Environmental Science: Atmospheres

ROYAL SOCIETY OF CHEMISTRY

PAPER

View Article Online
View Journal | View Issue

Cite this: *Environ. Sci.: Atmos.*, 2024, 4, 1183

Particle number size distribution evaluation of Plantower PMS5003 low-cost PM sensors – a field experiment†

Alexandre Caseiro,* Seán Schmitz and Erika von Schneidemesser

Received 20th June 2024
Accepted 28th August 2024

DOI: 10.1039/d4ea00086b

rsc.li/esatmospheres

The use of low-cost sensors (LCS) for the evaluation of the ambient pollution by particulate matter (PM) has grown and become significant for the scientific community in the past few years. However promising this novel technology is, the characterization of their limitations is still not satisfactory. Reports in the scientific literature rely on calibration, which implies the physical (or geographical) co-location of the LCS with reference *in situ* (or remote, *e.g.* onboard satellite platforms) instrumentation. However, calibration is not always feasible, and even when feasible, the validity of the developed relationship, even in similar settings, is subject to large uncertainties. In the present work, the performance of a popular LCS for PM, the Plantower PMS5003, is investigated. The LCS performs particle counts, which is the physical quantity that is input to the black-box model of the manufacturer to compute the ambient PM mass, which is output to the operator. The particle counts of LCS Plantower PMS5003 units were compared to those of the co-located research-grade Grimm EDM-164 monitor. The results show that humidity possibly has a reduced influence on the performance, but the performance can better be constrained, however spanning more than one order of magnitude in terms of agreement ratio, by functions of the actual particle count itself. In view of these results, further development in the field of LCS for PM monitoring should focus on improvements of the physical design of the devices, in order to enhance the sizing of the particles. The use of the actual Plantower PMS5003 models should be limited to the monitoring of PM mass in the smaller size bins.

Environmental significance

Ambient particulate matter is a complex phenomenon and a source of concern for human health worldwide. Monitoring is key to advance knowledge on the sources and dynamics of ambient particulate matter. Low-cost sensors have been emerging as a novel technology which, thanks to its ease of deployment, could offer the possibility to extend and complete the existing monitoring schemes. As a novel technology, little is known about their performance and functioning. In the present paper, we analyze the performance of a very popular low-cost sensor in terms of size distribution and therefore contribute to the much needed scientific body of knowledge regarding this technology.

1 Introduction

Air pollution is a global source of morbidity and premature deaths worldwide, with different regions experiencing different dynamics.[1] Air pollution in cities exhibits hyper-local variations[2–5] that traditional monitoring schemes, alone, are not suitable to study.[6] Low-cost sensors (LCS), on the other hand, offer the capability to expand monitoring in both the spatial and temporal scales,[3,7–17] to bring monitoring to cities where knowledge about local air pollution is limited,[18–20] or deepen our understanding and knowledge of PM source apportionment.[4,21–24]

LCS for PM report mass concentrations, which are calculated from particle counts. In the particular case of the Plantower LCS model PMS5003, mentioned as the most common LCS for PM with thousands in use worldwide, the PM mass concentration that is reported in three size fractions (PM_1, $PM_{2.5}$ and PM_{10}) is computed from particle counts in six size bins (>0.3, >0.5, >1.0, >2.5, >5.0, and >10.0 μm) using a black-box model.[25] The Plantower PMSx003 models report particle densities in six size bins in the same way as an optical particle counter, but research conducted under field and controlled laboratory conditions indicated that they respond to ensembles of particles, in the same way as a nephelometer.[26,27] However, a later study of the output of the photodiode concluded that they are imperfect

Research Institute for Sustainability – Helmholtz Centre Potsdam, Potsdam, Germany. E-mail: alexandre.caseiro@rifs-potsdam.de

† Electronic supplementary information (ESI) available. See DOI: https://doi.org/10.1039/d4ea00086b

particle counters which count single particle scattering events.[27,28]

Previous studies have indicated that the PM concentrations reported for different size bins by LCS was subject to significant bias [*e.g.* [29–31]], which varied from unit to unit.[32,33] Laboratory and field studies that have co-located LCS for PM measurements along reference or research grade instruments have identified the following factors as sources of bias: (1) the averaging time,[34,35] (2) relative humidity,[33,34,36–41] (3) the ambient temperature,[33,38,42] (4) the nature, composition and size, of the aerosol[33,34,36,38–43] and (5) its concentration.[27,34,36,39,44,45] The ambient temperature has also been reported as a source of bias, albeit mostly in ambient studies[33,38] and less in laboratory studies,[39,42] demonstrating its possible nature as a confounder. The instrumentation, both the design of the LCS and the measuring principle of the instrument it is calibrated against, is a further factor identified as a source of bias.[34]

In the particular case of the Plantower PMS5003, the observed bias has been linked to the sensor design. Because the PMS5003 model does not force the single particles through a single point in the laser beam (657 nm, 2.36×10^{-3} W), large particles that miss the focal point will still scatter some light that will reach the photodiode with an energy above its detection limit and will be misclassified as a particle of smaller size. An ambient mass scattering efficiency that reflects the local source mix and differs from that of the aerosol used to calibrate the sensor exacerbates the discrepancy. Flow rate, namely flow impedance at the inlet, influences the total number concentration, as does wind speed above 3 m s^{-1} (for particles larger than 1 μm).[28] The PMS5003 does not possess a heater at the inlet to regulate relative humidity, unlike reference-grade monitors.[37,46] As relative humidity varies, so do the mass median diameter, the density, the refractive index and the mass scattering efficiency of the aerosol, with an impact on the number and mass concentrations reported.[28,39]

In view of the manifest bias evidenced by research so far, LCS use for PM monitoring requires some kind of calibration,[47–50] with a thorough error characterization being desireable.[51–56] Calibration models reported in the literature are usually a machine-learning model [*e.g.* 26 and 57–59] which include ambient factors such as temperature and, mostly, relative humidity [*e.g.* 4 and 29] and/or local factors that are more complex to parameterize, such as the particle composition, *i.e.* the source mix, the size distribution and even the PM concentration [*e.g.* 60 and 61].

Calibrating methodologies range from local implementations [*e.g.* 62 and 63], to approaches aimed at a broader application [*e.g.* 64–71], in an effort to overcome the implications of the spatio-temporal variations of the ambient aerosol. Because of the complex nature of the sources of bias, the application of a particular calibration to other types of aerosol (size distribution and chemical composition) in laboratory studies or to other settings (in time and/or space) in field studies, degrades the quality of the results,[41,72] *e.g.* when the dominant source of PM is dust or smoke.[30,31,73–76]

Given the focus of the previous studies, which tend to be an evaluation of PM mass, in the present study we evaluate the field performance of the Plantower PMS5003 model in terms of the reported particle number distribution. Five PurpleAir PAII models, each comprising two Plantower PMS5003 units, were deployed alongside a Grimm EDM-164 monitor over the course of two months in the spring of 2019 at an urban site in Potsdam, Germany. The particle counts from the Plantowers were compared to the Grimm particle counts. Our research shows that the agreement between the research-grade instrument and a Plantower PMS5003, *i.e.* the ratio of the particle count by the Plantowers to the particle counts by the Grimm, can span several orders of magnitude. Over the span of 1–2 orders of magnitude, the agreement appears be log-linearly dependent on the relative humidity and constrained as a function of the Plantower-measured ambient particle number concentration. Our analysis does not evidence any dependence on temperature.

2 Methods

2.1 Sampling site

Ten Plantower LCS were co-located with a research-grade particle instrument (Grimm model EDM-164) between May 8 and June 30, 2019. Co-locations took place at the Research Institute for Sustainability – Helmholtz Centre Potsdam (RIFS, formerly Institute of Advanced Sustainability Studies, IASS) in Potsdam, Germany.

The measurement site was located on the RIFS building facing a main thoroughfare leading to the centre of the city of Potsdam (two car lanes, one each on either side of tram tracks in the center of the roadway), situated within a predominantly residential area, with some commercial properties present and substantial green space and trees. The instruments were deployed on the balcony of the first floor (European counting), approximately 15 m from the kerbside.

2.2 Plantower PMS5003 monitors

The Plantower LCS (Plantower Technology, Nanchang City, Jiangxi Province, China) were deployed as part of the PurpleAir low-cost systems. Each PurpleAir system deployed (firmware version 2.50i) comprises, among other equipment, two Plantower PMS5003 sensors, which are used as two independent channels which output particulate mass concentrations in three size ranges $PM_{1.0}$, $PM_{2.5}$ and PM_{10} at the time resolution of approximately one minute and twenty seconds. The PMS5003 units come factory calibrated (as stated by PurpleAir, (**https://www2.purpleair.com/pages/technology**)), and count suspended particles in six size bins: >0.3, >0.5, >1.0, >2.5, >5.0, and >10.0 μm.[25] The PM mass concentration values are provided on an open access map (or are directly downloadable from the internal SD card for some models) that documents all PurpleAir sensors in use and registered online.

