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Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?

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ABSTRACT

The emergence of low-cost, user-friendly and very compact air pollution platforms enable observations at high spatial resolution in near-real-time and provide new opportunities to simultaneously enhance existing monitoring systems, as well as engage citizens in active environmental monitoring. This provides a whole new set of capabilities in the assessment of human exposure to air pollution. However, the data generated by these platforms are often of questionable quality.

We have conducted an exhaustive evaluation of 24 identical units of a commercial low-cost sensor platform against CEN (European Standardization Organization) reference analyzers, evaluating their measurement capability over time and a range of environmental conditions. Our results show that their performance varies spatially and temporally, as it depends on the atmospheric composition and the meteorological conditions. Our results show that the performance varies from unit to unit, which makes it necessary to examine the data quality of each node before its use.

In general, guidance is lacking on how to test such sensor nodes and ensure adequate performance prior to marketing these platforms. We have implemented and tested diverse metrics in order to assess if the sensor can be employed for applications that require high accuracy (i.e., to meet the Data Quality Objectives defined in air quality legislation, epidemiological studies) or lower accuracy (i.e., to represent the pollution level on a coarse scale, for purposes such as awareness raising).

Data quality is a pertinent concern, especially in citizen science applications, where citizens are collecting and interpreting the data. In general, while low-cost platforms present low accuracy for regulatory or health purposes they can provide relative and aggregated information about the observed air quality.

1. Introduction

Urban air quality represents a major public health burden and is a long-standing concern to citizens. Air pollution is associated with a range of diseases, symptoms and conditions that impair health and quality of life (e.g., Bentayeb et al., 2015; Pascal et al., 2013; Raaschou-Nielsen et al., 2016; Wu et al., 2016). European cities, as with many other cities worldwide, are facing challenges in their fight against air pollution. Many efforts have been carried out to combat air pollution. However, levels of air pollution are still a problem in some cities. For instance, many European cities do not meet the requirements set out in air quality regulations (EEA, 2013, 2015).

1.1. Current monitoring systems

Historically, air quality monitoring has been conducted for two main purposes: legislation surveillance and scientific research. Currently air pollution concentrations are monitored by professional personnel (i.e., government authorities, scientists, health experts) using static monitoring stations equipped with certified reference instruments for measuring regulatory pollutants, such as carbon monoxide (CO), nitrogen oxides (NO_x, NO, NO_2), ozone (O_3) and particulate matter (PM_{10}, $PM_{2.5}$). The air pollutant analyzers are relatively large, heavy and expensive, with prices ranging between €5000 and €30,000 per device. Traditional fixed-site air quality monitoring stations are also subject to strict routines of maintenance and calibration of their instruments, to ensure high quality data and comparability between different stations and regions.

Large cities in developed countries are usually dotted with a network of reference monitoring stations that monitor air quality in real-time. However, the high costs of installation and maintenance of

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reference monitoring stations results in a relatively sparse monitoring, which provides accurate data but only in few locations, satisfying the legislative requirements but not providing information about localized gradients of potential importance to health protection. Moreover, in smaller cities or in underdeveloped regions, such air quality monitoring (AQM) stations may not exist. The fixed monitoring network is sometimes complemented by mobile air quality monitoring stations. These units usually have the same line of instrumentation as the fixed monitoring stations, mounted on vehicles, and the instruments have the same maintenance and calibration routines. Often, mobile monitoring stations are used for stationary measurements over a fixed period of time (e.g., a measurement campaign) in certain locations not covered by the fixed monitoring network (Glasius, 2006; Röösli et al., 2000). However, due to their high cost, mobile AQM vehicles cannot significantly increase spatial sampling density. The major limitation of mobile AQM data from the perspective of health protection is that their temporal coverage is incomplete.

Air quality monitoring may also be based on passive samplers. Such devices have the advantage in that they are inexpensive to deploy and operate (excluding laboratory analysis), easy to use and do not require electricity. The limitation of passive samplers is that they only allow the quantification of cumulative air pollutant levels, and therefore cannot identify short-term pollutant episodes or even track common temporal patterns (e.g., diurnal variability). Moreover, passive samplers are not as accurate as reference instrumentation, suffer from chemical interference, and are also affected by the atmospheric conditions (Krupa and Legge, 2000; Plaisance et al., 2004).

