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Atmospheric Measurement Techniques Discussions

Long-term Evaluation of Commercial Air Quality Sensors: An Overview from the QUANT Study

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Abstract. In times of growing concern about the impacts of air pollution across the globe, lower-cost sensor technology is giving the first steps in helping to enhance our understanding and ability to manage air quality issues. While the benefits of greater spatial coverage and real-time measurements that these systems offer are evident, challenges still need to be addressed regarding sensor reliability and data quality. Given the limitations imposed by intellectual property, commercial implementations are often "black boxes", which represents an extra challenge as it limits end-users' understanding of the data production process. In this paper we present an overview of the QUANT (Quantification of Utility of Atmospheric Network Technologies) study, a comprehensive 3-year assessment across a range of urban environments in the United Kingdom. QUANT stands out as one of the most comprehensive studies of commercial air quality sensor systems carried out to date, encompassing a wide variety of companies in a single evaluation and including two generations of sensor technologies. Integrated into an extensive data set open to the public, it was designed to provide a long-term evaluation of the precision, accuracy, and stability of commercially available sensor systems. This overview discusses the assessment methodology, and key findings showcasing the significance of the study. The results shown here highlight the significant variation between systems, the incidence of corrections made by manufacturers, the effects of relocation to different environments and the long-term behaviour of the systems. Additionally, the importance of accounting for uncertainties associated with reference instruments in sensor evaluations is emphasised. Practical considerations in the application of these sensors in real-world scenarios

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are also discussed, and potential solutions to end-users data challenges are presented. Offering key information about the sensor systems' capabilities the QUANT study will serve as a valuable resource for those seeking to implement commercial solutions as complementary tools to tackle air pollution.

Keywords: air pollution, commercial sensor systems, QUANT, long-term evaluation.

1. Introduction

Emerging lower-cost sensor systems[1] offer a promising alternative to the more expensive and complex monitoring equipment traditionally used for measuring air pollutants such as $PM_{2.5}$, NO_2, and O_3 (Okure et al., 2022). These innovative devices hold the potential to expand spatial coverage (Malings et al., 2020) and deliver real-time air pollution measurements (Tanzer-Gruener et al., 2020). However, concerns regarding the variable quality of the data they provide still hinder their acceptance as reliable measurement technologies (Karagulian et al., 2019; Zamora et al., 2020).

Sensors face key challenges such as cross-sensitivities (Cross et al., 2017; Levy Zamora et al., 2022; Pang et al., 2018), internal consistency (Feenstra et al., 2019; Ripoll et al., 2019), signal drift (A. Miech et al., 2023; Li et al., 2021; Sayahi et al., 2019), long term performance (Bulot et al., 2019; Liu et al., 2020) and data coverage (Brown & Martin, 2023; Duvall et al., 2021; Feinberg et al., 2018). Additionally, environmental factors such as temperature (Bittner et al., 2022; Farquhar et al., 2021), and humidity (Crilley et al., 2018; Williams, 2020) can significantly influence sensor signals.

In recent years, manufacturers of both sensing elements (Han et al., 2021; Nazemi et al., 2019) and sensor systems have made significant technological advances (Chojer et al., 2020). For example, there are now commercial and non-commercial systems equipped with multiple sensing elements to measure distinct pollutants (Buehler et al., 2021; Hagan et al., 2019; Pang et al., 2021) helping mitigating the effects of cross-interferences. Additionally, enhancements in electrochemical sensors have been demonstrated in terms of their specificity (Baron & Saffell, 2017; Ouyang, 2020).

However, the complex nature of their responses, coupled with their dependence on local conditions means sensor performance can be inconsistent (Bi et al., 2020). This complicates the comparison of results or anticipating sensor future performance across different studies. Moreover, assessments of sensor performance found in the academic literature often rely on a range of protocols (e.g., CEN (2021) and Duvall et al. (2021)) and data quality metrics (e.g., Spinelle et al. (2017) and Zimmerman et al. (2018)), with many studies limited to a single-site co-location and/or of short-term evaluations that do not fully account for broader environmental variations (Karagulian et al., 2019).

The calibration of any instrument used to measure atmospheric composition is fundamental to guarantee their accuracy (Alam et al., 2020; Long et al., 2021; Wu et al., 2022). Using out-of-the-box sensor data without fit-for-purpose calibration can produce misleading results (Liang & Daniels, 2022). An effective calibration involves identifying and correcting systematic errors in the sensor readings. For standard air pollution measurement techniques, calibration is

[1] The term "Sensor Systems" refers to sensors housed within a protective case, which includes a sampling and power system, electronic hardware and software for data acquisition, analog-to-digital conversion, data processing and their transfer (Karagulian et al., 2019). Unless specified otherwise, the term "sensor" will be used to refer to "Sensor Systems".

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often performed in a controlled laboratory environment (Liang, 2021), or by sampling gas from a certified standard cylinder in the field.

Yet, the aforementioned challenges with lower-cost sensor-based devices suggest that such calibrations may not always accurately reflect real-world conditions (Giordano et al., 2021). A frequent approach involves co-locating sensors alongside regulatory instruments in their intended deployment areas and/or conditions and using data-driven methods to match the reference data (Liang & Daniels, 2022). Numerous studies have investigated the effectiveness of calibration methods for sensors e.g. (Bigi et al., 2018; Bittner et al., 2022; Malings et al., 2020; Spinelle et al., 2017; Zimmerman et al., 2018), including selecting appropriate reference instruments (Kelly et al., 2017), the need for regular calibration to maintain accuracy (Gamboa et al., 2023), the necessity of rigorous calibration protocols to ensure consistency (Kang et al., 2022), and transferability (Nowack et al., 2021) of results. Ultimately, the reliability and associated uncertainty of any applied calibration will influence the final sensor data quality.

For end-users to make informed decisions on the applicability of air pollution sensors, a realistic understanding of the expected performance in their chosen application is necessary (Rai et al., 2017). Despite this, there has been relatively little progress in clarifying the performance of sensors for air pollution measurements outside of the academic arena. This is largely due to the significant variability in both the number of sensors and the variety of applications tested, as well as the availability of highly accurate measurement instrumentation and/or regulatory networks to those outside of the atmospheric measurement academic field (e.g. Lewis and Edwards (2016) and Popoola et al. (2018)). From a UK clean air perspective, this ambiguity represents a major problem. The lack of a consistent message undermines the exploitation of these devices' unique strengths, notably their capability to form spatially dense networks with rapid time resolution. Consequently, there is potential for a mismatch in users' expectations of what sensor systems can deliver and their actual operating characteristics, eroding trust and reliability.

In this work, as part of the UK Clean Air program funded QUANT project, we deployed a variety of sensor technologies (43 commercial devices, 119 gas and 118 PM measurements) at 3 representative UK urban sites — Manchester, London and York— alongside extensive reference measurements, to generate the data for an extensive in-depth performance assessment. This project aims to not only evaluate the performance of sensor devices in a UK urban climatological context but also provide critical information for the successful application of these technologies in various environmental settings. To our knowledge, QUANT is the most extensive and longest-running evaluation of commercial sensor systems globally to date. Furthermore, we tested multiple manufacturers' data products for a significant number of these sensors to understand the implications of local calibration. This comprehensive approach offers unprecedented insights into the operational capabilities and limitations of these sensors in real-world conditions. Significantly, some of the insights gathered during QUANT have contributed to the development of the Publicly Available Specification (PAS 4023, 2023), which provides guidelines for the selection, deployment, maintenance, and quality assurance of air quality sensor systems.

In the following sections, we delve into the methodology and provide an overview of the QUANT dataset, as well as a discussion of some of the key findings and potential considerations for end-users.

2. QUANT study design

2.1 Main study

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The Main QUANT assessment study aimed to perform a transparent long-term (19 Dec 2019 - 31 Oct 2022) evaluation of commercially available sensor technologies for outdoor air pollution monitoring in UK urban environments. Four duplicates of five different commercial sensor devices (Table 1) were purchased in Sept 2019 for inclusion in the study, with the selection criteria being: market penetration and/or previous performance reported in the literature, ability to measure pollutants of interest (e.g. NO_2, NO, O_3, and $PM_{2.5}$), and capacity to run continuously reporting high time resolution data (1-15 min data) ideally in near real-time with data accessible via an API.

Table 1. Main QUANT devices description. The 20 units offered 56 gas and 56 PM measurements in total. For a detailed description of the devices see Section S1 in the Supp.

Product* (# units)	Company	Measurements								Cost (£)**
		NO	NO_2	O_3	CO	CO_2	PM_1	$PM_{2.5}$	PM_{10}	
AQY (4)	Aeroqual	-	✓	✓	-	-	-	✓	✓	~4.7K
AQM (4)	AQMesh	✓	✓	✓	-	✓	✓	✓	✓	~8.6K
Ari (4)	QuantAQ	✓	✓	✓	✓	✓	✓	✓	✓	~8.6K
PA (4)	PurpleAir	-	-	-	-	-	✓	✓	✓	~0.3K
Zep (4)	Earthsense	✓	✓	✓	-	-	✓	✓	✓	~7K

*AQY: Aeroqual; AQM: AQMesh; Ari: Arisense; PA: PurpleAir; Zep: Zephyr.
**Cost (Sep 2019) per unit including UK taxes and associated contractual costs (i.e., communication, data access, sensor replacement, etc.).