Besides the particle density in the six size bins and the PM_1, $PM_{2.5}$ and PM_{10} mass concentrations, the PurpleAir system also outputs readings for temperature (T) and relative humidity (RH). Unlike to reference grade monitors, and contrary to what is prescribed by the legislation (*e.g.* the EU Air Quality directive 2008/50/EC[77]), no removal of humidity prior to detection is

Table 1 Start and end dates for the use of PurpleAir LCS, number of negatives per size bin and total number of data points

LCS	Channel	Start	End	$N_{0.3-0.5}$	$N_{0.5-1.0}$	$N_{1.0-2.5}$	$N_{2.5-5.0}$	$N_{5.0-10.0}$	n
60_1_94_4B_2B_47	chA	2019-05-29	2019-06-29	0	0	0	578	2266	20 435
	chB	2019-05-29	2019-06-29	0	0	0	926	2483	20 435
84_F3_EB_45_42_31	chA	2019-05-08	2019-05-29	0	0	0	623	2799	22 486
	chB	2019-05-08	2019-05-29	0	0	0	779	4582	22 486
5C_CF_7F_5C_9D_CF	chA	2019-05-29	2019-06-29	0	2	1	817	3991	32 976
	chB	2019-05-29	2019-06-29	0	0	0	840	4860	32 976
60_1_94_59_AA_E	chA	2019-05-29	2019-06-29	0	0	0	1034	4488	31 794
	chB	2019-05-29	2019-06-29	0	0	0	1233	4672	31 794
60_1_94_58_EC_95	chA	2019-05-08	2019-05-29	0	0	0	571	3588	22 581
	chB	2019-05-08	2019-05-29	0	0	0	534	2216	22 581

performed by the Plantower sensors, leading to a source of bias due to deliquescence. Indeed, models developed to enhance the quality of the mass concentration retrieved from LCS, *e.g.* by recalibration, demonstrate better performance when RH is taken into consideration [*e.g.* [78]].

Table 1 summarizes the sensors and systems used through the campaign.

The particle counts performed by the Plantower PMS5003 are based on the particle density derived from the amount of light (680 nm) scattered at a 90° angle.[74,78]

2.3 Research-grade Grimm EDM-164 monitor

The Plantower PMS5003 sensors, integrated within PurpleAir systems, were co-located with a GRIMM EDM 164 (GRIMM Aerosol Technik Ainring GmbH & Co. KG, Ainring, Bavaria, Germany). The GRIMM research-grade instrument deployed at the RIFS was manufacturer calibrated at the end of 2018 and measures PM_1, $PM_{2.5}$ and PM_{10} *via* optical detection of particulates in 31 size bins between 0.25 and 32 μm. The time resolution of the GRIMM instrument was set to one minute.

The Grimm instrument also has a meteorological station integrated, which measures relative humidity and temperature. Those measurements were used in the subsequent analysis.

2.4 Comparisons

In order to perform the comparison between the PMS5003 sensors and the GRIMM EDM 164 monitor, the particle densities given by the PMS5003 *via* the PurpleAir (saved locally on each system unit on a SD card, firmware version 2.50i) were converted from particles per decilitre[25] to particles per litre. Since the data is reported as *e.g.*, >2.5 μm, rather than discreet size bins, the smaller reported sizes were subtracted from the larger sizes so that the size bins 0.3–0.5, 0.5–1.0, 1.0–2.5, 2.5–5.0, and 5.0–10 μm could be used. This manipulation produced negative values which are reported in Table 1. The size resolution of the GRIMM EDM 164 output was reduced by summing the counts to match the size bins of the PMS5003 data. For the purpose of comparison (except when comparing time series), the obtained binned measurements were averaged to 5 minutes for each instrument.

3 Results

3.1 Comparison of particle counts

Fig. S1–S5† show the time series as the raw data output by the PurpleAir LCS and the Grimm (note the log scale of the *y*-axis). The plots show that although the Plantowers coincide in time with the Grimm, they do not in amplitude, and there are substantial differences between the instruments and between the size bins.

Fig. S1† shows that the Plantower sensors exhibit little noise and generally follow the temporal pattern of the Grimm (except for short spikes), even though with consistently lower values of about up to one order of magnitude, for the 0.3–0.5 μm size bin. Plantowers from the same LCS unit are in good agreement for the 0.3–0.5 μm fraction and the lines superimpose.

For the size bin 0.5–1.0 μm (Fig. S2†) there is less agreement between the temporal patterns than for the smallest particles. Not only the spikes shown by the Grimm are not followed by the Plantower, but both instruments show variations, longer in time and lower in intensity than spikes, that are not followed by the other. In addition to the discrepancies in the temporal pattern, the Plantowers exhibit generally higher number concentrations than the Grimm of one to two orders of magnitude. This overestimation is likely a consequence of the misclassification of larger particles which miss the focal point. The lines of the Plantowers within a same LCS unit superimpose, showing good agreement and little noise.

The Grimm instrument shows large variations for the size bin 1.0–2.5 μm which are not followed by the Plantowers, the latter showing little noise (Fig. S3†) The Plantower number concentrations differ from the Grimm number concentrations by approximately up to two orders of magnitude, in both under and overestimation. The time series of the two Plantowers present within the same LCS unit generally superimpose, but differences can be observed, usually at local maxima and minima.

The time series of the Plantowers located within the same Purple Air unit show some discrepancy for the 2.5–5.0 μm size bin, higher noise than at the smaller size bins, and do not follow the peaks exhibited in the time series of the Grimm instrument (Fig. S4†). The divergence between the values from the Plantowers and the Grimm span up to 2–3 orders of magnitude, with the Grimm showing larger particle number concentrations. This underestimation by the Plantowers is likely a consequence