Finally, air quality models are an effective tool to supplement air quality monitoring. Models can also be used for tasks that cannot be conducted by monitoring alone, (e.g., scenario analysis, forecasting). However, the use of models requires a highly specialized knowledge and input data that is not available in all places. Moreover, in most cases air quality models do not run in an operational mode but rather in a prospective mode. Modelled concentrations may also suffer from systematic errors, including bias, depending on the input data and on the modeller parametrization choices (Pannullo et al., 2016).

1.2. Low-cost air quality platforms

There is a current trend worldwide to increase the collection of air quality data beyond reference monitoring stations. However, legislation to regulate the usability of these data is not in place yet (Castell et al., 2013; Kumar et al., 2015; Lewis and Edwards, 2016).

Several research projects are exploring the possibility of collecting air quality data using low-cost sensor platforms. Examples include OpenSense (www.opensense.ethz.ch) and Citi-Sense-MOB (Castell et al., 2015) that use mobile platforms to monitor air pollution variation in cities, Everyaware (www.everyaware.eu) that helps citizens collect and share noise and air pollution data and Citi-Sense (www.citi-sense.eu) that empowers people to use low-cost air quality platforms in 8 cities across Europe.

Sensor platforms are currently available to monitor a range of air pollutants and new devices are continually being introduced (Aleixandre and Gerboles, 2012; Snyder et al., 2013; Piedrahita et al., 2014). Air pollution sensors can be classified into two groups; those that measure gas phase species and those that measure particulate matter.

Commercially available gas sensors operate by measuring either the electrochemical interaction between the sensing material and the pollutant (i.e., electrochemical or metal oxide technologies) or the absorption of light at the visible range (Aleixandre and Gerboles, 2012). Particulate matter is measured by light scattering or absorption, using algorithms to relate the attenuated signal to the particle size and/or composition.

These individual sensors need to be integrated into a sensor platform or node. The sensor node contains a sensor board, the sensors, and a control board that integrates all the required electronics (e.g., signal conditioning, GPS, communication ports, data storage). The number and type of commercially available sensor platforms is increasing at a rapid pace. Whereas the price of individual gas sensors ranges from €20 to €100, the cost of a commercial sensor node that includes several sensors can reach €500–€5000.

1.3. New opportunities for ubiquitous monitoring

All European countries are required to comply with the EU Directives. The framework and legal requirements for assessment and management of ambient air quality are described in the Air Quality Directive 2008/50/EC (EU, 2008). The Air Quality Directive (AQD) establishes the criteria for air quality monitoring. It defines the reference measurement methods that Member States shall apply when monitoring air quality. These methods are currently applied in the fixed monitoring station networks in European cities. However, the AQD also opens the door for the use of other supplementary techniques, such as air quality models and indicative measurements.

Low cost sensor platforms can play an important role in air quality monitoring. Sensor nodes can be deployed as dense networks (ubiquitous monitoring) or mounted on vehicles, facilitating the elaboration of high-resolution air quality maps (Hasenfratz et al., 2015; Schneider et al., 2016). The reduced size of the low-cost platforms also allows new research in personal exposure. 'Wearable' platforms are able to consider changes in exposure due to changes in location and activities and provide new capabilities to evaluate health risk from air pollution (Bossche et al., 2016; Nazelle et al., 2013).

Legislation requires measuring of PM_{10} and $PM_{2.5}$. However, there is a growing concern on whether mass-based measurements are indeed relevant for assessing health effects of particulate pollution, or number-based measurements should be eventually promoted (Kumar et al., 2010). Several toxicological and panel studies present significant associations between elevated nanoparticle number concentrations (10–100 nm) and daily total as well as cardio-respiratory mortality using time-series epidemiological analysis (Stölzel et al., 2007), promoting number concentrations measurements as an appropriate metric for assessing health effects (Nel et al., 2006; Peters et al., 1997 and Xia et al., 2009).