To capture the variability of UK urban environments, identical units were installed at three carefully selected field sites. Two of these sites are highly instrumented urban background measurement supersites: the London Air Quality Supersite (LAQS) and the Manchester Air Quality Supersite (MAQS), located in densely populated urban areas with unique air quality challenges. The third site is a roadside monitoring site in York, which is part of the Automatic Urban and Rural Network (AURN, https://uk-air.defra.gov.uk/data/), representing a urban environment more inlfuenced by traffic. This selection strategy ensures that the QUANT study's findings reflect the dynamics of urban air quality across different UK settings, while providing comprehensive reference measurements. Further details about each site can be found in Section S3 in the Supp., and the available reference instrumentation in Section S4.

Initially, all the sensors were deployed in Manchester for approximately 3 months (mid-Dec 2019 to mid-Mar 2020) before being split up amongst the three sites (Fig. 1). At least one unit per brand was re-deployed to the other two sites (mid-March 2020 to early-July 2022) leaving two devices per company in Manchester to assess inter-device consistency. In the final 4 months of the study, all the sensor systems were relocated back to Manchester (early July 2022 to the end of October 2022).

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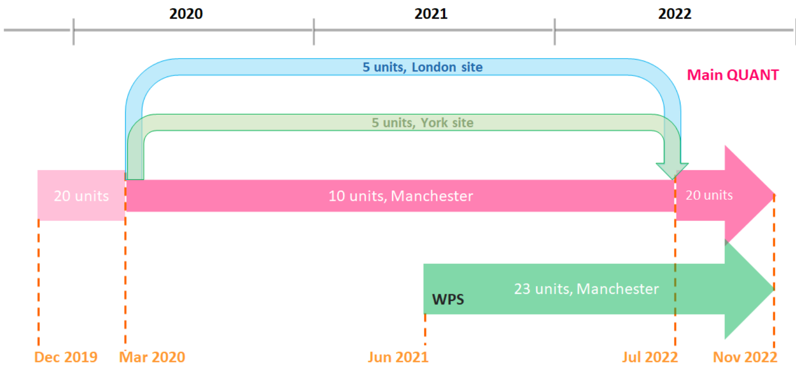

Figure 1. Main Quant and Wider Participation Study (WPS) timeline.

2.2 Wider Participation Study

The Wider Participation Study (WPS) was a no-cost complementary extension of the QUANT assessment, specifically designed to foster innovation within the air pollution sensors domain. This segment of the study took place entirely at the at MAQS from 10th June 2021 to 31st October 2022 (Fig. 1). It included a wider array of commercial platforms (9 different sensor systems brands), and offered manufacturers the opportunity to engage in a free-of-charge impartial evaluation process. Although participation criteria matched those of the Main QUANT study, a key distinction lay in the voluntary nature of participation: vendors were invited to contribute multiple sensor devices throughout the WPS study (see Table 2). Participants were able to demonstrate their systems' performance against collocated high-resolution (1-minute) reference data at a state-of-the-art measurement site such as the Manchester supersite.

Table 2. The 23 WPS devices deployed at the Manchester supersite provided 63 gases and 62 PM measurements in total. For a detailed description of the devices see the Section S2 in the Supp.

Product* (# units)	**Company**	**Measurements**							
		NO	**NO_2**	**O_3**	**CO**	**CO_2**	**PM_1**	**$PM_{2.5}$**	**PM_{10}**
Mod (3)	QuantAQ	-	-	-	-	-	✓	✓	✓
AQM (3)	AQMesh	✓	✓	✓	✓	✓	✓	✓	✓
Atm (2)	RLS**	-	-	-	-	-	✓	✓	✓
IMB (2)	Bosch	-	✓	✓	-	-	-	✓	✓
Poll (2)	Oizom	✓	✓	✓	✓	✓	-	✓	✓
AP (3)	Kunak	✓	✓	✓	✓	✓	✓	✓	✓
SA (3)	Vortex IoT	-	✓	✓	-	-	-	✓	✓
NS (3)	Clarity	-	✓	-	-	-	✓	✓	✓
Prax (2)	SCS***	✓	✓	✓	✓	✓	✓	✓	✓

*Mod: Modulair; AQM: AQMesh; Atm: Atmos, Polludrone: Poll; AP: Kunak Air Pro; SA: Silax Air, NS: Node-S, Prax: Praxis. **RLS: Respirer Living Sciences. ***SCS: South Coast Science.

2.3 Data collection, co-located reference data and data products

All sensor devices were installed at the measurement sites as per manufacturer recommendations. In addition to the device supplier's own cloud storage (accessed on-demand via each supplier's web portals), an automated daily scraping of each company's API was performed to save data onto a secure server at the University of York to ensure data integrity. PurpleAir units were exempt from this due to a lack of mobile data connection and poor internet signal at the sites; instead, readings were locally collected and manually uploaded. Minor pre-processing was applied at this stage to standardise the data format across all the devices. No outlier checks or data modifications were applied.

In addition to providing an independent assessment of sensor performance, QUANT also aimed to contribute to device manufacturers to help advance the field of air pollution sensors. To this end, three separate 1-month periods of reference data, spaced every 6 months, were shared with each supplier, provisional data soon after each period, and ratified data when available. For an overview of reference instrumentation at each site refer Table S1, and for details on the quality assurance procedures applied to the reference instruments see Table S2.

Access to colocated reference data allowed the companies to assess sensors' performance and, if they chose, to generate and provide additional calibrated data products. These products are distinct data versions provided by manufacturers throughout QUANT, before and/or after sharing reference data —for instance, "out-of-box", "cal1", "cal2", etc. Figures S1 and S2 show a time-line of the different data products. To see the dates and periods of the shared reference data refer to Table S3. All reference data was embargoed until it was released to all manufacturers simultaneously to ensure consistency across manufacturers. Not every manufacturer opted to use this data to apply corrections or improve calibrations, but if they chose to do so, the updated measurements were treated as a separate data product. Device calibrations were performed solely at the discretion of the manufacturers without any intervention from our team, thus limiting the involvement of vendors/manufacturers in the provision of standard sensor outputs and unit maintenance as would be required by any standard customer.

3. Results and discussion

A key challenge in sensor performance evaluation is the high spatial and temporal variability errors that impact the accuracy of their readings, making the application of laboratory corrections more challenging. Furthermore, the overreliance on global performance metrics, such as R^2 (i.e., the Coefficient of Determination), RMSE (i.e., the Root Mean Squared Error), and MAE (i.e., the Mean Absolute Error) is an important issue when assessing sensors. While these metrics provide a general understanding of sensor performance, they can be limiting or even misleading, restricting a comprehensive understanding of the error structure and the measurement information content (Diez et al., 2022).

In response to these challenges, the QUANT assessment represents the most extensive independent appraisal of air pollution sensors in UK urban atmospheres. As the results presented here illustrate, QUANT is dedicated to examining sensor performance through multiple complementary perspectives and metrics, aiming to integrate these to accurately reflect the complexity of this dataset. By making the dataset open-access, it enables other stakeholders to evaluate it based on criteria that align with their specific needs and contexts. The following sections aim to provide an overview of the data and provide initial findings, with a focus on those that are most relevant to end-users of these technologies.

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3.1 Inter-device precision

Inter-device precision refers to the consistency of measurements across multiple devices of the same type, an important characteristic to ensure the reliability of sensor outputs over time (Moreno-Rangel et al., 2018). During QUANT, all the devices were collocated for the first 3 months and the final 3 months of the deployment to assess inter-device precision and its changes over time. Fig. 2 shows the inter-device precision (as defined by the CEN/TS 17660-1:2021, i.e., the "between sensor system uncertainty" metric: $u_s(b_s, s)$) of $PM_{2.5}$ measurements during these periods. While most of the companies display a certain level of inter-device precision stability in each period (except for one, with a seemingly upward trend in the final period), there are evident long-term changes. Notably, out of the four manufacturers assessed in the final period (each having 3 devices running simultaneously), three experienced a decline in their inter-device precision compared to two years earlier. This is likely due to both hardware degradation but also drift in the calibration, which at this point had been applied between 16 and 34 months prior (depending on the manufacturer). For extended periods, inconsistencies among devices from the same manufacturer might emerge, leading to varying readings under similar conditions. Consequently, data collected from different devices may not be directly comparable, which could result in inaccuracies or misinterpretations when analyzing air quality trends or making decisions.

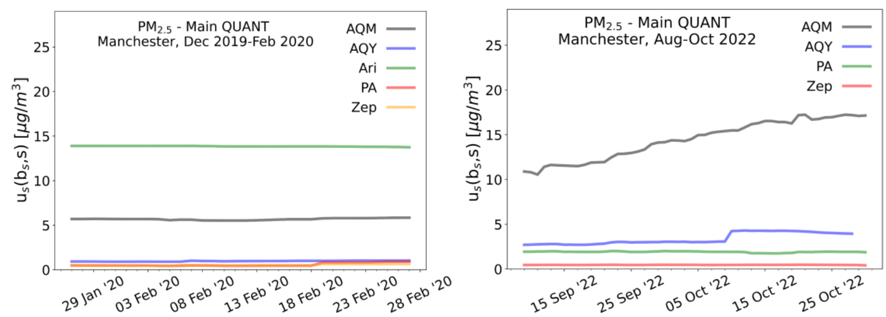

Figure 2. The inter-device precision of $PM_{2.5}$ measurements from "identical" devices across the 5 companies participating in QUANT is assessed using the "between sensor system uncertainty" metric (defined by the CEN/TS 17660-1:2021 as *u(bs, s)*). Each line represents this metric as a composite of all sensors per brand (excluding units with less than 70% data) within a 40-day sliding window.