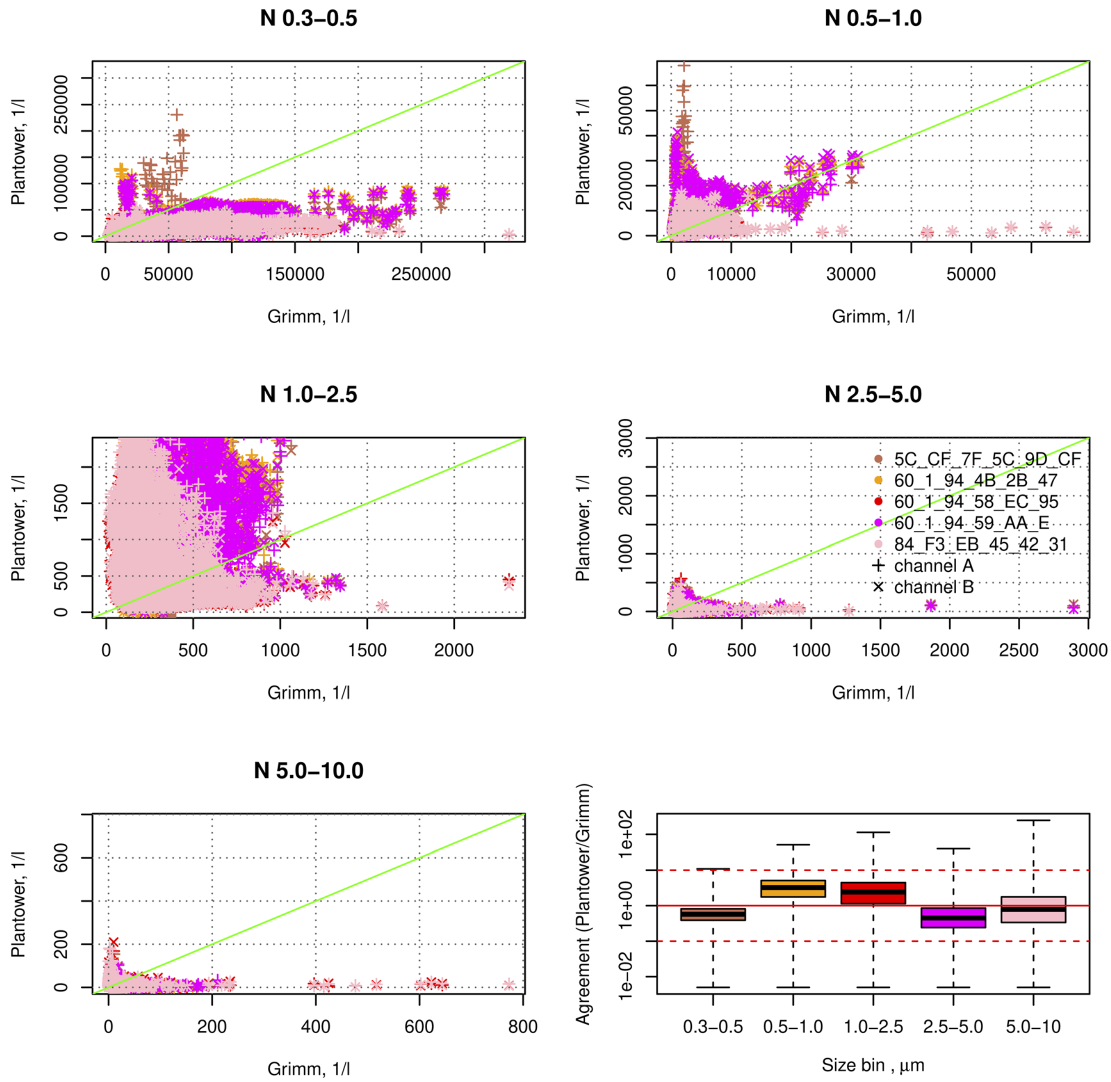

Fig. 1 Scatter plot of the particle counts for the size bins 0.3–0.5 µm, 0.5–1.0 µm, 1.0–2.5 µm, 2.5–5.0 µm and 5.0–10.0 µm. The raw particle counts for the Grimm and the Plantowers were aggregated at the time resolution of 5 minutes. Lower right panel: Box-and-whisker plots for the distribution of the agreement (ratio of the Plantower to the Grimm number concentration) of the particle counts in the five size bins. From bottom to top, the horizontal lines represent: the minimum, the 25th percentile, the median, the 75th percentile and the maximum. The raw particle counts for the Grimm and the Plantowers were aggregated at the time resolution of 5 minutes. Agreement values below a threshold of 0.001 were set to one half of the threshold. Only the minimum is affected by this operation, performed to increase the readability of the plot.

of the design of the LCS, which do not force particles through the focal point resulting in misclassification of these larger particles.

The divergence among the Plantowers operated within a same LCS is also strong for the 5.0–10 µm size bin (Fig. S5†), as is the discordance between the Grimm and the Plantowers (up to about 2 orders of magnitude, generally the Plantowers exhibit lower number concentrations). Again, this underestimation by the Plantowers is likely related to the particles path when crossing the beam.

Fig. 1 shows the relationship between the particle number concentrations derived by the Plantowers and measured by the Grimm. Because the time resolution of the original data was not identical, the original data from all instruments were aggregated into 5 minute averages.

For the size bin 0.3–0.5 µm, the Plantowers overwhelmingly exhibit lower concentrations than the Grimm. The scatter plot shown in Fig. 1 (upper left) suggests that number concentrations larger that approximately 6000 particles per litre cannot be reproduced by the Plantowers, which only seldomly report number concentrations larger than that plateau. One possibility for the under-counting would be that, although the larger particles which miss the focal point are misclassified as smaller particles, they are not classified into the smallest range, whereas small particles (0.3–0.5 µm) that miss the focal points do not reflect enough energy towards the detector and are therefore not counted. On the other hand, the seemingly existence of a plateau (approximately 6000 particles per litre) suggests the possibility of saturation at the detection step.

Table 2 Median agreement (95th percentile) for the Plantower sensors, differentiated by size bin. The agreement is computed as the ratio between the counts per litre by the Plantower and the counts per litre by the Grimm, averaged at the time resolution of 5 minutes

LCS	Channel	$N_{0.3-0.5}$	$N_{0.5-1.0}$	$N_{1.0-2.5}$	$N_{2.5-5.0}$	$N_{5.0-10.0}$
5C_CF_7F_5C_9D_CF	Channel A	0.6 (1.14)	4.03 (8.68)	2.44 (8.52)	0.36 (1.64)	0.51 (2.33)
	Channel B	0.7 (1.36)	4.58 (9.43)	2.6 (8.72)	0.47 (2.01)	0.61 (3.27)
60_1_94_4B_2B_47	Channel A	0.71 (1.34)	4.31 (9.06)	3.04 (10.3)	0.35 (1.66)	0.58 (3.59)
	Channel B	0.73 (1.39)	4.33 (9.38)	2.97 (9.82)	0.6 (2.43)	0.94 (5.75)
60_1_94_58_EC_95	Channel A	0.4 (0.98)	1.88 (4.89)	1.94 (13.38)	0.61 (3.84)	1.13 (10.38)
	Channel B	0.44 (1.1)	1.87 (4.97)	1.77 (12.54)	0.49 (2.99)	1.59 (13.14)
60_1_94_59_AA_E	Channel A	0.6 (1.12)	3.47 (7.3)	2.3 (7.66)	0.51 (1.91)	1.01 (5.29)
	Channel B	0.68 (1.29)	4.42 (9.29)	2.51 (8.6)	0.36 (1.52)	0.6 (3.37)
84_F3_EB_45_42_31	Channel A	0.47 (1.17)	1.96 (5.14)	2.07 (15.7)	0.4 (2.76)	1.27 (11.87)
	Channel B	0.43 (1.1)	1.86 (4.98)	1.89 (13.48)	0.52 (3.36)	0.84 (8.42)

Fig. 1 (upper right) shows that the Plantower overestimates number concentrations when the Grimm reports lower number concentrations in the size bin 0.5–1.0 μm (up to about 15 000 particles per litre), and underestimates for larger number concentrations. A similar behaviour can be observed for the 1.0–2.5 μm size bin, with the concentration of 1000 particles per litre being the threshold (Fig. 1, centre left).

For the size bins 2.5–5.0 μm and 5.0–10.0 μm, Fig. 1 (centre right and lower left), evidences a similar behaviour of overestimation by the Plantower at lower number concentrations and underestimation at higher number concentrations.

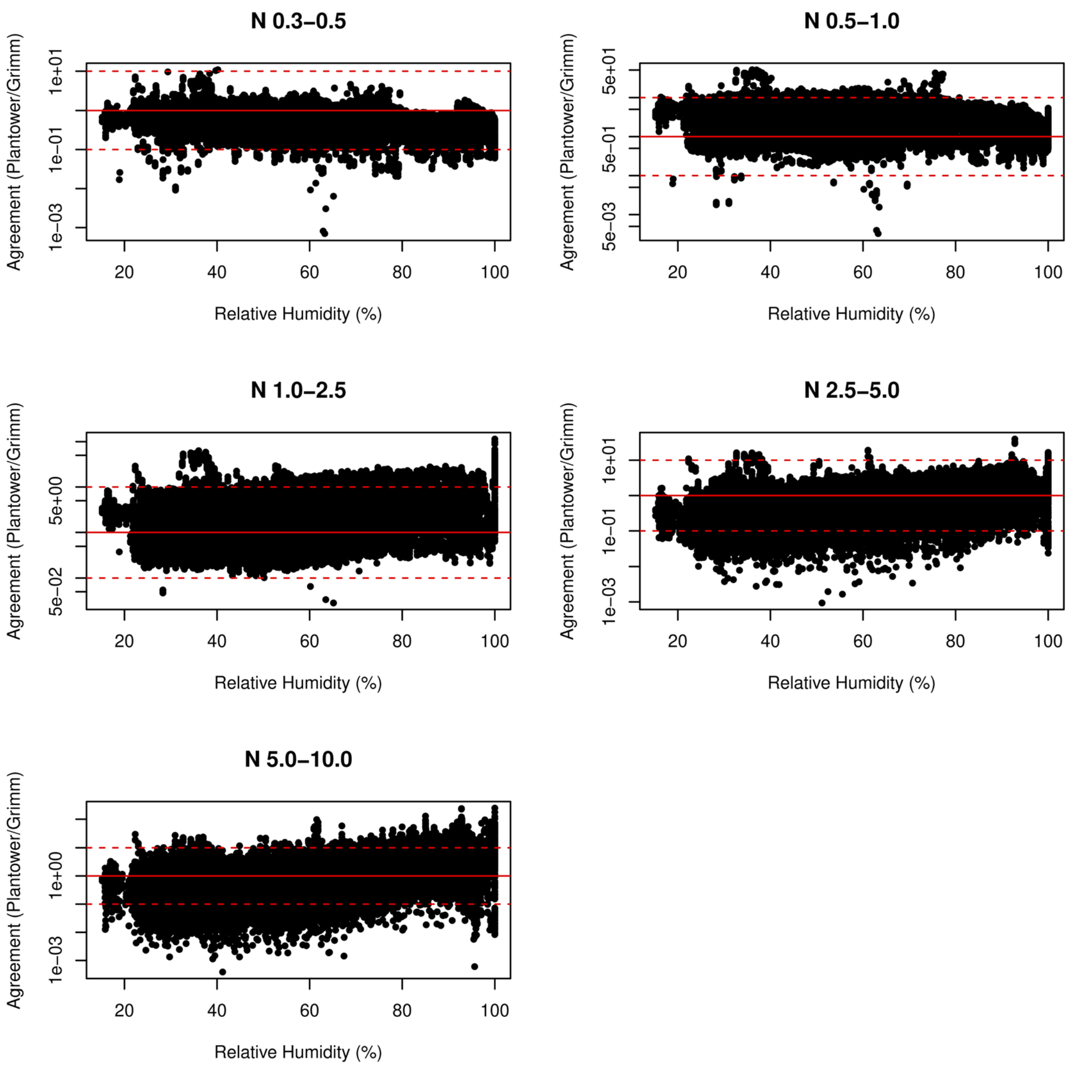

Fig. 2 Agreement (ratio of Plantower number concentration to Grimm number concentration) for the five size bins as a function of the ambient relative humidity. The solid line represents total agreement. The dashed lines represent disagreement by a factor of 10.

