more than 2 times over the suggested 24 hour WHO guidelines.

For the rainy season, similarly to the dry season, the separation of the sources was largely achieved using the observed diurnal variation, which presented distinct profiles for the indoor and outdoor sources.

In the rainy season, the contribution of the local factors within the classrooms is a lot greater compared to the outdoor environment. This is expected because the classroom windows

are often closed during the rainy period to protect the classrooms from water ingress. By closing the windows, the local sources will have a lesser effect on the outdoor sensor measurements.

It should be noted that the outdoor sensors were positioned close to the classrooms, meaning that some influence from local sources was inevitably captured outdoors. Consequently, the proportion of local source contributions measured at the outdoor location decreased by almost one-third during the rainy season compared with the dry season, when this ratio was close to 1 : 1.

During the rainy season, the combined effect of the local sources on the indoor environment was estimated to provide an average PM_{10} contribution of 71.2 μg m^{-3} and a very low $PM_{2.5}$1 : PM_{10} ratio (0.07), almost identical to the dry season, pointing to similar sources but with increased effect, probably due to the closed windows. The outdoor sources were significantly reduced within the classrooms, mainly affecting the $PM_{2.5}$ with an average contribution of about 11.7 μg m^{-3} and similar concentrations for the larger PM_{10} fraction. While the expected emissions affecting the air quality in the area are not expected to vary significantly, the combination of the increased precipitation and the closed windows are probably contributing to the reduced regional contributions found during the rainy period within the classrooms. As expected, there is no evidence of a Harmattan influence during the rainy season. None of the observed factors exhibit the distinct particle signatures characteristic of the Harmattan (dry F2 factor) in the dry season. Moreover, coarse particle concentrations are naturally reduced during this period due to the increased precipitation typical of the rainy season, which effectively removes larger particles from the atmosphere.[49]

Comparing the rainy season sources between the three schools provides useful information about the local and regional sources. Due to the Covid restrictions, the PS classroom only had limited use during the rainy season, and this is clearly reflected in the estimated local sources identified for the PS. This result gives significant confidence in the plausibility of the source apportionment analysis. Looking at the local sources for all three schools in the rainy season, the JS showed very significant spikes in factor 1, with the G contributions reaching greater than 40 for specific hours (*e.g.* morning of Wednesday 23rd October). This leads to the estimated PM_{10} contribution at the specific classroom to reach more than 1400 μg m^{-3} for specific hours, posing a significant threat for the health of the occupants in these classrooms.

During the rainy season, the absence of the Harmattan influence, combined with different atmospheric conditions and wind patterns, resulted in local anthropogenic emission sources becoming more prominent. By comparing the regional factor 1 for all schools, in the rainy season, using a polar plot analysis, we identify a source of air pollution that is common to all three schools, see Fig. 7. Factor 1 appears to be elevated for all three schools when the prevailing wind direction is from the smoke emission at the Amadi Creek. This triangulation of sources provides strong evidence of the importance of this source upon local air quality in Port Harcourt. Similar trends were found with the second regional factor 2, see Fig. S4.

The results from this section demonstrate the possibilities of source apportionment using low-cost sensor data and the PMF algorithm. Furthermore, by comparing multiple locations within an urban area, in both indoor and outdoor environments, we can pinpoint specific indoor and outdoor pollution