It is worth noting that the inter-device precision provides no information on the accuracy of the sensor measurements; a batch of devices may provide a highly consistent, but also highly inaccurate measurement of the target pollutant.

The "target plot" (as shown in Fig. 3) is a tool commonly used to depict the bias/variance decomposition of an instrument's error relative to a reference (for more details see Jolliff et al. (2009)). The mean error bias (MBE) is used to characterise accuracy and precision is quantified by the centered Root Mean Squared Error (cRMSE, e.g. Kim et al. (2022) also called unbiased Root Mean Squared Error (uRMSE, e.g. Guimarães et al. (2018)). Fig. 3 visualises the performance of a set of $PM_{2.5}$ sensors of the WPS deployment for the first 2 months (out-of-box data) and the last 3 months of colocation (manufacturer-supplied calibrations). In addition to highlighting which devices are most accurate, Fig. 3 also provides an additional perspective of inter-device precision.

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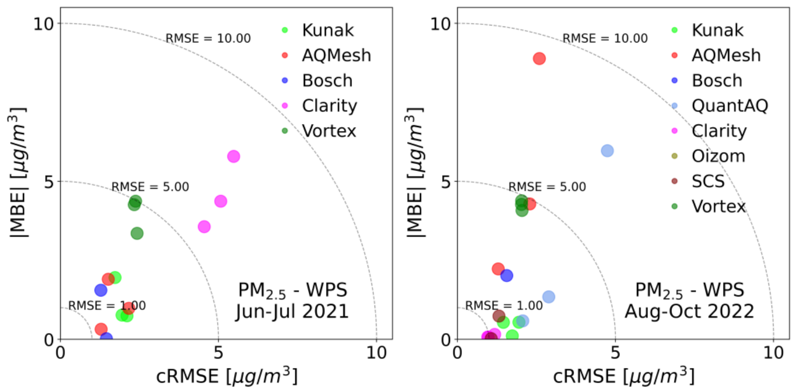

Figure 3. Target diagrams for the WPS $PM_{2.5}$ measurements during the initial co-location period (Jun-Jul 2021, left) and final co-location period (Aug-Oct 2022, right). The error (RMSE) for each instrument is decomposed into the MBE (y-axis) and cRMSE (x-axis). Each point represents an individual sensor device, with duplicate devices having the same colour. Since only units with more than 75% of the data were considered, the plot on the right shows fewer units than the plot on the left.

3.2 Device accuracy and collocation calibrations

Sensor measurement accuracy denotes how close a sensor's readings are to reference values (Wang et al., 2015). Characterizing this feature is imperative for establishing sensor reliability and making informed decisions based on its data. Fig. 4 shows that collocation calibration can greatly impact observed NO_2 sensor performance in a number of ways. Firstly, measurement bias is often, but not always, reduced following calibration, as evidenced by a general trend for devices to migrate towards the origin (RMSE = 0 ppb). Secondly, it can help to improve within-manufacturer precision by grouping sensor systems from the same company closer together. The figure also highlights a fundamental challenge with evaluating sensor systems: the measured performance can vary dramatically over time — and space— as the surrounding environmental conditions change. To quantify this, 95% Confidence Intervals (CIs) were estimated for each device using bootstrap simulation and are visualised as a shaded region. For the out-of-box data, these regions are noticeably larger than in the calibrated results for most manufacturers, suggesting that colocation calibration has helped to tailor the response of each device to the specific site conditions. This is reinforced by the cRMSE component reducing by a greater extent than the MBE, in the terminology of machine learning the calibration has helped reduce the variance portion of the bias-variance trade-off.

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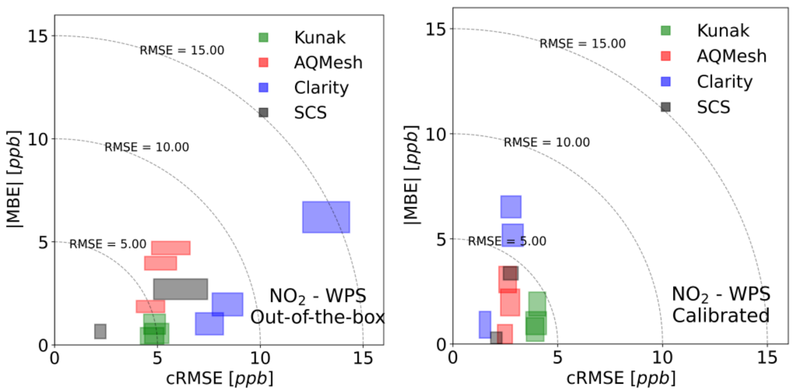

Figure 4. Effect of colocation calibration on NO$_2$ sensor accuracy. The accuracy is quantified using RMSE, which is decomposed into MBE (y-axis) and cRMSE (x-axis). 95% confidence regions were estimated using bootstrap sampling. The left panel displays results from the period Jun - Jul 2021 ('out-of-the-box' data), while the right-hand panel summarises Aug 2021 when calibrations were applied for all the WPS manufacturers.

However, it is important to note a limitation of Target Plots: they primarily focus on sensor behaviour around the mean. Therefore, the collective improvement evidenced by Fig. 4 might be only partial. For applications where it is important to understand how calibrations impact lower or higher percentiles, considering other metrics or visual tools would be advisable. An example of this is the absolute and Relative Expanded Uncertainty (REU, defined by the Technical Specification CEN/TS 17660-1:202). Fig. 5 illustrates how NO$_2$ calibrations might not only improve collective performance around the mean (as indicated by the dotted red line in Fig. 5 and previously displayed in the target plot) but across the entire concentration range.

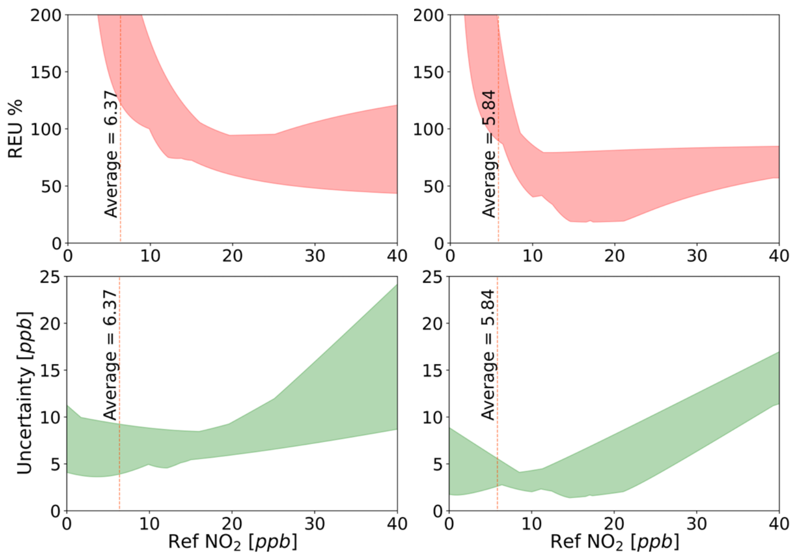

Figure 5. The top plots display the REU (%) across the concentration range, while the bottom plots depict the Absolute Uncertainty (ppb) —both before (left plots) and after (right plots) calibrating NO$_2$ WPS systems. The shaded areas

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represent the collective variability evolution (all sensors from all companies) of both metrics. These plots were constructed using the minimum and maximum value of the REU and the Absolute Uncertainty for the entire concentration range.

However, a note of caution when interpreting results from observational studies such as these is that it is impossible to ascertain a direct causal relationship between calibration and sensor performance as there are numerous other confounding factors at play (Diez et al., 2022). Notably these two data products are being assessed over different periods when many other factors will have changed, for example, the local meteorological conditions as well as human-made factors such as reduced traffic levels following the COVID-19 lockdown that commenced in March 2020.

3.3 Reference instrumentation is key

A common assumption when evaluating the performance of sensors is that the metrological characteristics of the sensor predominantly influence discrepancies detected in colocations. While this presumption can often be justified due to both devices' relative scales of measurement errors, it is not always the case. Since every measurement is subject to uncertainties, it is crucial to consider those associated with the reference when deriving the calibration factors of placement.