We are experiencing now a paradigm shift in how and who is monitoring air quality (Castell et al., 2013; Lewis and Edwards, 2016). Attributes of sensor platforms are relatively lower in cost, easier to use and less bulky than traditional equipment, and provide the possibility for citizens and communities to monitor their local air quality that may affect their health (Snyder et al., 2013). Indeed, interest in low cost sensors is on the rise even before the sensor performance has been evaluated, and widespread data collection and data sharing using these sensor technologies is already occurring (Snyder et al., 2013; Lewis and Edwards, 2016). Examples are AirVisual, a crowdsourced community that has developed a home air quality monitor (https://www.indiegogo.com/projects/airvisual-node-the-world-s-smartest-air-monitor#/) and AirCasting - an open-source solution for collecting, displaying and sharing air pollution data (http://aircasting.org/). However, in order to employ low-cost platforms for air quality management and health studies, it is necessary to ensure their measurement reproducibility and assess any associated uncertainty. For example, it is known that low-cost sensors suffer from chemical interference and are affected by environmental conditions (Aleixandre and Gerboles, 2012).

The main challenge that low cost sensor technology faces in relation to legally based monitoring is to reach data quality requirements set by the AQD. Namely, to supplement air quality monitoring networks for scientific research, these data need to meet an acceptable level of quality. However, for many other applications, such as citizen awareness or community monitoring, it may be not crucial to have sensor platforms

that meet the requirements set by the AQD, and other criteria for the acceptance of results may be developed and applied.

Information regarding low-cost sensor performance is only beginning to be available (Mead et al., 2013; Holstius et al., 2014; Marco, 2014; Järvinen et al., 2015; Jovasevic-Stojanovic et al., 2015; Moltchanov et al., 2015). However, there is currently lack of information provided by the platform manufacturers regarding the performance of their sensor platforms. In most cases, neither error characteristics nor data quality and stability over long-term deployment in the field, with varying environmental conditions, have been evaluated. Therefore, when acquiring a sensor platform it is difficult for the user to know if the platform performance is sufficient for the intended purpose.

In this manuscript we present an extensive performance evaluation of the commercial AQMesh platform (monitoring NO, NO_2, O_3, CO, PM_{10} and $PM_{2.5}$) in both laboratory and field conditions. Co-location of 24 identical AQMesh platforms in the field was performed over 6 months (April to September 2015) allowing for a detailed characterization of the temporal performance variability and the variation in performance across identical platforms. Additionally, the field campaign included studying the sensor nodes at different monitoring stations, which were distinctly affected by urban traffic and urban background pollutant levels.

There is insufficient guidance on how to test low-cost sensor platforms to ensure adequate performance. Spinelle et al. (2013) drafted a first protocol for evaluation of low-cost gas sensors. The European Committee for Standardization (CEN/TC264/WG42) is currently working on the definition of the technical specifications for performance requirements and test methods under prescribed laboratory and field conditions for low-cost sensors. To date, when acquiring a low-cost sensor platform, it is not possible to know if it will be fit for its purpose. In this manuscript, we investigate whether a low-cost monitoring system can provide reliable indications about air quality trends and patterns. As the required data quality may vary depending on the application, we have implemented and tested diverse metrics to examine to what extent the data quality is suitable for different applications (e.g., regulative purposes, exposure estimates, community monitoring, and education). As such, we have analysed the main challenges faced by sensor platforms: (i) differences between laboratory and field calibration; (ii) long-term performance; (iii) response to varying weather conditions; and (iv) effect of deployment location and proximity to sources.

2. Experimental methods and materials

2.1. The AQMesh platform

AQMesh units (Environmental Instruments Ltd, UK, www.aqmesh.com) are battery operated stationary platforms that measure four gaseous components (CO, NO, NO_2 and O_3) and the total particle count (as an integration over 32 particle size channels). PM_{10} and $PM_{2.5}$ are estimated by converting the particle counts into PM mass-based fractions assuming a spherical particle shape and standard density. The refraction index and density are part of the algorithm, but the values employed are not known to us. Typical values are $1.56 \pm 0.086i$ for the refraction index and 1.87 g/cm^3 for the density (Hand and Kreidenweis, 2002). A proprietary algorithm is used to post-process the data gathered by the gas sensors, aiming to correct for cross-interferences and for the effect of temperature and relative humidity. The AQMesh nodes measure also temperature, relative humidity and atmospheric pressure. Tables SI-1 and SI-2 in the Supplementary Information present the platform information for the gas and particle sensors, respectively. We tested AQMesh platforms from the v3.5 series. This version includes an O_3-filtered NO_2 sensor (Alphasense Ltd) that is designed to efficiently filter O_3 and, hence, eliminate cross-sensitivity issues.