3.2 Agreement between the Plantower and the Grimm

Table 2 and Fig. 1 (lower right) show the agreement distribution for the five size bins. The agreement is here defined as the ratio between the particle number concentration of a Plantower relative to the particle number concentration of the Grimm within the same timeframe. An agreement value of 1 means that both instruments output the same number concentration. An agreement value of >1 represents an overestimation by the Plantower, whereas a value <1 corresponds to an underestimation.

The agreement spans several orders of magnitude. In median (see Table 2), the agreement lies below unity for the size bins 0.3–0.5 μm (0.40–0.73) and 2.5–5.0 μm (0.35–0.61), and above unity for the size bins 0.5–1.0 μm (1.9–4.6) and 1.0–2.5 μm (1.8–3.0). The median agreement is closer to unity for the size bin 5.0–10.0 μm (0.58–1.6).

3.2.1 Effect of meteorology. Fig. 2 and S6† show the relationship between the agreement and the ambient relative humidity and temperature, respectively, for the five size bins.

The scatter plots (Fig. S6†) show that there may be a linear relationship between the logarithm of the agreement and the temperature only for the size bin 0.5–1.0 μm ($R = 0.49$, 95% confidence interval: 0.48–0.49). Despite the statistical significance of the slope (significantly different from 0, p-value = 0), the significance may not be practical. Indeed, the low effect size (the magnitude of the slope is 2.6×10^{-2}, 95% confidence interval: 2.5×10^{-2}–2.6×10^{-2}) and the low R^2 (0.24) suggest that the relationship is weak and that only a small proportion of the variance in the response variable (the logarithm of the agreement) is explained by the predictor variable (the temperature), indicating that there is considerable variability in the data that is not accounted for by the linear relationship. In the present case, the very large sample size (n above 70 000) may lead to even small differences being statistically significant. For the other size bins, the considerations above are exacerbated (R^2 below 0.1).

For the relative humidity, the scatter plots (Fig. 2) show some degree of negative linear relationship between the logarithm of the agreement and the ambient relative humidity for the size

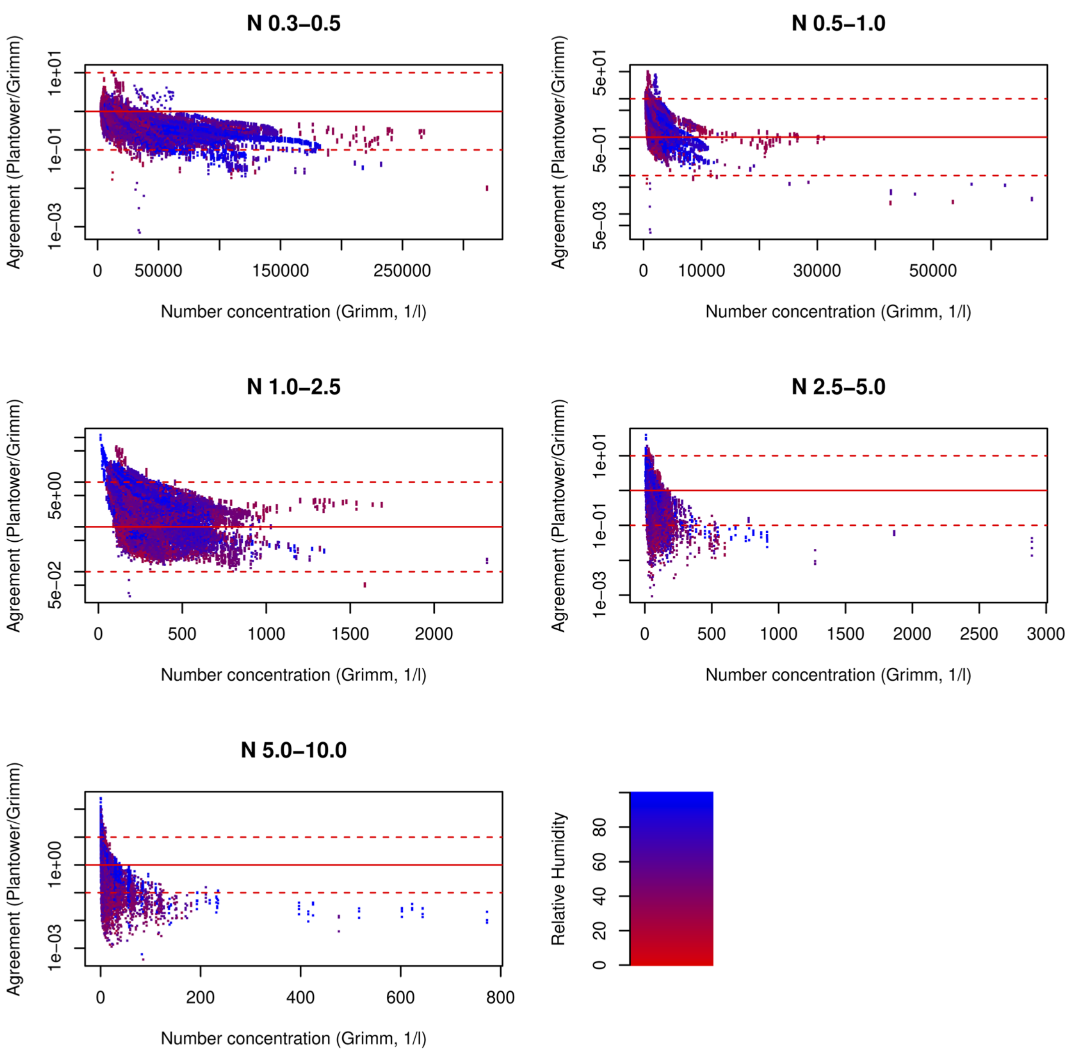

Fig. 3 Agreement (ratio of Plantower number concentration to Grimm number concentration) for the five size bins as a function of the Grimm-measured particle number concentration. The solid line represents total agreement. The dashed lines represent disagreement by a factor of 10.

bin 0.3–0.5 μm (correlation: −0.34, 95% confidence interval: −0.35 to −0.33, slope = -4.5×10^{-3}, 95% confidence interval: -4.6×10^{-3} to -4.4×10^{-3}, statistically different from 0, p-value = 0) and the size-bin 0.5–1.0 μm (correlation: −0.13, 95% confidence interval: −0.14 to −0.12, slope = -2.3×10^{-3}, 95% confidence interval: -2.4×10^{-3} to -2.2×10^{-3}, statistically different from 0, p-value = 0). A positive correlation is found for the size bins 1.0–2.5 μm (correlation: 0.22, 95% confidence interval: 0.21–0.23, slope = 4.9×10^{-3}, 95% confidence interval: 4.7×10^{-3}–5.1×10^{-3}, statistically different from 0, p-value = 0), 2.5–5.0 μm (correlation: 0.42, 95% confidence interval: 0.42–0.43, slope = 9.5×10^{-3}, 95% confidence interval: 9.4×10^{-3}–9.7×10^{-3}, statistically different from 0, p-value = 0), and 5.0–10.0 μm (correlation: 0.45, 95% confidence interval: 0.44–0.46, slope = 1.3 $\times 10^{-2}$, 95% confidence interval: 1.3 10^{-2}–1.3 $\times 10^{-2}$, statistically different from 0, p-value = 0). As for the ambient temperature, the significance of the relationship between the logarithm of the agreement and the relative humidity may be an artefact due to the sample size. Furthermore, the low size effect and the low R^2 indicate that the relationship is either very weak or practically non significant. The size bin 0.5–1.0 μm exhibits the minimum correlation (and absolute slope) between the agreement and the relative humidity, and also the maximum correlation (and slope) between the agreement and the temperature.