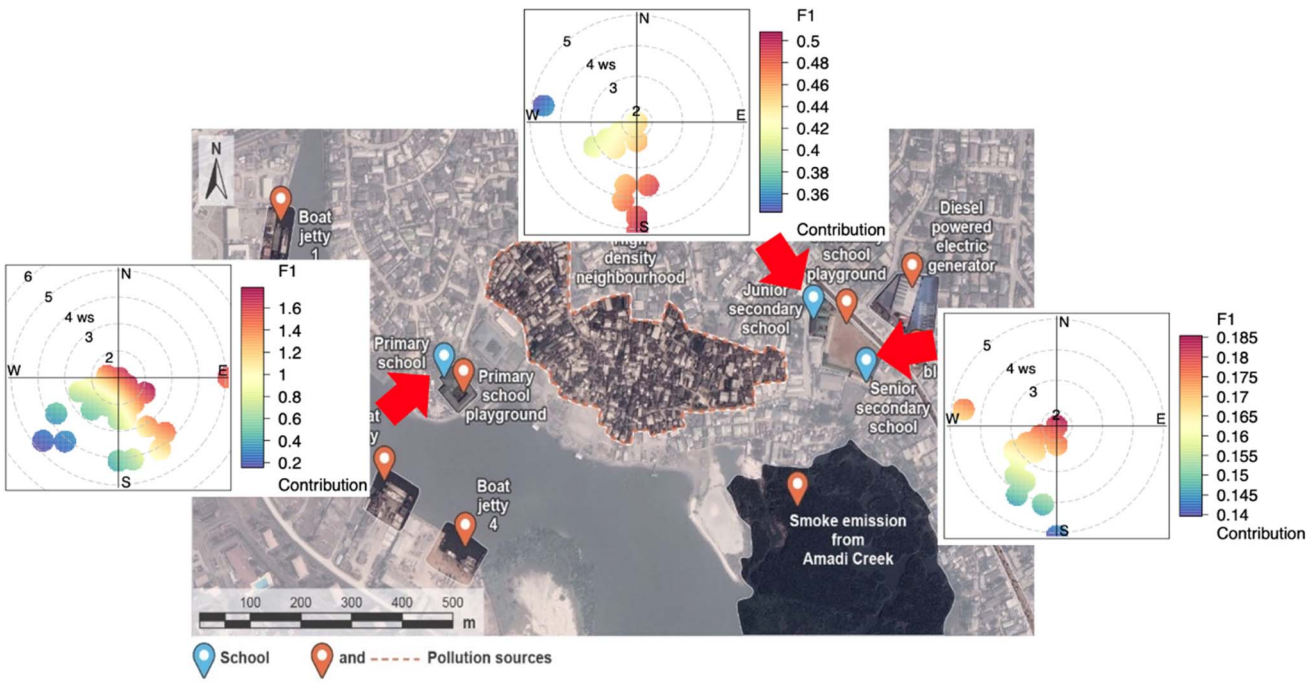

Fig. 7 Polar plots of the variation of the G contribution of factor 1 for all three studied schools. Higher contribution values point stronger influence of the factor with the specific wind conditions.

sources and highlight their relative spatial importance on different PM size fractions. Though in the present study the results only quantify the effect of indoor and outdoor sources in general, with the application of multiple LCS for longer periods and with the triangulation of the results, it is possible to more accurately assess the sources of pollution in a greater area. Furthermore, with the addition of indoor measurements and their parallel analysis, as highlighted in this study, we can understand the extent of the effect of outdoor sources in the indoor environments and along with the deciphering of the indoor sources to greatly improve the information of the factors affecting it, which can be used to take well-informed targeted action. Thus, this new approach can provide crucial information for public health policies and interventions using low-cost methodologies.

4. Study limitations

The limitations of this study include the lack of outdoor data for two of the school sites in the dry season, which limits the comprehensiveness of the analysis. The field work was hampered by the Covid period, which influenced the availability of batteries and presented operational challenges for sensor maintenance. For more efficient low-cost sensor deployment, it is advisable to use environmentally friendly solar panels with associated battery packs[50] to power the low-cost sensors, as operational setbacks in this study were primarily due to limited power supply. Campaigns in sensitive environments, such as schools, should be carefully designed to minimise disruption to students and staff and to maintain the potential for future cooperation. For this reason, two measurement periods of one week were agreed with the head of each school. While substantial information was collected within this timeframe, longer campaigns would have further strengthened the study's findings.

The lack of simultaneous measurements at all three schools did not allow for direct comparisons between the school sites. Different atmospheric conditions led to results that are significantly different, when the contribution of the regional sources is considered, thus not allowing the direct comparison.

5. Conclusions

The study looks at the air quality and the air pollution sources affecting it in three schools in Port Harcourt, Nigeria. This school-based study provides key information on the atmospheric pollution environment within Port Harcourt schools and highlights the importance of protecting the health and well-being of vulnerable populations through research on effective air quality monitoring, source apportionment and management.