Standard AQMesh nodes deliver one-hour averaged data but can be configured to deliver 15 min averaged data. An integrated GPRS modem allows data transfer to the AQMesh database server. The data can then be downloaded from a dedicated website.

2.2. Laboratory set-up

The laboratory study evaluated the performance of the sensors against traceable gas standards under reproducible and accurately controlled ambient conditions. The sensor node was located in a measurement chamber made of a borosilicate glass in a thermostatic bath. Temperature and relative humidity were kept constant at 20 °C and 30%, respectively. Both parameters showed relative standard deviation below 1% during the testing sequence. The selection of the ambient temperature was imposed by the laboratory set-up whereas humidity level was an arbitrary choice. A standard dilution system generated all the necessary concentrations by diluting traceable primary gas standards with zero-air. NO_2 was automatically produced by the dilution device which includes an O_3 generator, with NO_2 production relying on stoichiometric reaction between diluted NO and produced O_3. The test protocol consists of a multi-point calibration involving five different gas levels plus zero-air.

CEN approved gas analyzers were connected to the output of the measurement chamber. Measurements of CO were made using non-dispersive infrared spectroscopy (EN14626) with a Teledyne API 300E (detection limit of 40 ppb). Measurements of NO_x were performed using the chemiluminescence reaction of O_3 with NO along with the catalytic reduction of NO_2 to NO (EN 14211) with a Teledyne API 200A (detection limit of 0.4 ppb). Measurements of O_3 are made using the principle of UV photometry (EN14625) with a Teledyne API 400 (detection limit of 0.4 ppb).

2.3. Air quality monitoring stations

The characterization of the AQMesh low-cost platforms included field testing against reference instruments (co-location) for a range of different environmental conditions (e.g., weather, traffic). The field tests were designed to identify additional errors that can be introduced when sensors are exposed to real-world conditions, which could not be tested in the laboratory. For field evaluation, Spinelle et al. (2013) recommend to have the sensor measuring for at least 3 months on the field.

Between April and June 2015, 24 AQMesh nodes were co-located at the reference AQM station of Kirkeveien, Oslo, Norway. From July to September 2015, the nodes were distributed between four AQM stations in Oslo: Kirkeveien (10 units), Manglerud (4 units), Åkebergveien (5 units) and Alnabru (4 units). Unfortunately, the station at Alnabru was not operative during most of the co-location period and cannot be included in the analysis. The AQM stations at Kirkeveien and Manglerud are close to streets with busy traffic, while the AQM station at Åkebergveien is in the intersection of two streets with low to medium traffic. The distribution of the nodes to the different AQM stations has allowed us to evaluate the performance in different urban environments. A total of 10 nodes were co-located at the Kirkeveien AQM station between April and September 2015, allowing evaluating long-term performance.

All the AQM stations are equipped with CEN approved gas and PM analyzers. The station at Kirkeveien is equipped with CO, NO_x, O_3 and PM analyzers. The stations at Manglerud and Åkebergveien are equipped with NO_x and PM analyzers. CO is measured using non-dispersive infrared spectroscopy (EN14626), NO_x is measured using chemiluminescence (EN14211) and O_3 is measured using UV photometry (EN14625). PM is measured using TEOM (inertial measurement) with a Thermo TEOM (EN12341) in Kirkeveien and Manglerud and by Mie diffraction (optical measurement) with a Grimm 180 (EN12341) in Åkebergveien.