3.2.2 Effect of the particle number concentration. Fig. 1 suggests that the response of the Plantower units could be dependent on the concentration itself. Fig. 3 and 4 show the relationship between the logarithm of the agreement and the number concentration measured with the Grimm and the Plantower, respectively. In the plots, the points are color-coded to the ambient relative humidity.

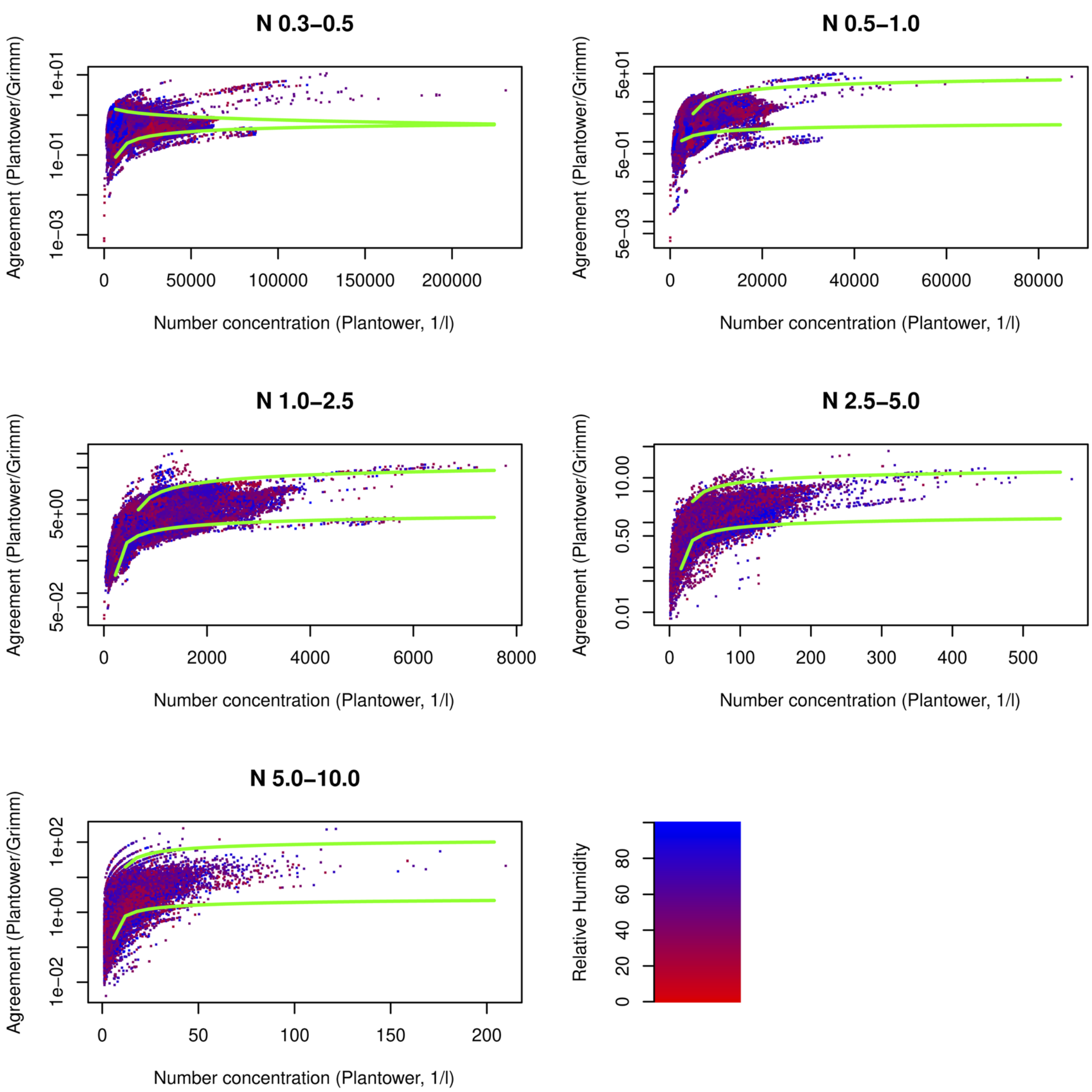

Fig. 4 Agreement (ratio of Plantower number concentration to Grimm number concentration) for the five size bins as a function of the Plantower-measured particle number concentration. The green lines represent the proposed functions to constrain the agreement and were obtained by fitting en equation of the type agreement ratio = $a \times \log(\log(x)) + b$, with x being the Plantower-reported number concentration, to the points representing the 5th and 95th percentiles over 40 bins through the range of the Plantower-reported number concentrations.

Table 3 Parameters of the functions agreement ratio = $a \times \log(\log(x)) + b$, for the 90% bounding of the Plantower-reported number concentration (x)

	Lower (P05)		Upper (P95)	
	a	b	a	b
$N_{0.3-0.5}$	−3.0	1.4	6.6	−2.4
$N_{0.5-1.0}$	−7.8	4.3	−217	104
$N_{1.0-2.5}$	−13	7.9	−214	118
$N_{2.5-5.0}$	−1.3	1.4	−19	17
$N_{5.0-10.0}$	−0.89	1.8	−77	106

The scatter plots (Fig. 3) show that the agreement is tendentially highly variable at low ambient number concentrations. The variability narrows as the number concentration increases, towards underestimation of up to about one order of magnitude for the smallest size bins (0.3–0.5 μm, 0.5–1.0 μm and 1.0–2.5 μm) or even lower for the largest size bins (2.5–5.0 μm and 5.0–10.0 μm). The plots also show that there is no relationship between the agreement and the ambient relative humidity.

Fig. 4 suggests that, although spanning more than one order of magnitude, it is possible to constrain the agreement ratio as a function of the type agreement ratio = $a \times \log(\log(x)) + b$, where x is the reported concentration. In order to develop functions to constrain the agreement ratio for each size bin, the range of the reported Plantower number concentrations was divided into 40 bins. For each bin the 5th and 95th percentiles were computed and a function was fit to the points (green lines in Fig. 4). The functions (parameters reported in Table 3), effectively represent the bounds to compute a 90% confidence interval given a Plantower-reported PM number concentration.

4 Conclusion

In the present work, five PurpleAir low-cost sensors were deployed at a traffic-impacted site in the city of Potsdam, Germany, over the course of two months. Each PurpleAir unit comprises two Plantower PMS5003 sensors. The 10 PMS5003 sensors were investigated against a research-grade Grimm instrument positioned alongside the PurpleAir units.

Analysis shows that the noise of a Plantower sensor increases with particle size, as does the discrepancy between sensors operated within the same LCS unit. A possible explanation could be the conjunction of the lesser number of particles at larger size ranges and the seemingly aleatory misclassification due to missing the focal point. As the former gains in importance, the relative effect of the latter increases. The disparity between the Grimm and the Plantowers is also larger, both in terms of absolute difference and of temporal patterns, for the largest size bins.

A point-by-point comparison after averaging at the time resolution of 300 s shows that in the size ranges above 0.5 μm the Plantowers tend to overestimate the number concentrations below a certain, bin-dependent, particle number concentration threshold and underestimate above that threshold. For the smallest size bin, the Plantowers underestimate below the number concentration of approximately 6000 particles per litre and only seldomly report concentrations above: a possible indication of saturation.

The Plantower to Grimm ratio of particle number concentrations was investigated after averaging at the time resolution of 300 s and spans several orders of magnitude within a same size bin. The agreement was below unity for the smaller size bins (0.3–0.5 μm and 0.5–1.0 μm) and close to unity for the largest size bin (5.0–10 μm). For the intermediate size bins (1.0–2.5 μm and 2.5–5.0 μm) the median agreement was above 1. Previous laboratory research using known particle size distributions has shown that, because the particles are not forced through the focal point of the lens, the amount of scattered light measured is biased and therefore the derived particle density and particle counts suffer from considerable error,[27,28] as do the PM mass down the processing chain, as it was shown by several works which tried to conciliate the PM mass reported by the Plantower PMS sensors and the PM mass measured by reference monitors.[39,74] In the case of fine PM mass (PM_1 or $PM_{2.5}$), it is possible to recalibrate correcting for both the deliquescence and the erroneous size distribution sources of bias. However, for the latter, the robustness of such corrections can only be guaranteed within similar number and mass distributions, and the relationship between those.[33,41]

The agreement ratio does not exhibit any dependence on temperature, but possibly some negative log-linear dependence on relative humidity, albeit spanning several orders of magnitude and of reduced effect size.

The strongest effect on the agreement ratio comes from the particle number concentration itself. From our analysis we derived functions to bound the accuracy of the Plantower-reported number concentrations as a function of itself. Although the range covering the 90% confidence interval spans more than one order of magnitude, such information can be important and useful when analyzing results from deployments of Plantower LCS.