Overall, the PM mass concentrations measured within and outside the study schools are generally higher during the dry season than the rainy season across all schools. The analysis pointed the decisive but variable effect of the Harmattan, as well as of the proximity of the schools to the major sources of pollution in the area, such as the jetties or gas flaring. Thus, the junior secondary school (JS) tends to have higher PM concentrations compared to the primary school (PS) and senior secondary school (SS), especially during the dry season. However, all schools exhibit similar trends regarding the impact of outdoor pollution on indoor air quality, pointing to air pollution sources with a more regional character. Furthermore, indoor PM levels often exceeded outdoor levels, particularly in the dry season, underscoring the significance of indoor pollution sources, added to the outdoor ones. The data set suggests that air pollution within Port Harcourt schools greatly surpasses the 2021 annual WHO air quality guidelines, many times also exceeding the 24 h recommendations up to 5 times the recommended concentrations.

To better understand the drivers of the air quality at the schools, this study utilised PMF to analyse the PM measurements in classrooms across the three schools during the dry and rainy seasons. The results indicate that the primary ambient sources of PM pollution were different for the two periods studied, pointing either to the effect of the Harmattan winds in the dry season, mainly affecting the coarse particle component in the area, and the smoke from gas flaring activities during the rainy season, the effect of which was mainly observed on the fine particles. Interestingly, a clear effect from the Harmattan was not found for the rainy season, even though it is expected to be present in the area during January, probably supressed by the increased precipitation anticipated during that period. The results pointed significant infiltration of the outdoor emissions in the indoor environment, the contribution of which was sometimes higher indoor than outdoor due to their accumulation in the indoor environment and resuspension from the occupants. Finally, the analysis of the low-cost sensor data using PMF followed by triangulation of its results demonstrated the capabilities of identifying not only the sources of pollution in an area, but the variable effect these have on different locations in the nearby vicinity, providing the information needed for better policy making and focused actions to improve the air quality.

This study highlights the potential of using low-cost sensors for continuous monitoring and Low-Cost Source Apportionment (LoCoSA) analysis, as recently reviewed in,[51] to inform targeted actions for better air quality management in school environments. The study has elucidated the relationships between indoor and outdoor PM concentrations in schools in Port Harcourt, Nigeria, across different seasons. The findings from this study can be applicable to many other schools and public buildings in high-traffic areas in Port Harcourt and other cities of Nigeria, and point to the critical need for immediate intervention to improve the air quality in the area. Specifically, the high PM levels pose significant health risks to students and teachers, including respiratory, cardiovascular and cognitive problems. Locally, emphasis should be placed on mitigating the causes of rising anthropogenic PM concentrations. While meteorological and climatic effects of natural PM sources are harder to control, public advisories could recommend the use of ergonomic face masks or better outdoor to indoor filtration during periods of peak PM concentration, such as during the Harmattan season.

Author contributions

Vitalis C. Nwokorie: conceptualization, data curation, methodology, original draft preparation, visualization, writing – reviewing and editing, Dimitrios Bousiotis: methodology, supervision, writing – reviewing and editing, Francis Pope: conceptualization, supervision, methodology, writing – reviewing and editing, funding acquisition.

Conflicts of interest

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.

Data availability

Data supporting this publication are openly available from the UBIRA eData repository at https://doi.org/10.25500/edata.bham.00001192.

Supplementary information (SI) is available. See DOI: https://doi.org/10.1039/d5ea00096c.

Acknowledgements

We thank Andrew Tanner from the University of Birmingham, UK, for his technical work on functionalising the Alphasense OPC sensors for the purposes of this study. We thank the studied schools and community council for access and logistical help. We acknowledge the funding support of the Natural Environment Research Council (NERC) through the grant "Quantification of Utility of Atmospheric Network Technologies (QUANT)" (NE/T001968/1). Travel funding was provided to VN from the University of Birmingham Institute of Global Innovation 'Resilient Cities' program.

References

1 D. W. Dockery and C. A. Pope, Acute Respiratory Effects of Particulate Air Pollution, *Annu. Rev. Public Health*, 2003, **15**, 107–132, DOI: 10.1146/ANNUREV.PU.15.050194.000543.

2 F. J. Kelly and J. C. Fussell, Size, source and chemical composition as determinants of toxicity attributable to ambient particulate matter, *Atmos. Environ.*, 2012, **60**, 504–526, DOI: 10.1016/J.ATMOSENV.2012.06.039.