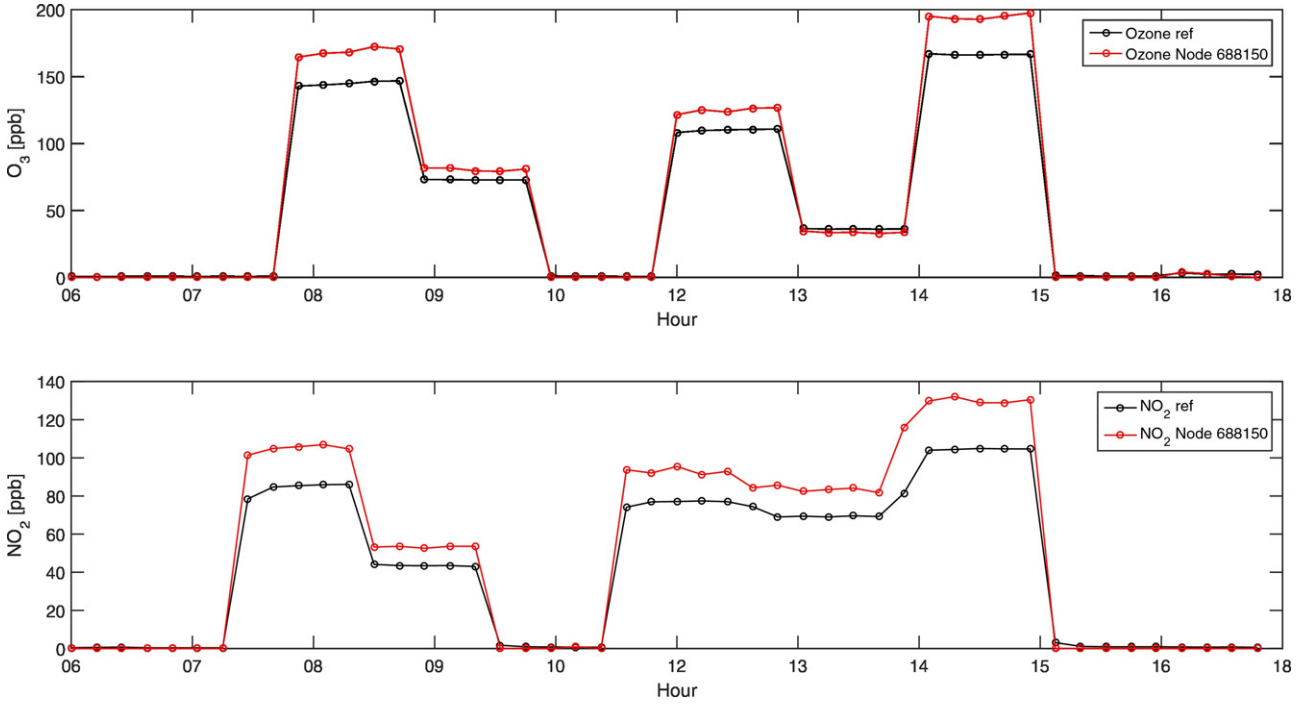

Fig. 1. Calibration sequences for O_3 and NO_2 sensors from the AQMesh node 688150.

2.4. Performance evaluation methods

2.4.1. Basic data analysis

The comparison between the data collected by the AQMesh platforms and the reference instrumentation is based on widely used statistical measures (e.g., Yuval and Broday, 2013; Table SI-3).

2.4.2. Data Quality Objective analysis

The European Air Quality Directive (EU, 2008) defines the Data Quality Objective (DQO) that monitoring methods need to comply with to be used as indicative measurements for regulative purposes. The DQO is a measure of the acceptable uncertainty for indicative measurements. According to the Directive, allowed uncertainties are 50% for PM_{10} and $PM_{2.5}$, 30% for O_3 and 25% for CO, NO_x, NO_2 and SO_2.