Fig. 6 (left plots) displays the performance of a NO_2 reference instrument (Teledyne T200U) specifically installed for QUANT, located next to the usual instrument at the Manchester supersite (Teledyne T500). Although they use different analytical techniques (chemiluminescence for the T200U and Cavity Attenuated Phase Shift Spectroscopy for the T500), their measurements are highly correlated (R^2~0.95). However, it's possible to identify a proportional bias (slope=0.69), attributed to retaining the initial calibration (conducted in York) without subsequent adjustments, a situation exacerbated by an unnoticed mechanical failure of one of the instrument's components. The REU demonstrates that, under these circumstances, an instrument designated as a reference does not meet the minimum requirements set out by the Data Quality Objectives (DQOs) of the EU Air Quality Directive 2008/50/EC. Figure S3 shows a unique sensor evaluated against both the T500 and the T200U. The comparison against the T200U yields better results, suggesting that, in a hypothetical scenario where it was the only instrument at the site, this could lead to misleading conclusions. This situation reinforces the idea that instruments should not only be adequately characterised but also undergo rigorous quality assurance and data quality control programs, as well as receive appropriate maintenance (Pinder et al., 2019). All of this must be performed before and during the use of any instrument.

For PM monitoring the current EU reference method is the gravimetric technique (CEN EN 12341 , 2023), which is a non-continuous monitoring method that requires weighing the sampled filters and off-line processing of the results. Techniques that have proven to be equivalent to the reference method (called “equivalent to reference” in the EU Air Quality Directive) are very often used in practice. In the UK context, the Beta Attenuated Monitor (BAM) and FIDAS (optical aerosol spectrometer) are equivalent-to-reference methods commonly used as part of the Urban AURN Network (Allan et al., 2022). To illustrate these differences in practice, Fig. 6 compares these two equivalent-to-reference $PM_{2.5}$ measurements obtained with a BAM (AURN York site, located on a busy avenue), and a FIDAS unit specifically installed for QUANT. During this specific period, they do not fully agree (R^2 = 0.87). Despite a not very pronounced bias (slope=0.80), the dispersion of points around the best-fit line is noticeable, limiting the linearity of the FIDAS compared to the BAM.

In the hypothetical case that the BAM were to be considered the reference method (arbitrarily chosen for this example as it is the current instrument at the AURN York site) when assessing the FIDAS under these test conditions, it would only meet the criterion stipulated by the EU DQOs for indicative measurements, but not for fixed (i.e., reference) measurements. Of course, this example is primarily intended to illustrate the magnitude of differences between both methods for this particular application, and by no means does this observation imply that the FIDAS measurements are inherently problematic.

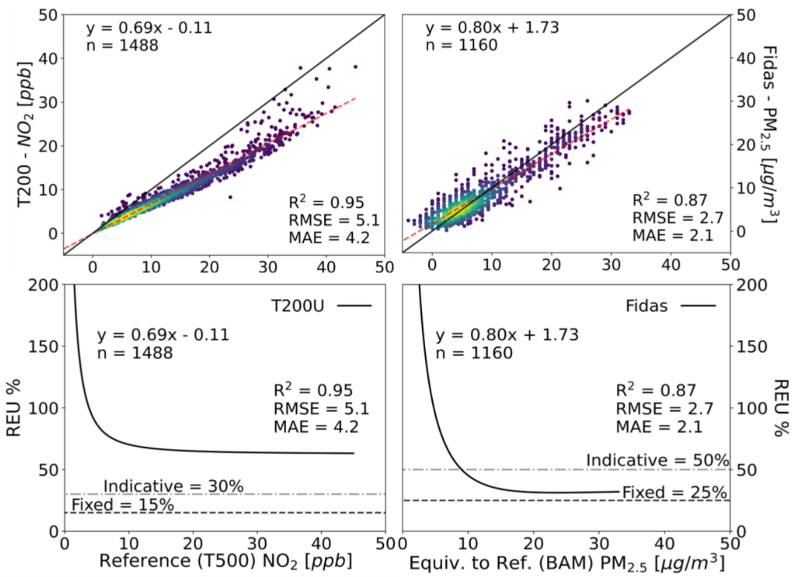

Figure 6. The left plots depict the comparison between the Teledyne T200U (chemiluminescence analyzer) and the reference method (Teledyne T500 CAPS analyzer) at the Manchester supersite. The plots to the right illustrate $PM_{2.5}$ measurements in York, taken with a FIDAS instrument (optical aerosol spectrometer) and a BAM 1020 (beta attenuation monitor), both equivalent-to-reference methods. While the top plots show the regression (including some typical single-value metrics), those on the bottom present the REU alongside the DQOs defined by the European Directive 2008/50/EC.

Although these two instruments (BAM and Fidas) show a greater concordance between themselves than with sensors (for the comparison of two sensor systems against the BAM and the Fidas, refer to Fig. S4), the choice of the measurement method can have a considerable impact on evaluations of this type. This underscores the importance of adequately characterising the uncertainties of the reference monitor when evaluating sensors.

3.4 Systems performance after location transfer

An extreme example of sensor performance varying due to environmental conditions is when sensors are moved between locations, as their apparent performance may vary drastically. Fig. 7 displays the REU and regression plots for four of the same $PM_{2.5}$ sensor system in two periods: April-June 2022 when the devices were working across the 3 sites (York, Manchester and London), and August-October 2022 when they were all reunited in Manchester. The RMSE remains reasonably consistent between the devices across the periods and locations. However, the device that moved from York to Manchester saw its slope change from 0.69 to 0.86. Because this device's slope is consistent with the other units when running in Manchester, this is likely due to the different

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sensor responses in the specific environments. The precise cause of this change is not immediately evident and will be the focus of a follow-up study, but could be due to changes in local conditions impacting sensor calibration and/or differences in actual $PM_{2.5}$ sources and particle characteristics at the sites (Raheja et al., 2022).

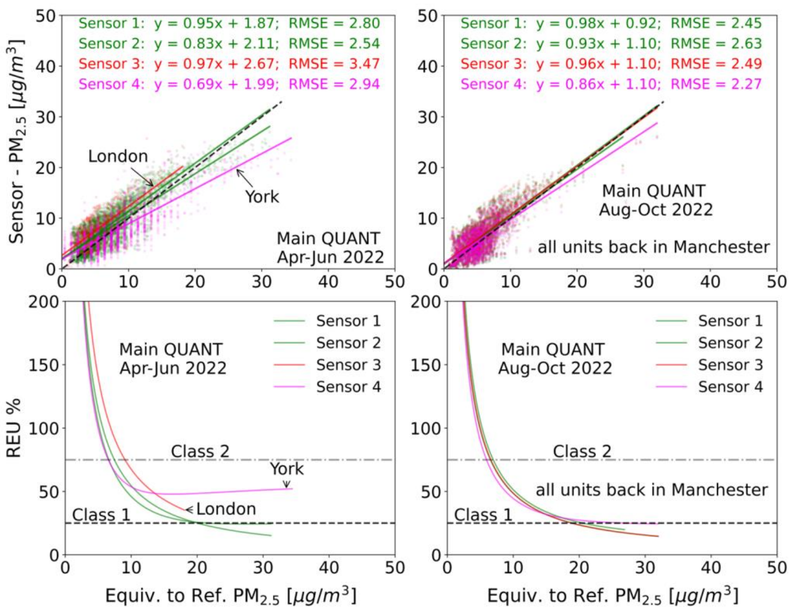

Figure 7. Regression (top) and REU (bottom) plots showing data from four $PM_{2.5}$ sensors (same manufacturer) over 2 time periods: Apr-Jun 2022 and Aug-Oct 2022. The four devices were in separate locations in the first period, but all deployed in Manchester in the second.

A second example of performance changing between locations is presented in Fig. 8, showing NO_2 data from two sensor systems (different brands, one shown on top of the other) before (left plots) and after (right plots) they were moved from Manchester to London in March 2020. Both sensors saw a reduction in agreement with the reference instrument at the London site compared to Manchester, despite both these sites being classified as urban-background with reference instrument performance regularly audited by the UK National Physical Laboratory.

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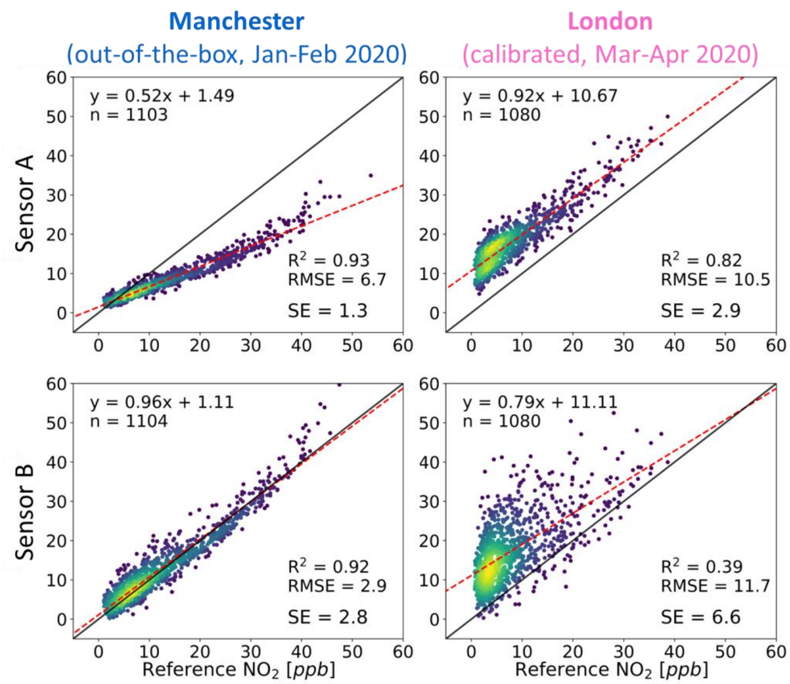

Figure 8. Comparison of NO_2 measurements for two systems (A and B) that were moved between Manchester (left plots) and London (right plots). The Manchester deployment was from January - February 2020, and the London data was recorded from April - May 2020.