3 Y. Yu, Q. Sun, T. Li, X. Ren, L. Lin, M. Sun, J. Duan and Z. Sun, Adverse outcome pathway of fine particulate matter leading to increased cardiovascular morbidity and mortality: an integrated perspective from toxicology and epidemiology, *J. Hazard. Mater.*, 2022, **430**, 128368, DOI: 10.1016/j.jhazmat.2022.128368.

4 F. Ren and G. Liu, Global, regional, and national burden and trends of air pollution-related neoplasms from 1990 to 2019: an observational trend study from the Global Burden of Disease Study 2019, *Ecotoxicol. Environ. Saf.*, 2024, **285**, 117068, DOI: 10.1016/J.ECOENV.2024.117068.

5 A. Ambroz, V. Vlkova, P. Rossner, A. Rossnerova, V. Svecova, A. Milcova, J. Pulkrabova, J. Hajslova, M. Veleminsky, I. Solansky and R. J. Sram, Impact of air pollution on oxidative DNA damage and lipid peroxidation in mothers and their newborns, *Int. J. Hyg. Environ. Health*, 2016, **219**(6), 545–556, DOI: 10.1016/J.IJHEH.2016.05.010.

6 World Health Organisation (WHO), *More than 90% of the World's Children Breathe Toxic Air Every Day*, WHO, 2018, https://www.who.int/news/item/29-10-2018-more-than-90-of-the-worlds-children-breathe-toxic-air-every-day, last access: 1/12/2025.

7 T. Faherty, J. E. Raymond, G. McFiggans and F. D. Pope, Acute particulate matter exposure diminishes executive cognitive functioning after four hours regardless of inhalation pathway, *Nat. Commun.*, 2025, **16**(1), 1339, DOI: 10.1038/s41467-025-56508-3.

8 World Health Organisation (WHO), *What Are the WHO Air Quality Guidelines? WHO*, 2021, https://www.who.int/news-room/feature-stories/detail/what-are-the-who-air-quality-guidelines, last access: 1/12/2025.

9 G. Oberdörster, Pulmonary effects of inhaled ultrafine particles, *Int. Arch. Occup. Environ. Health*, 2000, **74**(1), 1–8, DOI: 10.1007/S004200000185/METRICS.

10 S. Salana, H. Yu, Z. Dai, P. S. G. Subramanian, J. V. Puthussery, Y. Wang, A. Singh, F. D. Pope, M. A. Leiva G, N. Rastogi, S. N. Tripathi, R. J. Weber and V. Verma, Inter-continental variability in the relationship of oxidative potential and cytotoxicity with PM2.5 mass, *Nat. Commun.*, 2024, **15**(1), 1–13, DOI: 10.1038/s41467-024-49649-4.

11 W. D. Bennett, K. L. Zeman and A. M. Jarabek, Nasal contribution to breathing and fine particle deposition in children *versus* adults, *J. Toxicol. Environ. Health, Part A*, 2008, **71**(3), 227–237, DOI: 10.1080/15287390701598200.

12 V. Fuentes-Leonarte, J. M. Tenías and F. Ballester, Levels of pollutants in indoor air and respiratory health in preschool children: a systematic review, *Pediatr. Pulmonol.*, 2009, **44**(3), 231–243, DOI: 10.1002/PPUL.20965.

13 F. P. Perera, Multiple Threats to Child Health from Fossil Fuel Combustion: Impacts of Air Pollution and Climate Change, *Environ. Health Perspect.*, 2017, **125**(2), 141–148, DOI: 10.1289/EHP299.

14 E. Kalisa, V. Kuuire and M. Adams, Children's exposure to indoor and outdoor black carbon and particulate matter air pollution at school in Rwanda, Central-East Africa, *Environ. Adv.*, 2023, **11**, 100334, DOI: 10.1016/J.ENVADV.2022.100334.

15 I. Rivas, X. Querol, J. Wright and J. Sunyer, How to protect school children from the neurodevelopmental harms of air pollution by interventions in the school environment in the urban context, *Environ. Int.*, 2018, **121**, 199–206, DOI: 10.1016/j.envint.2018.08.063.