To assess the performance of each sensor and of the sensor platform as a whole, the measurement of uncertainty has been calculated following the methodology described in JCGM (2008) and Spinelle et al. (2015). The relative expanded uncertainty U_r was estimated using Eq. (1), where b_0 and b_1 are the slope and intercept of the orthogonal regression, respectively, *RSS* is the sum of squares of the residuals (Eq. (2)), and u is the uncertainty of the reference instrument, obtained from the CEN standards (e.g., 14211). Further details on the calculation of the expanded uncertainty can be found in the Guide for the demonstration of equivalence (EC WG, 2010).

$$U_r(y_i) = \frac{2\left(\frac{RSS}{(n-2)} - u^2(x_i) + [b_0 + (b_1 - 1)x_i]^2\right)^{1/2}}{y_i} \quad (1)$$

$$RSS = \sum (y_i - b_0 - b_1 x_i)^2 \quad (2)$$

2.4.3. Match score analysis

The measure of the capacity to represent the pollution level on a coarse scale is interesting when the application does not require precise measurements but rather a more general advice whether the air pollution is high or low. This is the case, for example, in community monitoring and raising citizen awareness. The match score computes the proportion of agreement among strata for increasing amount of sub-partitions between the reference and the sensor platform measurements (Supplementary Information Fig. SI-1). The sub-partitions do not consider the possible bias between the two data sets. A match score of 1 indicates that the agreement between the sensor platform and the reference instrument is perfect (Castell et al., 2016; Fishbain et al., 2016).

3. Results

3.1. Laboratory evaluation

Two sensor nodes were tested in the laboratory (id = 688150 and id = 864150). Node 688150 was tested before being deployed in the field, while node 864150 was tested after 3 months of field deployment. The reason for testing 864150 in the laboratory after field deployment was that the results in field showed low correlations for NO_2 and O_3 with the AQM data ($r < 0.3$).

As mentioned earlier, the instruments were tested with repeated multi-point calibration sequences including four to five different gas concentrations plus zero-air. Fig. 1 displays the responses for O_3 and NO_2 sensors to step changes in the respective calibration gases for a full calibration sequence of the node 688150. For all the gases, there is a close correspondence between reference instruments and the data from the sensors, although there are differences in absolute values. Both O_3 and NO_2 sensors overestimate the measured concentrations. The CO sensor underestimates the measurand whereas the response from the NO sensor is very close to the one from the reference analyzer (Fig. SI-2).

The correlation plots (Figs. SI-3 and SI-4) show that all the tested sensors presented a linear response, with the slope and intercept close to 1 and 0, respectively. Table 1 shows the results obtained in the test performed in the laboratory, under controlled conditions. The results show that both platforms have good correlations with reference values ($r > 0.9$) for all the parameter analyzer. We also analyzed the cross-sensitivity with other gases, i.e., the contribution of compounds other than the desired compound to the overall sensor response. The results showed that while the O_3 sensor in node 688150 has low cross-

Table 1
Summary of the calibration of AQMesh nodes 688150 and 864150 in the laboratory. The cross-sensitivity has been rated as N = no, L = low and H = high.

Platform	Data Average Time (seconds)	Species/parameter	Correlation (r)	Slope	Intercept [ppb]	Observed cross-sensitivity between gas (species)
688150	900	CO	0.99	0.86	0.07	NO_2:N, O_3:N, NO:N
		NO	0.99	0.97	−1.13	NO_2:N, O_3:N, CO:N
		NO_2	0.99	1.22	−1.02	O_3:N, NO:N, CO:N
		O_3	0.99	1.16	−1.27	NO_2:L, CO:N, NO:N
864150	900	CO	–	–	–	–
		NO	–	–	–	–
		NO_2	0.96	1.21	3.85	O_3:N
		O_3	0.99	0.99	3.25	NO_2:H

sensitivity with NO_2, the cross-sensitivity is high for node 864150. The NO_2 sensor does not show cross-sensitivity with O_3 in the laboratory tests. Both nodes use the Alphasense NO_2 sensor (series B), which incorporates a filter to reduce or eliminate O_3 cross-interference.

Table SI-4 displays the mean and standard deviation for the reference instruments and the AQMesh for zero-air and concentrations of 100 ppb for NO, NO_2 and O_3 and 1300 ppb for CO (refered as span values). The mean and standard deviation were calculated considering 24 measurements.