Further development of LCS for PM monitoring should particularly focus on a technical solution that forces all particles through the focal point. The use of a dryer upstream of the LCS entry point to control for the water content of the aerosol and deliquescence could also be advantageous when using LCS to measure PM mass. Under the current conditions, the use of Plantower PMSx003 models should be limited to monitoring PM mass in the smaller (below 2.5 μm) size bins, and a correction taking into account the influence of relative humidity should be used.

Data availability

The data which served for the manuscript "Particle number size distribution evaluation of Plantower PMS5003 low-cost PM sensors – a field experiment" is available under **https://10.5281/zenodo.12180451**.

Conflicts of interest

There are no conflicts to declare.

Acknowledgements

We wish to acknowledge the Research Institute for Sustainability – Helmholtz Centre Potsdam (RIFS Potsdam) (formerly IASS) for funding the research of Erika von Schneidemesser, Seán Schmitz and Alexandre Caseiro with financial support provided by the Federal Ministry of Education and Research of Germany (BMBF) and the Ministry for Science, Research and Culture of the State of Brandenburg (MWFK).

References

1 K. Vohra, E. A. Marais, W. J. Bloss, J. Schwartz, L. J. Mickley, M. V. Damme, *et al.*, Rapid rise in premature mortality due to anthropogenic air pollution in fast-growing tropical cities from 2005 to 2018, *Sci. Adv.*, 2022, **8**(14), eabm4435. available from: https://www.science.org/doi/abs/10.1126/sciadv.abm4435.

2 M. Gao, J. Cao and E. Seto, A distributed network of low-cost continuous reading sensors to measure spatiotemporal variations of PM2.5 in Xi'an, China, *Environ. Pollut.*, 2015, **199**, 56–65. available from: https://www.sciencedirect.com/science/article/pii/S0269749115000160.

3 L. B. Frederickson, R. Sidaraviciute, J. A. Schmidt, O. Hertel and M. S. Johnson, Are dense networks of low-cost nodes really useful for monitoring air pollution? A case study in Staffordshire, *Atmos. Chem. Phys.*, 2022, **22**(21), 13949–13965. available from: https://acp.copernicus.org/articles/22/13949/2022/.

4 R. Byrne, K. Ryan, D. S. Venables, J. C. Wenger and S. Hellebust, Highly local sources and large spatial variations in PM2.5 across a city: evidence from a city-wide sensor network in Cork, Ireland, *Environ. Sci.: Atmos.*, 2023, **3**, 919–930, DOI: 10.1039/D2EA00177B.

5 R. Sarroeira, J. Henriques, A. M. Sousa, C. Ferreira da Silva, N. Nunes, S. Moro, *et al.*, Monitoring Sensors for Urban Air Quality: The Case of the Municipality of Lisbon, *Sensors*, 2023, **23**(18), 7702 available from: https://www.mdpi.com/1424-8220/23/18/7702.

6 S. Munir, M. Mayfield, D. Coca and S. A. Jubb, Structuring an integrated air quality monitoring network in large urban areas – Discussing the purpose, criteria and deployment strategy, *Atmos. Environ.*, 2019, **2**, 100027. available from http://www.sciencedirect.com/science/article/pii/S2590162119300309.

7 A. de Nazelle, E. Seto, D. Donaire-Gonzalez, M. Mendez, J. Matamala, M. J. Nieuwenhuijsen, *et al.*, Improving estimates of air pollution exposure through ubiquitous sensing technologies, *Environ. Pollut.*, 2013, **176**, 92–99. available from: https://www.sciencedirect.com/science/article/pii/S0269749113000080.

8 P. Kumar, L. Morawska, C. Martani, G. Biskos, M. Neophytou, S. Di Sabatino, *et al.*, The rise of low-cost sensing for managing air pollution in cities, *Environ. Int.*, 2015, **75**, 199–205. available from https://www.sciencedirect.com/science/article/pii/S0160412014003547.

9 K. K. Johnson, M. H. Bergin, A. G. Russell and G. S. W. Hagler, Using Low Cost Sensors to Measure Ambient Particulate Matter Concentrations and On-Road Emissions Factors, *Atmos. Meas. Tech.*, 2016, **2016**, 1–22. available from http://www.atmos-meas-tech-discuss.net/amt-2015-331/.

10 P. J. D. Peterson, A. Aujla, K. H. Grant, A. G. Brundle, M. R. Thompson, J. Vande Hey, *et al.*, Practical Use of Metal Oxide Semiconductor Gas Sensors for Measuring Nitrogen Dioxide and Ozone in Urban Environments, *Sensors*, 2017, **17**(7), 1653. available from: https://www.mdpi.com/1424-8220/17/7/1653.

11 J. Kim, A. A. Shusterman, K. J. Lieschke, C. Newman and R. C. Cohen, The BErkeley Atmospheric CO_2 Observation Network: field calibration and evaluation of low-cost air quality sensors, *Atmos. Meas. Tech.*, 2018, **11**(4), 1937–1946. available from: https://amt.copernicus.org/articles/11/1937/2018/.

12 J. J. Caubel, T. E. Cados, C. V. Preble and T. W. Kirchstetter, A Distributed Network of 100 Black Carbon Sensors for 100 Days of Air Quality Monitoring in West Oakland, California, *Environ. Sci. Technol.*, 2019, **53**(13), 7564–7573. available from: https://doi.org/10.1021/acs.est.9b00282.

13 C. C. Lim, H. Kim, M. J. R. Vilcassim, G. D. Thurston, T. Gordon, L. C. Chen, *et al.*, Mapping urban air quality using mobile sampling with low-cost sensors and machine learning in Seoul, South Korea, *Environ. Int.*, 2019, **131**, 105022. available from: https://www.sciencedirect.com/science/article/pii/S0160412019304854.

14 Y. M. Park, S. Sousan, D. Streuber and K. Zhao, GeoAir—A Novel Portable, GPS-Enabled, Low-Cost Air-Pollution Sensor: Design Strategies to Facilitate Citizen Science Research and Geospatial Assessments of Personal Exposure, *Sensors*, 2021, **21**(11), 3761. available from: https://www.mdpi.com/1424-8220/21/11/3761.

15 Y. Sun, P. Brimblecombe, P. Wei, Y. Duan, J. Pan, Q. Liu, *et al.*, High Resolution On-Road Air Pollution Using a Large Taxi-Based Mobile Sensor Network, *Sensors*, 2022, **22**(16), 6005. available from: https://www.mdpi.com/1424-8220/22/16/6005.

16 J. Tryner, C. Quinn, E. Molina Rueda, M. J. Andales, C. L'Orange, J. Mehaffy, *et al.*, AirPen: A Wearable Monitor for Characterizing Exposures to Particulate Matter and Volatile Organic Compounds, *Environ. Sci. Technol.*, 2023, **57**(29), 10604–10614. available from: https://doi.org/10.1021/acs.est.3c02238.

17 M. van Poppel, P. Schneider, J. Peters, S. Yatkin, M. Gerboles, C. Matheeussen, *et al.*, SensEURCity: A multi-city air quality dataset collected for 2020/2021 using open low-cost sensor systems, *Sci. Data*, 2023, **10**, 322, DOI: 10.1038/s41597-023-02135-w.

18 K. Chan, D. N. Schillereff, A. C. Baas, M. A. Chadwick, B. Main, M. Mulligan, *et al.*, Low-cost electronic sensors for environmental research: Pitfalls and opportunities, *Prog. Phys. Geogr. Earth Environ.*, 2020, **45**(3), 305–338, DOI: 10.1177/0309133320956567.