The primary distinction between both systems' behaviour lies in the fact that the sensor located in the top row, even after being relocated to London, maintains a linear response (albeit slightly more degraded than that observed in Manchester, as the R^2 and RMSE show). In contrast, in the second system (bottom row), the response is notably noisier as the Standard Error (SE) —which is the dispersion of the data around the best-line fit line, i.e., the remaining error after bias correction. In scenarios akin to this latter, where there is a high variance in the residuals, a linear correction will not provide a significant improvement. While more sophisticated corrections could be applied, these will be limited by domain knowledge of the end-user, and potentially by other complex data sources that might be available. However, it is important to remember that additional post-processing could increase the risk of overfitting (Aula et al., 2022). On the other hand, for cases like the top plots, users might benefit from trying to correct them using simple linear correction (e.g. using reference instruments if available) or other approaches that could provide means for zero and span correction. A straightforward and cost-effective example could be the use of diffusion tubes for the case of NO_2, as discussed in Section 3.6.

3.5 Long-term stability

The long-term stability of sensor response is also an important facet of its performance, especially for certain use cases such as multi-year network deployments. There can be multiple causes of long-term changes to sensor response, for example, particles settling inside the sampling chamber in optical-based sensors(e.g. Hofman et al. (2022)), or the gradually changing composition of electrochemical cells (e.g. Williams (2020)). How these changes manifest themselves in the data must be identified if ways to account for them are to be implemented.

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Fig. 9 shows the temporal nature of the O_3 and NO_2 errors (MBE, cRMSE and RMSE) from a sensor system between February 2020 and October 2022. The O_3 shows (Fig. 9a) a gradual increase in the overall measurement error, largely due to an increase in the MBE. It also shows a distinct seasonality MBE, increasing by a factor of 3-4 between March and July compared to the August-February period. The cRMSE component shows fluctuations during the study but only has a small increasing trend. The NO_2 system (Fig. 9b) demonstrates a consistently increasing overall error, with a less pronounced seasonal influence. The bias contributes greatly to the total error (see Section 3.6 for NO_2 sensor correction, Fig. 9c).

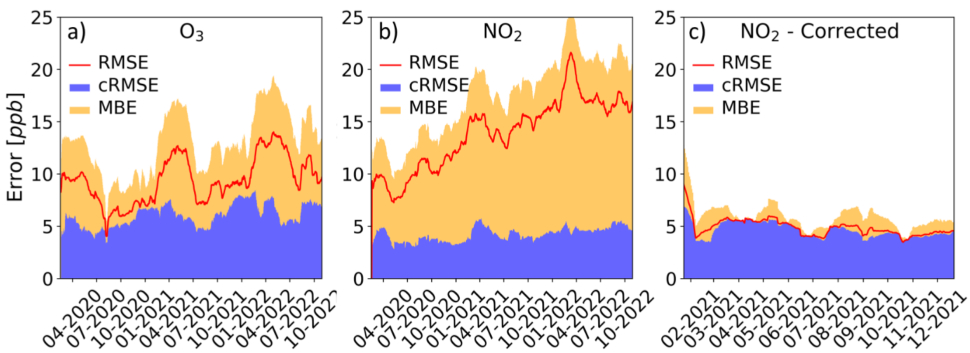

Figure 9. Error (as RMSE, red line) of one of the systems belonging to the Main QUANT, decomposed into cRMSE (in blue) and MBE (in yellow) estimated based on a 40-day (1-day slide) moving window. Panel a) is for O_3 measurements, and panel b) is for NO_2 (April 2020-Oct 2022). Panel c) is also for NO_2, this time showing the effect of a linear correction using diffusion tubes (see next section for more details).

3.6 Informing end-use applications

Ultimately, for any air pollution monitoring application, the requirements of the task should dictate the measurement technology options available. For example, if the requirement for a particular measurement is to assess legal compliance, then lower measurement uncertainty must be a key consideration as the reported values need to be compared to a limit value. In contrast, if an application aimed to look at long-term trends in pollutants, then absolute accuracy may not be as important as the long-term stability of sensor response. In order to realise the potential of air pollution sensor technologies, end users need to be provided with the information required to critically assess the strengths and weaknesses of potential candidate sensor devices, ideally in an easy-to-access and interpret manner.

Understanding the uncertainty associated with a measurement instrument is essential for recognizing its capabilities and limitations. Accurate instruments are crucial, especially in areas like public health decision-making, where inaccurate data can have profound implications (Molina Rueda et al., 2023). Furthermore, instruments that operate autonomously ensure consistent, uninterrupted data collection, making them more efficient and cost-effective in terms of maintenance and calibration. Figure 10 shows the REU (y-axis) and Data Coverage (DC, x-axis) of companies measuring NO_2 with more than 2 systems running to avoid ambiguity in the results. Using multiple systems, not only avoids ambiguity in results but also enhances the robustness of the data collected. Both REU and DC are key criteria within the EU scheme (EU 2008/50/EC) for evaluating the performance of measurement methods, and are complemented by the CEN/TS 17660-1:2021 specifically for sensors. This document defines three different sensor system tiers. Class 1 sensors, bounded by the green rectangle, offer higher accuracy than Class 2 sensors, highlighted by the red rectangle (Class 3 sensors have no set requirements). Presenting the data like this helps users anticipate the performance of sensor systems —under the assumption that all sensors from the same brand will behave similarly in equivalent environmental conditions— providing more insight into selecting the appropriate instrument for a given project or study.

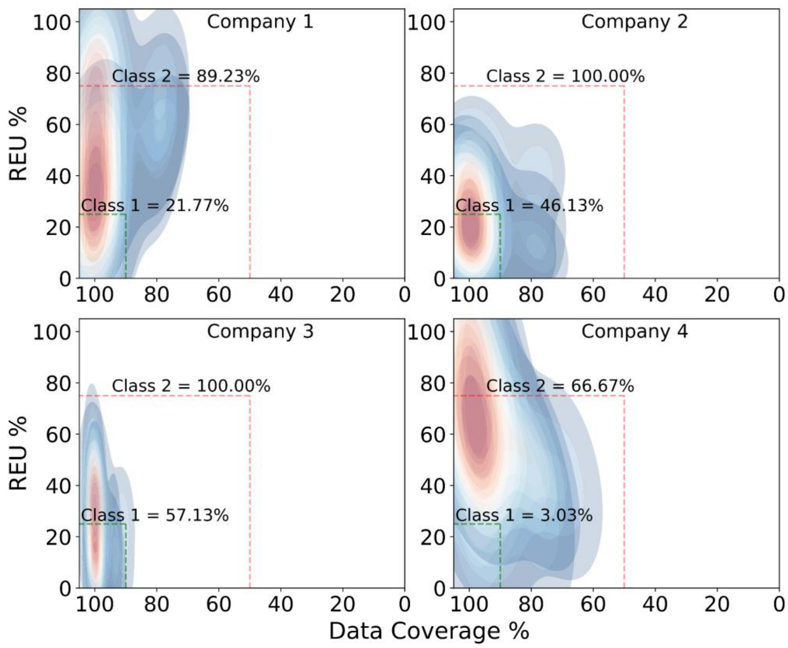

Figure 10. The REU vs. Data Coverage (DC) for 4 systems companies was evaluated during the WPS for the period Nov 2021-Oct 2022 (after all companies had at least one calibrated product). Both the REU and the DC were estimated based on a 40-day size (which is the number of days used by CEN/TS 17660-1:2021 for on-field tests) moving window (1-day slide). While the green rectangle represents the DQOs for Class 1 sensors, the red one limits the DQOs for Class 2 sensors (Class 3 sensors have no requirements).

Depending on the nature of the sensor data uncertainty, methods can be implemented to improve certain aspects of the data quality for a particular application. One such example is the use of distributed networks to estimate sensor measurement errors, such as that described by (J. Kim et al., 2018). Depending on the application, simpler methods could also be available to reduce the magnitude of the changing bias, and thus significantly improve the accuracy of an individual sensor system, but also that of broader sensor networks. For the case shown in Fig.9b, one possible way to do this would be using supporting observations of NO_2 made via diffusion tubes. These measurements are widely used to monitor NO_2 concentrations in UK urban environments, due to their lower cost (~£5 per tube) and ease of deployment, but only provide average concentrations over periods of weeks to months (Butterfield et al., 2021). During QUANT, NO_2 diffusion tubes were deployed at the 3 colocation sites (see Section S8 at the Supp. for more details). Combining these measurements offers the possibility of quantifying the average

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sensor bias, thus reducing the error on the sensor measurement whilst maintaining the benefits of its high-time resolution observations. It is important to note that while bias correction has been applied to the sensor data, the NO2 diffusion tube concentrations used for comparison purposes must also be adjusted (e.g. following DEFRA (2022)). Fig. 9c shows the accuracy of the same NO_2 sensor data shown in Fig. 9b but applies a monthly offset calculated as the difference between its monthly average measurement and that from the diffusion tube (see Figure S5). This shows a dramatic reduction in overall error largely driven by its bias correction. What remains largely resulting from the cRMSE, i.e. the error variance that might arise from limitations from the sensing technology itself and/or the conversion algorithms used to transform the raw signals into the concentration output. To validate the efficacy and reliability of this bias correction method, further long-term studies are warranted.