The limit of detection (LOD) of low-cost sensors can be estimated as 3 times the standard deviation when measuring zero-air (Spinelle et al., 2013). Before estimating the LOD all the sensor outputs were corrected based on the results from the calibration (i.e., applying a linear calibration with the slope and intercept obtained in the laboratory). The responses of NO, NO_2 and O_3 sensors were constantly 0 for zero-air. In that case, the LOD can be estimated by analyzing the relation between different measured concentrations (i.e., five different points) and their associated standard deviations. Assuming the standard deviation varies linearly with the concentration, the regression line between the two variables can be extrapolated down to zero concentration. This method gives a LOD for NO, NO_2 and O_3 of 2.4 ppb, 2.7 ppb and 1.8 ppb, respectively. The LOD for the CO sensor can be calculated directly by multiplying the standard deviation of the sensor signal when measuring zero-air by 3, obtaining a LOD of 21 ppb.

The repeatability of the sensor response at selected concentrations can be calculated by multiplying the standard deviation of the signal at the span concentration by a factor of $2\sqrt{2}$ (Spinelle et al., 2013). The results (Table SI-4) show that all tested sensors have relatively good precision during the tests performed under stable laboratory conditions.

3.2. Field results

3.2.1. Calibration

Observations from 24 AQMesh nodes were evaluated against data from the reference instruments at the Kirkeveien AQM station for the period 13th April–24th June 2015. Meteorological conditions during the co-location period show an average relative humidity of 63% (range: 19%–98%) and an average temperature of 10 °C (range: −0.7 °C–23.3 °C).

Table 2 summarizes the calibration results from both the laboratory and the field studies for nodes 688150 and 864150. The results show a clear need for field calibration. For instance, field calibration of node 688150 reveal an offset of 166 ppb for CO, compared with an offset of 0.07 ppb obtained during the laboratory tests. The slope and intercept for NO were very similar in the laboratory and the field. The other gases, NO_2 and O_3, showed a large difference in both the slope and the intercept.

Correlations between node and reference data were also significantly lower in the field than in the laboratory. The highest correlation was obtained for the NO sensor, and was comparable to the one found in the laboratory.

On the basis of the laboratory study, the sensors for the different gases appear to respond at the ppb level and to show a linear behavior. Also, based solely on the laboratory tests, the limit of detection and repeatability of the different sensors are compatible with their use for air quality management. However, when deployed in field other sensor characteristics appear, such as sensitivity to the varying ambient temperature and relative humidity (see also Section 3.2.4).

3.2.2. Performance evaluation

Table 3 shows the basic statistics obtained during the co-location of 24 identical AQMesh nodes for the period 13th April–24th June 2015, at the reference station of Kirkeveien.

Results for CO showed an inter-nodal correlation that ranges between 0.47 and 0.67, with 1 out of the 24 nodes showing a correlation below 0.5. The nodes showed a bias in the range 133–156 ppb. NO showed the highest correlation among all the measured species, with an average of 0.86 and with all the nodes showing correlations higher than 0.5. In contrast, for NO_2 12 out of the 24 nodes had a correlation < 0.5. The mean bias for NO_2 was 75 ppb. For O_3, the correlations spanned the range of 0.09–0.8, with 8 nodes out of the 24 having a correlation below 0.5. For particulate matter, the RMSE is higher for PM_{10} than for $PM_{2.5}$, with an average value of 64 ppb for PM_{10} and 7 ppb for $PM_{2.5}$. For PM_{10}, 5 out of 24 nodes showed correlations < 0.5, while for $PM_{2.5}$ 8 nodes had correlations < 0.5.

The results show that even for identical sensors and platform, the performance can vary from sensor to sensor. Carotta et al. (2001) described the need for careful control of the sensor manufacturing process for ensuring sensor repeatability. Our results show that performance of two sensors from the same series can be very different in the field. Performing field calibration will help to reduce the bias and measurement errors, especially for those sensors that have higher offsets. In our case, after performing a linear regression, the average RMSE of the 24 pods was reduced from 181 ppb to 87 ppb for CO, from 31 ppb to

Table 2
Summary of calibration results of AQMesh nodes 688150 and 864150 in the laboratory and the field (collocation with AQM station).