16 J. Sunyer, M. Esnaola, M. Alvarez-Pedrerol, J. Forns, I. Rivas, M. López-Vicente, E. Suades-González, M. Foraster, R. Garcia-Esteban, X. Basagaña, M. Viana, M. Cirach, T. Moreno, A. Alastuey, N. Sebastian-Galles, M. Nieuwenhuijsen and X. Querol, Association between Traffic-Related Air Pollution in Schools and Cognitive

Development in Primary School Children: A Prospective Cohort Study, *PLoS Med.*, 2015, **12**(3), e1001792, DOI: 10.1371/JOURNAL.PMED.1001792.

17 J. Forns, P. Dadvand, M. Esnaola, M. Alvarez-Pedrerol, M. López-Vicente, R. Garcia-Esteban, M. Cirach, X. Basagaña, M. Guxens and J. Sunyer, Longitudinal association between air pollution exposure at school and cognitive development in school children over a period of 3.5 years, *Environ. Res.*, 2017, **159**, 416–421, DOI: 10.1016/J.ENVRES.2017.08.031.

18 A. Ferreira and S. M. Cardoso, Effects of indoor air quality on respiratory function of children in the 1st cycle of basic education of Coimbra, Portugal, *Occupational Safety and Hygiene II - Selected Extended and Revised Contributions from the International Symposium Occupational Safety and Hygiene*, 2014, pp. 347–350, DOI: 10.1201/B16490-62/MODEL-ASSESSING-MATURITY-INTEGRATED-MANAGEMENT-SYSTEMS-DOMINGUES-SAMPAIO-AREZES.

19 S. Lim, B. Said, L. Zurba, G. Mosler, E. Addo-Yobo, O. O. Adeyeye, B. Arhin, D. Evangelopoulos, V. T. Fapohunda, F. Fortune and C. J. Griffiths, Characterising sources of PM2· 5 exposure for school children with asthma: a personal exposure study across six cities in sub-Saharan Africa, *Lancet Child Adolesc. Health*, 2024, **8**(1), 17–27, DOI: 10.1016/S2352-4642(23)00261-4.

20 H. E. Wood, N. Marlin, I. S. Mudway, S. A. Bremner, L. Cross, I. Dundas, A. Grieve, J. Grigg, J. B. Jamaludin, F. J. Kelly, T. Lee, A. Sheikh, R. Walton and C. J. Griffiths, Effects of air pollution and the introduction of the London Low Emission Zone on the prevalence of respiratory and allergic symptoms in schoolchildren in East London, *PLOS One*, 2015, **10**(8), DOI: 10.1371/journal.pone.0109121.

21 N. Kulkarni and J. Grigg, Effect of air pollution on children, *Paediatr. Child Health*, 2008, **18**(5), 238–243, DOI: 10.1016/J.PAED.2008.02.007.

22 N. J. Nassikas, M. C. McCormack, H. M. Kipen, J. R. Balmes, T. C. Bond, E. M. D. Brigham, K. Cromar, G. Ewart, A. H. Goldstein, A. Hicks, P. K. Hopke, B. Meyer, W. W. Nazaroff, L. M. Paulin, M. B. Rice, G. D. Thurston, B. J. Turpin, M. E. Vance, C. J. Weschler and J. Zhang, Indoor Air Sources of Outdoor Air Pollution: Health Consequences, Policy, and Recommendations: An Official American Thoracic Society Workshop Report, *Ann. Am. Thorac. Soc.*, 2024, **21**(3), 365–376, DOI: 10.1513/ANNALSATS.202312-1067ST.

23 W. W. Nazaroff, Indoor particle dynamics, *Indoor Air*, 2004, **14**(7), 175–183, DOI: 10.1111/J.1600-0668.2004.00286.X.

24 O. G. Rose, D. Bousiotis, C. Rathbone and F. D. Pope, Investigating Indoor Air Pollution Sources and Student's Exposure Within School Classrooms: Using a Low-Cost Sensor and Source Apportionment Approach, *Indoor Air*, 2024, (1), 5544298, DOI: 10.1155/2024/5544298.

25 N. Zabbey, K. Sam, C. A. Newsom and P. B. Nyiaghan, The COVID-19 lockdown: An opportunity for conducting an air quality baseline in Port Harcourt, Nigeria, *Extr. Ind. Soc.*, 2021, **8**(1), 244–256, DOI: 10.1016/J.EXIS.2020.12.011.