The development and communication of methods that improve sensor data quality, ideally in digestible case studies, would likely increase the successful application of sensor devices for local air quality management. There is also a need for similar case studies showcasing the successful application of sensor devices for particular monitoring tasks. An example of this from the QUANT dataset is the use of sensor devices to successfully identify change points in a pollutant's concentration profile. Determining when a specific pollutant has changed its temporal nature is a challenging task as there are a large number of confounding factors that influence a pollutant's concentration at a specific point in time, including but not limited to seasonal factors, environmental conditions (both natural and arising from human behaviour), and meteorological factors. A novel statistical approach to smoothing air quality measurements was applied, accounting for these external factors (Lacy & Moller). This method was applied to NO_2 concentrations determined from the sensor systems that had remained in Manchester throughout 2020, aiming to identify whether the well-documented reduction in ambient NO_2 concentrations could be observed due to changes in travel patterns associated with COVID-19 restrictions. To provide an objective quantification of whether a change-point had occurred, the Bayesian online change-point detection (Adams & MacKay, 2007) was applied. Of the 8 devices that measured NO_2, clear changepoints corresponding to the introduction of a lockdown were identified in 2 (Fig.11). While this is an unsupervised analysis, it demonstrates the potential of these devices to identify long-term trends with appropriate processing, even with only having had 3 months of training data to fit the model to. This is especially aided by the given algorithm's ability to use reference data as a prior allowing sensor systems to fine-tune the model.

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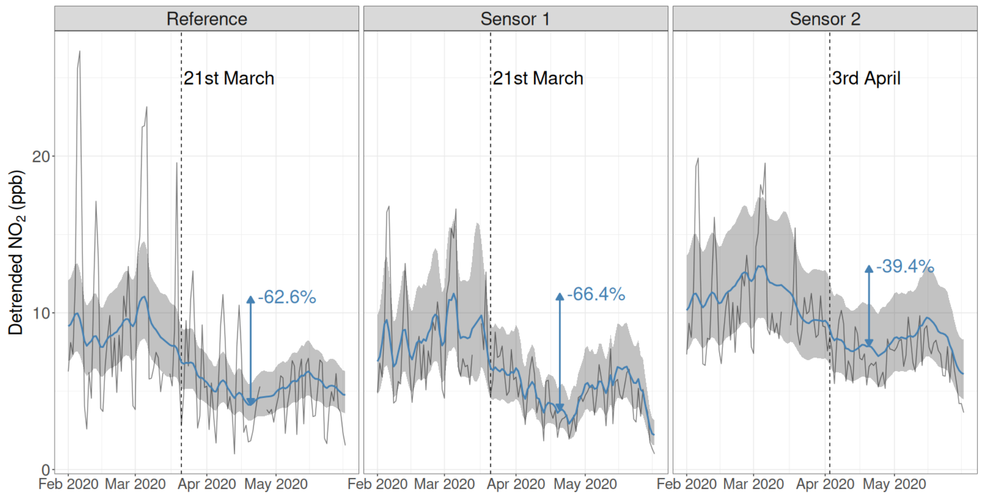

Figure 11. NO_2 measurements (black solid line) and detrended estimates (blue solid line with 95% confidence interval in the shaded grey region) from the reference instrument (left panel) and 2 sensor systems (middle and right panels) from Manchester in 2020. Vertical dashed lines and their corresponding dates indicate identified change points, which correspond to the introduction of the first national lockdown due to COVID-19 on the 23rd of March 2020. The percentage in blue represents the relative peak-trough decrease from 5th March to 20th April.

4. Conclusions

Lower-cost air pollution sensor technologies have significant potential to improve our understanding and ability to manage air pollution issues. Large-scale uptake in the use of these devices has been primarily limited by concerns over data quality and a general lack of a realistic characterisation of the measurement uncertainties making it difficult to design end uses that make the most of the data information content. Developments in the field of air pollution sensor technology are also developing rapidly, with advances in both the measurement technology and particularly in the data post-processing and calibration. A challenge with the use of sensor-based devices is that many of the end-use communities do not have access to extensive reference-grade air pollution measurement capability (Lewis & Edwards, 2016), or in many cases expertise in making atmospheric measurements. For this reason, reliable information on expected sensor performance needs to be available to aid effective end-use applications. Large-scale independent assessments of air sensor technologies are non-trivial and costly, however, making it difficult for end users to find relevant performance information on current sensor technologies. The QUANT assessment is a multi-year study across multiple locations, that aims to provide relevant information on the strengths and weaknesses of commercial air pollution sensors in UK urban environments.

The QUANT sensor systems were installed at two highly instrumented urban background measurement sites, in Manchester and London, and one roadside monitoring station in York. The study design ensured that multiple devices were collocated to assess inter-device precision, and devices were also moved between locations and able to test additional calibration data products to assess and enable developments in sensor performance under realistic end-use scenarios. A wider participation component of the Main QUANT assessment was also run at the Manchester site to expand the market representation of devices included in the study, and also to assess recent developments in the field.

A high-level analysis of the dataset has highlighted multiple facets of air pollution sensor performance that will help inform their future usage. Inter-device precision has been shown to vary, both between different device types and over different periods of time, with the most accurate devices generally showing the highest levels of inter-device precision. The accuracy of the reported data for a particular device can be impacted by a variety of factors, from the calibrations applied to its location or seasonality. This has important implications for the way sensor-based technologies are deployed and supports the case made by others (Bittner et al., 2022; Farquhar et al., 2021; Crilley et al., 2018; Williams, 2020; Bi et al., 2020) that practical methods to monitor sensor bias will be crucial in uses where data accuracy is paramount.

In addition to these findings, this overview lays the groundwork for more detailed research to be presented in future publications. Subsequent analyses will focus on on providing a more nuanced understanding of the uncertainty in air pollution sensor measurements, thus equipping end-users with better insights into of the capability of sensor data. Future studies will delve into specific aspects of air pollution sensor performance: 1) a comprehensive performance evaluation of $PM_{2.5}$ data, assessing their accuracy and reliability under different environmental conditions; 2) an in-depth analysis of NO_2 measurements, examining their sensitivity and response in various urban environments; and 3) a detailed investigation into the detection limits of these sensor technologies, targeting their optimized application in low concentration scenarios. These focused studies are basic steps needed to further advance our understanding of sensors' capabilities and limitations, ensuring informed and effective application in air quality monitoring.

Supplementary

The supplement related to this article is available online at:

Data availability

The data for this study can be found at the Centre for Environmental Data Analysis (CEDA): Lacy, S.; Diez, S.; Edwards, P. (2023): Quantification of Utility of Atmospheric Network Technologies: (QUANT): Low-cost air quality measurements from 52 commercial devices at three UK urban monitoring sites. NERC EDS Centre for Environmental Data Analysis, date of citation. https://catalogue.ceda.ac.uk/uuid/ae1df3ef736f4248927984b7aa079d2e.

Author contributions

The initial draft of the manuscript was created by SD, PME, and SL. The research was conceptualized, designed, and conducted by PME and SD. Methodological framework and conceptualization were developed by SD, PME, and SL. Data analysis was primarily conducted by SD and SL. The software tools for data visualization and analysis were developed by SD and enhanced by SL. MF, MP and NM supplied the reference data critical for the study. TB, HC, DH, SG, NAM and JU made substantive revisions to the manuscript, enriching the final submission.

Competing interests

The authors declare that they have no conflict of interest.

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Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques
Discussions

References

Adams, R. P., & MacKay, D. J. C. (2007). *Bayesian Online Changepoint Detection* (arXiv:0710.3742). arXiv. https://doi.org/10.48550/arXiv.0710.3742

Alam, M. S., Crilley, L. R., Lee, J. D., Kramer, L. J., Pfrang, C., Vázquez-Moreno, M., Ródenas, M., Muñoz, A., & Bloss, W. J. (2020). Interference from alkenes in chemiluminescent NO_x measurements. *Atmospheric Measurement Techniques*, *13*(11), 5977–5991. https://doi.org/10.5194/amt-13-5977-2020

Allan, J., Harrison, R., & Maggs, R. (2022). *Measurement Uncertainty for PM2.5 in the Context of the UK National Network*. https://uk-air.defra.gov.uk/library/reports?report_id=1074

A. Miech, J., Stanton, L., Gao, M., Micalizzi, P., Uebelherr, J., Herckes, P., & P. Fraser, M. (2023). In situ drift correction for a low-cost NO 2 sensor network. *Environmental Science: Atmospheres*, *3*(5), 894–904. https://doi.org/10.1039/D2EA00145D

Aula, K., Lagerspetz, E., Nurmi, P., & Tarkoma, S. (2022). Evaluation of Low-cost Air Quality Sensor Calibration Models. *ACM Transactions on Sensor Networks*, *18*(4), 72:1-72:32. https://doi.org/10.1145/3512889