19 R. Subramanian, K. Safari, V. Baharane, S. Guhirwa, M. C. SindayigayaClaver, *et al.*, Air pollution in Kigali, Rwanda: spatial and temporal variability, source contributions, and the impact of car-free Sundays, *Clean Air J.*, 2020, **30**(2), DOI: 10.17159/caj/2020/30/2.8023. available from: https://cleanairjournal.org.za/article/view/8023.
20 R. Subramanian and R. Garland, Editorial: The powerful potential of low-cost sensors for air quality research in Africa, *Clean Air J.*, 2021, **31**(1), DOI: 10.17159/caj/2021/31/1.11274. available from: https://cleanairjournal.org.za/article/view/11274.
21 I. Heimann, V. B. Bright, M. W. McLeod, M. I. Mead, O. A. M. Popoola, G. B. Stewart, *et al.*, Source attribution of air pollution by spatial scale separation using high spatial density networks of low cost air quality sensors, *Atmos. Environ.*, 2015, **113**, 10–19. available from: https://www.sciencedirect.com/science/article/pii/S1352231015300583.
22 D. Bousiotis, A. Singh, M. Haugen, D. C. S. Beddows, S. Diez, K. L. Murphy, *et al.*, 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. available from: https://amt.copernicus.org/articles/14/4139/2021/.
23 E. Chadwick, K. Le, Z. Pei, T. Sayahi, C. Rapp, A. E. Butterfield, *et al.*, Technical note: Understanding the effect of COVID-19 on particle pollution using a low-cost sensor network, *J. Aerosol Sci.*, 2021, **155**, 105766. available from: https://www.sciencedirect.com/science/article/pii/S0021850221004997.
24 D. Bousiotis, D. C. S. Beddows, A. Singh, M. Haugen, S. Diez, P. M. Edwards, *et al.*, 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. available from: https://amt.copernicus.org/articles/15/4047/2022/.
25 Z. Yong *Digital Universal Particle Concentration Sensor - PMS5003 Series Data Manual*, V2.3; 2016.
26 N. K. Meilu He and S. Dhaniyala, Performance characteristics of the low-cost Plantower PMS optical sensor, *Aerosol Sci. Technol.*, 2020, **54**(2), 232–241, DOI: 10.1080/02786826.2019.1696015.
27 J. R. Ouimette, W. C. Malm, B. A. Schichtel, P. J. Sheridan, E. Andrews, J. A. Ogren, *et al.*, Evaluating the PurpleAir monitor as an aerosol light scattering instrument, *Atmos. Meas. Tech.*, 2022, **15**(3), 655–676. available from: https://amt.copernicus.org/articles/15/655/2022/.
28 J. Ouimette, W. P. Arnott, P. Laven, R. Whitwell, N. Radhakrishnan, S. Dhaniyala, *et al.*, Fundamentals of low-cost aerosol sensor design and operation, *Aerosol Sci. Technol.*, 2023, 1–44, DOI: 10.1080/02786826.2023.2285935.
29 K. Ardon-Dryer, Y. Dryer, J. N. Williams and N. Moghimi, Measurements of $PM_{2.5}$ with PurpleAir under atmospheric conditions, *Atmos. Meas. Tech.*, 2020, **13**(10), 5441–5458. available from: https://amt.copernicus.org/articles/13/5441/2020/.
30 L. Wallace, J. Bi, W. R. Ott, J. Sarnat and Y. Liu, Calibration of low-cost PurpleAir outdoor monitors using an improved method of calculating PM2.5, *Atmos. Environ.*, 2021, **256**, 118432. available from: https://www.sciencedirect.com/science/article/pii/S135223102100251X.
31 E. Molina Rueda, E. Carter, C. L'Orange, C. Quinn and J. Volckens, Size-Resolved Field Performance of Low-Cost Sensors for Particulate Matter Air Pollution, *Environ. Sci. Technol. Lett.*, 2023, **10**(3), 247–253. available from: https://doi.org/10.1021/acs.estlett.3c00030.
32 N. Castell, F. R. Dauge, P. Schneider, M. Vogt, U. Lerner, B. Fishbain, *et al.*, Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?, *Environ. Int.*, 2017, **99**, 293–302. available from: https://www.sciencedirect.com/science/article/pii/S0160412016309989.
33 A. Caseiro, S. Schmitz, G. Villena, J. V. Jagatha and E. von Schneidemesser, Ambient characterisation of PurpleAir particulate matter monitors for measurements to be considered as indicative, *Environ. Sci.: Atmos.*, 2022, **2**, 1400–1410, DOI: 10.1039/D2EA00085G.
34 J. K. Bean, Evaluation methods for low-cost particulate matter sensors, *Atmos. Meas. Tech.*, 2021, **14**(11), 7369–7379. available from: https://amt.copernicus.org/articles/14/7369/2021/.
35 G. H. Hong, T. C. Le, J. W. Tu, C. Wang, S. C. Chang, J. Y. Yu, *et al.*, Long-term evaluation and calibration of three types of low-cost PM2.5 sensors at different air quality monitoring stations, *J. Aerosol Sci.*, 2021, **157**, 105829. available from: https://www.sciencedirect.com/science/article/pii/S0021850221005607.
36 Y. Wang, J. Li, H. Jing, Q. Zhang, J. Jiang and P. Biswas, Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement, *Aerosol Sci. Technol.*, 2015, **49**(11), 1063–1077, DOI: 10.1080/02786826.2015.1100710.
37 R. Jayaratne, X. Liu, P. Thai, M. Dunbabin and L. Morawska, The influence of humidity on the performance of a low-cost air particle mass sensor and the effect of atmospheric fog, *Atmos. Meas. Tech.*, 2018, **11**(8), 4883–4890. available from: https://amt.copernicus.org/articles/11/4883/2018/.
38 F. M. J. Bulot, S. J. Johnston, P. J. Basford, N. H. C. Easton, F. G. L. Apetroaie, *et al.*, Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment, *Sci. Rep.*, 2019, **9**(1), 7497. available from: https://www.nature.com/articles/s41598-019-43716-3.
39 M. Levy Zamora, F. Xiong, D. Gentner, B. Kerkez, J. Kohrman-Glaser and K. Koehler, Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor, *Environmental Science Technology*, 2019, **53**(2), 838–849. available from: https://doi.org/10.1021/acs.est.8b05174.
40 D. H. Hagan and J. H. Kroll, Assessing the accuracy of low-cost optical particle sensors using a physics-based approach, *Atmos. Meas. Tech.*, 2020, **13**(11), 6343–6355. available from: https://amt.copernicus.org/articles/13/6343/2020/.

41 J. Tryner, J. Mehaffy, D. Miller-Lionberg and J. Volckens, Effects of aerosol type and simulated aging on performance of low-cost PM sensors, *J. Aerosol Sci.*, 2020, **150**, 105654. available from: https://www.sciencedirect.com/science/article/pii/S0021850220301415.

42 Y. Zou, J. D. Clark and A. A. May, A systematic investigation on the effects of temperature and relative humidity on the performance of eight low-cost particle sensors and devices, *J. Aerosol Sci.*, 2021, **152**, 105715. available from: https://www.sciencedirect.com/science/article/pii/S0021850220302007.

43 J. Kuula, T. Mäkelä, M. Aurela, K. Teinilä, S. Varjonen, S. González, *et al.*, Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors, *Atmos. Meas. Tech.*, 2020, **13**(5), 2413–2423, DOI: 10.5194/amt-13-2413-2020.

44 T. Zheng, M. H. Bergin, K. K. Johnson, S. N. Tripathi, S. Shirodkar, M. S. Landis, *et al.*, Field evaluation of low-cost particulate matter sensors in high- and low-concentration environments, *Atmos. Meas. Tech.*, 2018, **11**(8), 4823–4846. available from: https://www.atmos-meas-tech.net/11/4823/2018/.

45 A. Masic, D. Bibic, B. Pikula, A. Blazevic, J. Huremovic and S. Zero, Evaluation of optical particulate matter sensors under realistic conditions of strong and mild urban pollution, *Atmos. Meas. Tech.*, 2020, **13**(12), 6427–6443. available from: https://amt.copernicus.org/articles/13/6427/2020/.

46 A. Samad, F. E. Melchor Mimiaga, B. Laquai and U. Vogt, Investigating a Low-Cost Dryer Designed for Low-Cost PM Sensors Measuring Ambient Air Quality, *Sensors*, 2021, **21**(3), 804. available from: https://www.mdpi.com/1424-8220/21/3/804.

47 N. Zikova, P. K. Hopke and A. R. Ferro, Evaluation of new low-cost particle monitors for PM2.5 concentrations measurements, *J. Aerosol Sci.*, 2017, **105**, 24–34. available from: https://www.sciencedirect.com/science/article/pii/S0021850216301835.

48 J. Li, S. K. Mattewal, S. Patel and P. Biswas, Evaluation of Nine Low-cost-sensor-based Particulate Matter Monitors, *Aerosol Air Qual. Res.*, 2020, **20**(2), 254–270, DOI: 10.4209/aaqr.2018.12.0485.

49 M. R. Giordano, C. Malings, S. N. Pandis, A. A. Presto, V. F. McNeill, D. M. Westervelt, *et al.*, From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors, *J. Aerosol Sci.*, 2021, **158**, 105833. available from: https://www.sciencedirect.com/science/article/pii/S0021850221005644.

50 N. Zimmerman, Tutorial: Guidelines for implementing low-cost sensor networks for aerosol monitoring, *J. Aerosol Sci.*, 2022, **159**, 105872. available from: https://www.sciencedirect.com/science/article/pii/S0021850221006017.

51 M. I. Mead, O. A. M. Popoola, G. B. Stewart, P. Landshoff, M. Calleja, M. Hayes, *et al.*, The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks, *Atmos. Environ.*, 2013, **70**, 186–203. available from: https://www.sciencedirect.com/science/article/pii/S1352231012011284.