26 NOSDRA, *Nigerian Gas Flare Tracker*, 2024, https://nosdra.gasflaretracker.ng/, last access: 1/12/2025.

27 N. Zabbey, F. D. Giadom and B. B. Babatunde, *Chapter 36 - Nigerian Coastal Environments, World Seas: An Environmental Evaluation*, vol. 1, Europe, the Americas and West Africa, 2019, pp. 835–854, DOI: 10.1016/B978-0-12-805068-2.00042-5.

28 A. Akintola, M. Odutola, T. Olayinka, A. Akinjiola, U. E. Nwokwu and C. Adebamowo, *Cancer in Nigeria: 2009 – 2016, Nigerian National System of Cancer Registries*, 2021, ISBN-13: 978-978-979-992-3.

29 G. Sagbara, N. Zabbey, K. Sam and G. N. Nwipie, Heavy metal concentration in soil and maize (*Zea mays L.*) in partially reclaimed refuse dumpsite 'borrow-pit' in Port Harcourt, Nigeria, *Environ. Technol. Innovation*, 2020, **18**, 100745, DOI: 10.1016/J.ETI.2020.100745.

30 D. Naku, *Rivers Council Raids Illegal Oil Dump, Arrests Suspects*, 2022, https://punchng.com/rivers-council-raids-illegal-oil-dump-arrests-suspects/, last access: 1/12/2025.

31 F. D. Pope, M. Gatari, D. Ng'ang'a, A. Poynter and R. Blake, Airborne particulate matter monitoring in Kenya using calibrated low-cost sensors, *Atmos. Chem. Phys.*, 2018, **18**, 15403–15418, DOI: 10.5194/acp-18-15403-2018.

32 S. Sousan, K. Koehler, G. Thomas, J. H. Park, M. Hillman, A. Halterman and T. M. Peters, Inter-comparison of low-cost sensors for measuring the mass concentration of occupational aerosols, *Aerosol Sci. Technol.*, 2016, **50**, 462–473, DOI: 10.1080/02786826.2016.1162901.

33 L. R. Crilley, M. Shaw, R. Pound, L. J. Kramer, R. Price, S. Young, A. C. Lewis and F. D. Pope, Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring, *Atmos. Meas. Tech.*, 2018, **11**(2), 709–720, DOI: 10.5194/AMT-11-709-2018.

34 L. R. Crilley, A. Singh, L. J. Kramer, M. D. Shaw, M. S. Alam, J. S. Apte, W. J. Bloss, L. Hildebrandt Ruiz, P. Fu, W. Fu, S. Gani, M. Gatari, E. Ilyinskaya, A. C. Lewis, D. Ng'ang'a, Y. Sun, R. C. W. Whitty, S. Yue, S. Young and F. D. Pope, Effect of aerosol composition on the performance of low-cost optical particle counter correction factors, *Atmos. Meas. Tech.*, 2020, **13**(3), 1181–1193, DOI: 10.5194/AMT-13-1181-2020.

35 P. Paatero, P. K. Hopke, X. H. Song and Z. Ramadan, Understanding and controlling rotations in factor analytic models, *Chemom. Intell. Lab. Syst.*, 2002, **60**(1–2), 253–264, DOI: 10.1016/S0169-7439(01)00200-3.

36 P. Paatero and U. Tapper, Positive matrix factorization: A non-negative factor model with optimal utilization of error estimates of data values, *Environmetrics*, 1994, **5**(2), 111–126, DOI: 10.1002/ENV.3170050203.

37 D. C. S. Beddows and R. M. Harrison, Receptor modelling of both particle composition and size distribution from a background site in London, UK - A two-step approach, *Atmos. Chem. Phys.*, 2019, **19**(7), 4863–4876, DOI: 10.5194/ACP-19-4863-2019.

38 R. M. Harrison, D. C. S. Beddows and M. Dall'Osto, PMF analysis of wide-range particle size spectra collected on

a major highway, *Environ. Sci. Technol.*, 2011, **45**(13), 5522–5528, DOI: 10.1021/ES2006622.