Baron, R., & Saffell, J. (2017). Amperometric Gas Sensors as a Low Cost Emerging Technology Platform for Air Quality Monitoring Applications: A Review. *ACS Sensors*, *2*(11), 1553–1566. https://doi.org/10.1021/acssensors.7b00620

Bi, J., Wildani, A., Chang, H. H., & Liu, Y. (2020). Incorporating Low-Cost Sensor Measurements into High-Resolution PM2.5 Modeling at a Large Spatial Scale. *Environmental Science & Technology*, *54*(4), 2152–2162. https://doi.org/10.1021/acs.est.9b06046

Bigi, A., Mueller, M., Grange, S. K., Ghermandi, G., & Hueglin, C. (2018). Performance of NO, NO_2 low cost sensors and three calibration approaches within a real world application. *Atmospheric Measurement Techniques*, *11*(6), 3717–3735. https://doi.org/10.5194/amt-11-3717-2018

Bittner, A. S., Cross, E. S., Hagan, D. H., Malings, C., Lipsky, E., & Grieshop, A. P. (2022). Performance characterization of low-cost air quality sensors for off-grid deployment in rural Malawi. *Atmospheric Measurement Techniques*, *15*(11), 3353–3376. https://doi.org/10.5194/amt-15-3353-2022

Brown, R. J. C., & Martin, N. A. (2023). How standardizing ‘low-cost’ air quality monitors will help measure pollution. *Nature Reviews Physics*, *5*(3), Article 3. https://doi.org/10.1038/s42254-023-00561-8

Buehler, C., Xiong, F., Zamora, M. L., Skog, K. M., Kohrman-Glaser, J., Colton, S., McNamara, M., Ryan, K., Redlich, C., Bartos, M., Wong, B., Kerkez, B., Koehler, K., & Gentner, D. R. (2021). Stationary and portable multipollutant monitors for high-spatiotemporal-resolution air quality studies including online calibration. *Atmospheric Measurement Techniques*, *14*(2), 995–1013. https://doi.org/10.5194/amt-14-995-

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques Discussions
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Bulot, F. M. J., Johnston, S. J., Basford, P. J., Easton, N. H. C., Apetroaie-Cristea, M., Foster, G. L., Morris, A. K. R., Cox, S. J., & Loxham, M. (2019). Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Scientific Reports*, *9*(1), Article 1. https://doi.org/10.1038/s41598-019-43716-3

Butterfield, D., Martin, N. A., Coppin, G., & Fryer, D. E. (2021). Equivalence of UK nitrogen dioxide diffusion tube data to the EU reference method. *Atmospheric Environment*, *262*, 118614. https://doi.org/10.1016/j.atmosenv.2021.118614

CEN. (2021). *CEN/TS 17660-1 Air quality—Performance evaluation of air quality sensor systems—Part 1: Gaseous pollutants in ambient air* [Technical Specification].

CEN EN 12341. (2023). European Committee for Standardization (CEN).

Chojer, H., Branco, P. T. B. S., Martins, F. G., Alvim-Ferraz, M. C. M., & Sousa, S. I. V. (2020). Development of low-cost indoor air quality monitoring devices: Recent advancements. *Science of The Total Environment*, *727*, 138385. https://doi.org/10.1016/j.scitotenv.2020.138385

Crilley, L. R., Shaw, M., Pound, R., Kramer, L. J., Price, R., Young, S., Lewis, A. C., & Pope, F. D. (2018). Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. *Atmospheric Measurement Techniques*, *11*(2), 709–720. https://doi.org/10.5194/amt-11-709-2018

Cross, E. S., Williams, L. R., Lewis, D. K., Magoon, G. R., Onasch, T. B., Kaminsky, M. L., Worsnop, D. R., & Jayne, J. T. (2017). Use of electrochemical sensors for measurement of air pollution: Correcting interference response and validating measurements. *Atmospheric Measurement Techniques*, *10*(9), 3575–3588. https://doi.org/10.5194/amt-10-3575-2017

DEFRA. (2022). *Technical Guidance (TG22). Local Air Quality Management*. https://laqm.defra.gov.uk/wp-content/uploads/2022/08/LAQM-TG22-August-22-v1.0.pdf

Diez, S., Lacy, S. E., Bannan, T. J., Flynn, M., Gardiner, T., Harrison, D., Marsden, N., Martin, N. A., Read, K., & Edwards, P. M. (2022). Air pollution measurement errors: Is your data fit for purpose? *Atmospheric Measurement Techniques*, *15*(13), 4091–4105. https://doi.org/10.5194/amt-15-4091-2022

Duvall, R. M., Clements, A. L., Hagler, G., Kamal, A., Kilaru, V., Goodman, L., Frederick, S., Barkjohn, K. K., Greene, D., & Dye, T. (2021). *Performance Testing Protocols, Metrics, and Target Values for Fine Particulate Matter Air Sensors* (EPA/600/R-20/280).

Farquhar, A. K., Henshaw, G. S., & Williams, D. E. (2021). Understanding and Correcting Unwanted Influences on the Signal from Electrochemical Gas Sensors. *ACS Sensors*, *6*(3), 1295–1304. https://doi.org/10.1021/acssensors.0c02589

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques Discussions

Feenstra, B., Papapostolou, V., Hasheminassab, S., Zhang, H., Boghossian, B. D., Cocker, D., & Polidori, A. (2019). Performance evaluation of twelve low-cost PM2.5 sensors at an ambient air monitoring site. *Atmospheric Environment*, *216*, 116946. https://doi.org/10.1016/j.atmosenv.2019.116946

Feinberg, S., Williams, R., Hagler, G. S. W., Rickard, J., Brown, R., Garver, D., Harshfield, G., Stauffer, P., Mattson, E., Judge, R., & Garvey, S. (2018). Long-term evaluation of air sensor technology under ambient conditions in Denver, Colorado. *Atmospheric Measurement Techniques*, *11*(8), 4605–4615. https://doi.org/10.5194/amt-11-4605-2018

Gamboa, V. S., Kinast, É. J., & Pires, M. (2023). System for performance evaluation and calibration of low-cost gas sensors applied to air quality monitoring. *Atmospheric Pollution Research*, *14*(2), 101645. https://doi.org/10.1016/j.apr.2022.101645

Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V. F., Westervelt, D. M., Beekmann, M., & Subramanian, R. (2021). From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors. *Journal of Aerosol Science*, *158*, 105833. https://doi.org/10.1016/j.jaerosci.2021.105833

Guimarães, U. S., Narvaes, I. da S., Galo, M. de L. B. T., da Silva, A. de Q., & Camargo, P. de O. (2018). Radargrammetric approaches to the flat relief of the amazon coast using COSMO-SkyMed and TerraSAR-X datasets. *ISPRS Journal of Photogrammetry and Remote Sensing*, *145*, 284–296. https://doi.org/10.1016/j.isprsjprs.2018.09.001

Hagan, D. H., Gani, S., Bhandari, S., Patel, K., Habib, G., Apte, J. S., Hildebrandt Ruiz, L., & Kroll, J. H. (2019). Inferring Aerosol Sources from Low-Cost Air Quality Sensor Measurements: A Case Study in Delhi, India. *Environmental Science & Technology Letters*, *6*(8), 467–472. https://doi.org/10.1021/acs.estlett.9b00393

Han, J., Liu, X., Jiang, M., Wang, Z., & Xu, M. (2021). A novel light scattering method with size analysis and correction for on-line measurement of particulate matter concentration. *Journal of Hazardous Materials*, *401*, 123721. https://doi.org/10.1016/j.jhazmat.2020.123721

Hofman, J., Nikolaou, M., Shantharam, S. P., Stroobants, C., Weijs, S., & La Manna, V. P. (2022). Distant calibration of low-cost PM and NO2 sensors; evidence from multiple sensor testbeds. *Atmospheric Pollution Research*, *13*(1), 101246. https://doi.org/10.1016/j.apr.2021.101246

Jolliff, J. K., Kindle, J. C., Shulman, I., Penta, B., Friedrichs, M. A. M., Helber, R., & Arnone, R. A. (2009). Summary diagrams for coupled hydrodynamic-ecosystem model skill assessment. *Journal of Marine Systems*, *76*(1), 64–82. https://doi.org/10.1016/j.jmarsys.2008.05.014

Kang, Y., Aye, L., Ngo, T. D., & Zhou, J. (2022). Performance evaluation of low-cost air quality sensors: A review. *Science of The Total Environment*, *818*, 151769. https://doi.org/10.1016/j.scitotenv.2021.151769

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques Discussions

Karagulian, F., Barbiere, M., Kotsev, A., Spinelle, L., Gerboles, M., Lagler, F., Redon, N., Crunaire, S., & Borowiak, A. (2019). Review of the Performance of Low-Cost Sensors for Air Quality Monitoring. *Atmosphere*, *10*(9), Article 9. https://doi.org/10.3390/atmos10090506

Kelly, K. E., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., Martin, R., & Butterfield, A. (2017). Ambient and laboratory evaluation of a low-cost particulate matter sensor. *Environmental Pollution*, *221*, 491–500. https://doi.org/10.1016/j.envpol.2016.12.039