52 F. Karagulian, M. Barbiere, A. Kotsev, L. Spinelle, M. Gerboles, F. Lagler, *et al.*, Review of the Performance of Low-Cost Sensors for Air Quality Monitoring, *Atmosphere*, 2019, **10**(9), 506. available from: https://www.mdpi.com/2073-4433/10/9/506.

53 D. E. Williams, Electrochemical sensors for environmental gas analysis, *Curr. Opin. Electrochem.Environmental*, 2020, **22**, 145–153. available from: https://www.sciencedirect.com/science/article/pii/S2451910320301307.

54 C. Zuidema, C. S. Schumacher, E. Austin, G. Carvlin, T. V. Larson, E. W. Spalt, *et al.*, Deployment, Calibration, and Cross-Validation of Low-Cost Electrochemical Sensors for Carbon Monoxide, Nitrogen Oxides, and Ozone for an Epidemiological Study, *Sensors*, 2021, **21**(12), 4214. available from: https://www.mdpi.com/1424-8220/21/12/4214.

55 S. Diez, S. E. Lacy, T. J. Bannan, M. Flynn, T. Gardiner, D. Harrison, *et al.*, Air pollution measurement errors: is your data fit for purpose?, *Atmos. Meas. Tech.*, 2022, **15**(13), 4091–4105. available from: https://amt.copernicus.org/articles/15/4091/2022/.

56 G. Tancev, A. Ackermann, G. Schaller and C. Pascale, Efficient and Automated Generation of Orthogonal Atmospheres for the Characterization of Low-Cost Gas Sensor Systems in Air Quality Monitoring, *IEEE Trans. Instrum. Meas.*, 2022, **71**, 1–10.

57 N. Zimmerman, A. A. Presto, S. P. N. Kumar, J. Gu, A. Hauryliuk, E. S. Robinson, *et al.*, A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring, *Atmos. Meas. Tech.*, 2018, **11**(1), 291–313. available from: https://amt.copernicus.org/articles/11/291/2018/.

58 S. Srishti, P. Agrawal, P. Kulkarni, H. C. Gautam, M. Kushwaha and V. Sreekanth, Multiple PM Low-Cost Sensors, Multiple Seasons' Data, and Multiple Calibration Models, *Aerosol Air Qual. Res.*, 2023, **23**(3), 220428, DOI: 10.4209/aaqr.220428.

59 M. Yu, S. Zhang, K. Zhang, J. Yin, M. Varela and J. Miao, Developing high-resolution PM2.5 exposure models by integrating low-cost sensors, automated machine learning, and big human mobility data, *Front. Environ. Sci.*, 2023, **11**, 1223160. available from: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1223160.

60 C. Malings, R. Tanzer, A. Hauryliuk, P. K. Saha, A. L. Robinson, A. A. Presto, *et al.*, Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation, *Aerosol Sci. Technol.*, 2020, **54**(2), 160–174, DOI: 10.1080/02786826.2019.1623863.

61 V. Kumar, D. Senarathna, S. Gurajala, W. Olsen, S. Sur, S. Mondal, *et al.*, Spectral analysis approach for assessing the accuracy of low-cost air quality sensor network data,

Atmos. Meas. Tech., 2023, **16**(21), 5415–5427. available from: https://amt.copernicus.org/articles/16/5415/2023/.

62 Y. Jiang, X. Zhu, C. Chen, Y. Ge, W. Wang, Z. Zhao, *et al.*, On-field test and data calibration of a low-cost sensor for fine particles exposure assessment, *Ecotoxicol. Environ. Saf.*, 2021, **211**, 111958. available from: https://www.sciencedirect.com/science/article/pii/S0147651321000695.

63 S. Jain, R. Gardner-Frolick, N. Martinussen, D. Jackson, A. Giang and N. Zimmerman, Identification of Neighborhood Hotspots via the Cumulative Hazard Index: Results From a Community-Partnered Low-Cost Sensor Deployment, *GeoHealth*, 2024, **8**(2), e2023GH000935. available from: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2023GH000935.

64 C. Lin, N. Masey, H. Wu, M. Jackson, D. J. Carruthers, S. Reis, *et al.*, Practical Field Calibration of Portable Monitors for Mobile Measurements of Multiple Air Pollutants, *Atmosphere*, 2017, **8**(12), 231. available from: https://www.mdpi.com/2073-4433/8/12/231.

65 H. J. Chu, M. Z. Ali and Y. C. He, Spatial calibration and PM2.5 mapping of low-cost air quality sensors, *Sci. Rep.*, 2020, **10**(1), 22079, DOI: 10.1038/s41598-020-79064-w.

66 J. Li, H. Zhang, C. Y. Chao, C. H. Chien, C. Y. Wu, C. H. Luo, *et al.*, Integrating low-cost air quality sensor networks with fixed and satellite monitoring systems to study ground-level PM2.5, *Atmos. Environ.*, 2020, **223**, 117293. available from: https://www.sciencedirect.com/science/article/pii/S1352231020300352.

67 V. Kumar and M. Sahu, Evaluation of nine machine learning regression algorithms for calibration of low-cost PM2.5 sensor, *J. Aerosol Sci.*, 2021, **157**, 105809. available from: https://www.sciencedirect.com/science/article/pii/S0021850221005401.

68 K. K. Barkjohn, B. Gantt and A. L. Clements, Development and application of a United States-wide correction for $PM_{2.5}$ data collected with the PurpleAir sensor, *Atmos. Meas. Tech.*, 2021, **14**(6), 4617–4637. available from: https://amt.copernicus.org/articles/14/4617/2021/.

69 K. E. Kelly, W. W. Xing, T. Sayahi, L. Mitchell, T. Becnel, P. E. Gaillardon, *et al.*, Community-Based Measurements Reveal Unseen Differences during Air Pollution Episodes, *Environ. Sci. Technol.*, 2021, **55**(1), 120–128. available from: https://doi.org/10.1021/acs.est.0c02341.

70 P. deSouza, R. Kahn, T. Stockman, W. Obermann, B. Crawford, A. Wang, *et al.*, Calibrating networks of low-cost air quality sensors, *Atmos. Meas. Tech.*, 2022, **15**(21), 6309–6328. available from: https://amt.copernicus.org/articles/15/6309/2022/.

71 R. R. Kureshi, B. K. Mishra, D. Thakker, R. John, A. Walker, S. Simpson, *et al.*, Data-Driven Techniques for Low-Cost Sensor Selection and Calibration for the Use Case of Air Quality Monitoring, *Sensors*, 2022, **22**(3), 1093. available from: https://www.mdpi.com/1424-8220/22/3/1093.

72 G. Tancev and C. Pascale, The Relocation Problem of Field Calibrated Low-Cost Sensor Systems in Air Quality Monitoring: A Sampling Bias, *Sensors*, 2020, **20**(21), 6198. available from: https://www.mdpi.com/1424-8220/20/21/6198.

73 D. Liu, Q. Zhang, J. Jiang and D. R. Chen, Performance calibration of low-cost and portable particular matter (PM) sensors, *J. Aerosol Sci.*, 2017, **112**, 1–10. available from: https://www.sciencedirect.com/science/article/pii/S0021850217300848.

74 T. Sayahi, A. Butterfield and K. E. Kelly, Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors, *Environ. Pollut.*, 2019, **245**, 932–940. available from: http://www.sciencedirect.com/science/article/pii/S0269749118316129.

75 D. A. Jaffe, C. Miller, K. Thompson, B. Finley, M. Nelson, J. Ouimette, *et al.*, An evaluation of the U.S. EPA's correction equation for PurpleAir sensor data in smoke, dust, and wintertime urban pollution events, *Atmos. Meas. Tech.*, 2023, **16**(5), 1311–1322. available from: https://amt.copernicus.org/articles/16/1311/2023/.

76 K. Kaur and K. E. Kelly, Performance evaluation of the Alphasense OPC-N3 and Plantower PMS5003 sensor in measuring dust events in the Salt Lake Valley, Utah, *Atmos. Meas. Tech.*, 2023, **16**(10), 2455–2470. available from: https://amt.copernicus.org/articles/16/2455/2023/.

77 European Parliament and Council of the European Union, *Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe*, 2008, available from: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02008L0050-20150918.

78 J. Tryner, C. L'Orange, J. Mehaffy, D. Miller-Lionberg, J. C. Hofstetter, A. Wilson, *et al.*, Laboratory evaluation of low-cost PurpleAir PM monitors and in-field correction using co-located portable filter samplers, *Atmos. Environ.*, 2020, **220**, 117067. available from: http://www.sciencedirect.com/science/article/pii/S135223101930706X.