39 D. Bousiotis, L. N. S. Alconcel, D. C. S. Beddows, R. M. Harrison and F. D. Pope, Monitoring and apportioning sources of indoor air quality using low-cost particulate matter sensors, *Environ. Int.*, 2023, **174**, 107907, DOI: 10.1016/J.ENVINT.2023.107907.

40 D. Bousiotis, D. C. S. Beddows, A. Singh, M. Haugen, S. Diez, P. M. Edwards, A. Boies, R. M. Harrison and F. D. Pope, A study on the performance of low-cost sensors for source apportionment at an urban background site, *Atmos. Meas. Tech.*, 2022, **15**(13), 4047–4061, DOI: 10.5194/AMT-15-4047-2022.

41 D. Bousiotis, A. Singh, M. Haugen, D. C. S. Beddows, S. Diez, K. L. Murphy, P. M. Edwards, A. Boies, R. M. Harrison and F. D. Pope, Assessing the sources of particles at an urban background site using both regulatory instruments and low-cost sensors – a comparative study, *Atmos. Meas. Tech.*, 2021, **14**(6), 4139–4155, DOI: 10.5194/AMT-14-4139-2021.

42 A. Reff, S. I. Eberly and P. V. Bhave, Receptor modeling of ambient particulate matter data using positive matrix factorization: review of existing methods, *J. Air Waste Manage. Assoc.*, 2007, **57**(2), 146–154, DOI: 10.1080/10473289.2007.10465319.

43 D. C. Carslaw and K. Ropkins, Tools for the Analysis of Air Pollution Data [R package openair version 2.18-2], *Environ. Model. Softw.*, 2024, **27–28**, 52–61, DOI: 10.1016/J.ENVSOFT.2011.09.008.

44 C. Monn, Exposure assessment of air pollutants: a review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended particulate matter, nitrogen dioxide and ozone, *Atmos. Environ.*, 2001, **35**(1), 1–32, DOI: 10.1016/S1352-2310(00)00330-7.

45 H. Z. Li, P. Gu, Q. Ye, N. Zimmerman, E. S. Robinson, R. Subramanian, J. S. Apte, A. L. Robinson and A. A. Presto, Spatially dense air pollutant sampling: implications of spatial variability on the representativeness of stationary air pollutant monitors, *Atmos. Environ.*, 2019, **2**, 100012, DOI: 10.1016/J.AEAOA.2019.100012.

46 L. B. Frederickson, R. Sidavaviciute, J. A. Schmidt, O. Hertel and M. S. Johnson, Are dense networks of low-cost nodes really useful for monitoing air pollution? A case study in Staffordshire, *Atmos. Chem. Phys.*, 2022, **22**, 13949–13965, DOI: 10.5194/acp22-13949-2022.

47 C. J. Rathbone, D. Bousiotis, O. G. Rose and F. D. Pope, Using low-cost sensors to assess common air pollution sources across multiple residences, *Sci. Rep.*, 2025, **15**, 1803, DOI: 10.1038/s41598-025-85985-1.

48 Z. S. Sajani, P. Bonasoni, P. Cristofanelli, A. Marinoni and P. Lauriota, Only coarse particles from the Sahara?, *Epidemiology*, 2012, **23**(4), 642–643, DOI: 10.1097/EDE.0b013e318258c23f.

49 A. de Souza, J. F. de Oliveira, K. R. A. Cardoso, W. A. Fernandes and H. G. Pavao, The impact of Meteorological variables on particulate matter concentrations, *Atmosphere*, 2025, **16**(7), 875, DOI: 10.3390/atmos16070875.

50 D. S. Proppe, M. M. Pandit, E. S. Bridge, P. Jasperse and C. Holwerda, Semi-portable solar power to facilitate continuous operation of technology in the field, *Methods Ecol. Evol.*, 2020, **11**(11), 1388–1394, DOI: 10.1111/2041-210X.13456.

51 D. Bousiotis, L. A. Shaqiri, D. S. Sanghera, D. Tinker and F. D. Pope, Low-Cost Source Apportionment (LoCoSA) of air pollution-literature review of the state of the art, *Sci. Total Environ.*, 2025, **998**, 180257, DOI: 10.1016/j.scitotenv.2025.180257.