Kim, H., Müller, M., Henne, S., & Hüglin, C. (2022). Long-term behavior and stability of calibration models for NO and NO_2 low-cost sensors. *Atmospheric Measurement Techniques*, *15*(9), 2979–2992. https://doi.org/10.5194/amt-15-2979-2022

Kim, J., Shusterman, A. A., Lieschke, K. J., Newman, C., & Cohen, R. C. (2018). The BErkeley Atmospheric CO_2 Observation Network: Field calibration and evaluation of low-cost air quality sensors. *Atmospheric Measurement Techniques*, *11*(4), 1937–1946. https://doi.org/10.5194/amt-11-1937-2018

Levy Zamora, M., Buehler, C., Lei, H., Datta, A., Xiong, F., Gentner, D. R., & Koehler, K. (2022). Evaluating the Performance of Using Low-Cost Sensors to Calibrate for Cross-Sensitivities in a Multipollutant Network. *ACS ES&T Engineering*, *2*(5), 780–793. https://doi.org/10.1021/acsestengg.1c00367

Lewis, A., & Edwards, P. (2016). Validate personal air-pollution sensors. *Nature News*, *535*(7610), 29. https://doi.org/10.1038/535029a

Li, J., Hauryliuk, A., Malings, C., Eilenberg, S. R., Subramanian, R., & Presto, A. A. (2021). Characterizing the Aging of Alphasense NO2 Sensors in Long-Term Field Deployments. *ACS Sensors*, *6*(8), 2952–2959. https://doi.org/10.1021/acssensors.1c00729

Liang, L. (2021). Calibrating low-cost sensors for ambient air monitoring: Techniques, trends, and challenges. *Environmental Research*, *197*, 111163. https://doi.org/10.1016/j.envres.2021.111163

Liang, L., & Daniels, J. (2022). What Influences Low-cost Sensor Data Calibration? - A Systematic Assessment of Algorithms, Duration, and Predictor Selection. *Aerosol and Air Quality Research*, *22*(9), 220076. https://doi.org/10.4209/aaqr.220076

Liu, X., Jayaratne, R., Thai, P., Kuhn, T., Zing, I., Christensen, B., Lamont, R., Dunbabin, M., Zhu, S., Gao, J., Wainwright, D., Neale, D., Kan, R., Kirkwood, J., & Morawska, L. (2020). Low-cost sensors as an alternative for long-term air quality monitoring. *Environmental Research*, *185*, 109438. https://doi.org/10.1016/j.envres.2020.109438

Long, R. W., Whitehill, A., Habel, A., Urbanski, S., Halliday, H., Colón, M., Kaushik, S., & Landis, M. S. (2021). Comparison of ozone measurement methods in biomass burning smoke: An evaluation under field and laboratory conditions. *Atmospheric Measurement Techniques*, *14*(3), 1783–1800.

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques Discussions

https://doi.org/10.5194/amt-14-1783-2021

Malings, C., Tanzer, R., Hauryliuk, A., Saha, P. K., Robinson, A. L., Presto, A. A., & Subramanian, R. (2020). Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation. *Aerosol Science and Technology*, *54*(2), 160–174. https://doi.org/10.1080/02786826.2019.1623863

Molina Rueda, E., Carter, E., L'Orange, C., Quinn, C., & Volckens, J. (2023). Size-Resolved Field Performance of Low-Cost Sensors for Particulate Matter Air Pollution. *Environmental Science & Technology Letters*, *10*(3), 247–253. https://doi.org/10.1021/acs.estlett.3c00030

Moreno-Rangel, A., Sharpe, T., Musau, F., & McGill, G. (2018). Field evaluation of a low-cost indoor air quality monitor to quantify exposure to pollutants in residential environments. *Journal of Sensors and Sensor Systems*, *7*(1), 373–388. https://doi.org/10.5194/jsss-7-373-2018

Nazemi, H., Joseph, A., Park, J., & Emadi, A. (2019). Advanced Micro- and Nano-Gas Sensor Technology: A Review. *Sensors*, *19*(6), Article 6. https://doi.org/10.3390/s19061285

Nowack, P., Konstantinovskiy, L., Gardiner, H., & Cant, J. (2021). Machine learning calibration of low-cost NO_2 and PM_{10} sensors: Non-linear algorithms and their impact on site transferability. *Atmospheric Measurement Techniques*, *14*(8), 5637–5655. https://doi.org/10.5194/amt-14-5637-2021

Okure, D., Ssematimba, J., Sserunjogi, R., Gracia, N. L., Soppelsa, M. E., & Bainomugisha, E. (2022). Characterization of Ambient Air Quality in Selected Urban Areas in Uganda Using Low-Cost Sensing and Measurement Technologies. *Environmental Science & Technology*, *56*(6), 3324–3339. https://doi.org/10.1021/acs.est.1c01443

Ouyang, B. (2020). First-Principles Algorithm for Air Quality Electrochemical Gas Sensors. *ACS Sensors*, *5*(9), 2742–2746. https://doi.org/10.1021/acssensors.0c01129

Pang, X., Chen, L., Shi, K., Wu, F., Chen, J., Fang, S., Wang, J., & Xu, M. (2021). A lightweight low-cost and multipollutant sensor package for aerial observations of air pollutants in atmospheric boundary layer. *Science of The Total Environment*, *764*, 142828. https://doi.org/10.1016/j.scitotenv.2020.142828

Pang, X., Shaw, M. D., Gillot, S., & Lewis, A. C. (2018). The impacts of water vapour and co-pollutants on the performance of electrochemical gas sensors used for air quality monitoring. *Sensors and Actuators B: Chemical*, *266*, 674–684. https://doi.org/10.1016/j.snb.2018.03.144

PAS 4023. (2023). *Selection, deployment, and quality control of low-cost air quality sensor systems in outdoor ambient air – Code of practice*.

Pinder, R. W., Klopp, J. M., Kleiman, G., Hagler, G. S. W., Awe, Y., & Terry, S. (2019). Opportunities and challenges for filling the air quality data gap in low- and middle-income countries. *Atmospheric Environment*, *215*, 116794. https://doi.org/10.1016/j.atmosenv.2019.06.032

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Raheja, G., Sabi, K., Sonla, H., Gbedjangni, E. K., McFarlane, C. M., Hodoli, C. G., & Westervelt, D. M. (2022). A Network of Field-Calibrated Low-Cost Sensor Measurements of PM2.5 in Lomé, Togo, Over One to Two Years. *ACS Earth and Space Chemistry*, *6*(4), 1011–1021. https://doi.org/10.1021/acsearthspacechem.1c00391

Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., & Rickerby, D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of The Total Environment*, *607–608*, 691–705. https://doi.org/10.1016/j.scitotenv.2017.06.266

Ripoll, A., Viana, M., Padrosa, M., Querol, X., Minutolo, A., Hou, K. M., Barcelo-Ordinas, J. M., & Garcia-Vidal, J. (2019). Testing the performance of sensors for ozone pollution monitoring in a citizen science approach. *Science of The Total Environment*, *651*, 1166–1179. https://doi.org/10.1016/j.scitotenv.2018.09.257

Sayahi, T., Butterfield, A., & Kelly, K. E. (2019). Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. *Environmental Pollution*, *245*, 932–940. https://doi.org/10.1016/j.envpol.2018.11.065

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2017). Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. *Sensors and Actuators B: Chemical*, *238*, 706–715. https://doi.org/10.1016/j.snb.2016.07.036

Tanzer-Gruener, R., Li, J., Eilenberg, S. R., Robinson, A. L., & Presto, A. A. (2020). Impacts of Modifiable Factors on Ambient Air Pollution: A Case Study of COVID-19 Shutdowns. *Environmental Science & Technology Letters*, *7*(8), 554–559. https://doi.org/10.1021/acs.estlett.0c00365

Wang, Y., Li, J., Jing, H., Zhang, Q., Jiang, J., & Biswas, P. (2015). Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement. *Aerosol Science and Technology*, *49*(11), 1063–1077. https://doi.org/10.1080/02786826.2015.1100710

Williams, D. E. (2020). Electrochemical sensors for environmental gas analysis. *Current Opinion in Electrochemistry*, *22*, 145–153. https://doi.org/10.1016/j.coelec.2020.06.006

Wu, T. Y., Horender, S., Tancev, G., & Vasilatou, K. (2022). Evaluation of aerosol-spectrometer based PM2.5 and PM10 mass concentration measurement using ambient-like model aerosols in the laboratory. *Measurement*, *201*, 111761. https://doi.org/10.1016/j.measurement.2022.111761

Zamora, M. L., Rice, J., & Koehler, K. (2020). One year evaluation of three low-cost PM2.5 monitors. *Atmospheric Environment*, *235*, 117615. https://doi.org/10.1016/j.atmosenv.2020.117615

Zimmerman, N., Presto, A. A., Kumar, S. P. N., Gu, J., Hauryliuk, A., Robinson, E. S., Robinson, A. L., & R. Subramanian. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. *Atmospheric Measurement Techniques*, *11*(1), 291–313.

https://doi.org/10.5194/amt-2023-251
Preprint. Discussion started: 13 December 2023

Atmospheric Measurement Techniques Discussions
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692 https://doi.org/10.5194/amt-11-291-2018