AQMesh unit	Species/parameter	Correlation (laboratory)	Correlation (field)	Slope (laboratory)	Slope (field)	Intercept (laboratory) [ppb]	Intercept (field) [ppb]
688150	CO	0.99	0.58	0.86	0.88	0.07	166
	NO	0.99	0.96	0.97	0.93	−1.13	−0.12
	NO_2	0.99	0.65	1.22	0.38	−1.02	3.8
	O_3	0.99	0.81	1.16	0.26	−1.27	7.2
864150	NO_2	0.96	0.30	1.21	0.2	3.85	16
	O_3	0.99	0.32	0.99	0.11	3.25	9

Table 3
Summary statistics for the 24 AQMesh sensor nodes during their collocation at Kirkeveien, April–June 2015.

Species		MB	MGE	NMB	NMGE	RMSE	*r*
CO	Average	−147.21	149.35	−0.68	0.69	170.99	0.60
	Max	−132.90	157.96	−0.62	0.71	181.28	0.67
	Min	−156.21	136.05	−0.70	0.63	159.04	0.47
NO	Average	−0.54	12.48	0.00	0.64	16.35	0.86
	Max	12.75	22.01	0.73	1.34	30.94	0.98
	Min	−15.05	4.84	−0.71	0.25	6.97	0.60
NO_2	Average	13.30	26.23	0.98	1.79	30.27	0.49
	Max	74.66	74.69	5.42	5.42	81.60	0.72
	Min	−22.73	12.56	−1.31	0.85	15.52	0.21
O_3	Average	6.76	19.87	0.62	1.64	22.20	0.54
	Max	40.71	40.96	3.52	3.53	44.27	0.81
	Min	−28.66	9.60	−1.90	0.79	11.77	0.09
PM_{10}	Average	−2.00	7.92	−0.14	0.55	18.50	0.56
	Max	1.31	9.40	0.09	0.64	64.38	0.73
	Min	−8.12	6.58	−0.54	0.45	13.82	0.19
$PM_{2.5}$	Average	−0.03	3.08	−0.01	0.69	5.57	0.51
	Max	0.56	3.47	0.12	0.77	6.55	0.63
	Min	−2.00	2.83	−0.44	0.62	4.13	0.42

10 ppb for NO, from 30 ppb to 9 ppb for NO_2, from 22 ppb to 3 ppb for O_3, from 19 ppb to 13 ppb for PM_{10} and from 6 ppb to 3 ppb for $PM_{2.5}$.

De Vito et al. (2008, 2009) and Tsujita et al. (2005) stressed the importance of calibration of urban air quality sensors in the reduction of measurement error. Spinelle et al. (2015, 2017) showed that field calibration employing supervised learning techniques is more effective than linear or multilinear regression techniques. Although various methods have been developed, field calibration of low-cost sensors still represents a challenge (Spinelle et al., 2017; Moltchanov et al., 2015).

3.2.3. Long term performance evaluation

Ten AQMesh units were co-located at Kirkeveien station for 6 months, between April and September 2015. The results show a clear change in behavior of the sensor platforms during the co-location period. This might be related to the sensors' detection limit and to the varying air composition and meteorological conditions. We observed that the performance for CO, NO and NO_2 worsened during the month of July and improved again in August and September (Fig. 2). During July, CO and NO_x levels were lower than during other months because there is less traffic, as this is the time when most people take vacation. O_3 coefficient of determination did not show significant changes, and on average was below 0.3 during the 6 months. For PM_{10} we observed that the performance was lower during May and July (Fig. SI-5). May, June and July were the months with lower PM_{10} average concentrations (8–10 μg/m^3 monthly average for 2015). For $PM_{2.5}$, the performance was lower during June and July, also coinciding with the months with lower $PM_{2.5}$ ambient concentrations.

The monthly average values of the slope and intercept show that the month to month variation can be significant. This can lead to increased errors and biases that can pass unnoticed once the sensor nodes are deployed in the field. Fig. 2 shows an example of how the linear calibration parameters vary for the NO concentrations measured by a node co-located at Kirkeveien station.

3.2.4. Dependence on meteorological conditions

One of the main challenges when using electrochemical low-cost sensors is that they suffer from interference with temperature and relative humidity (Aleixandre and Gerboles, 2012; Mead et al., 2013). Generic data describing the relationship between the sensor current response, the temperature and the relative humidity are available from the sensor manufacturer, and the manufacturer of the AQMesh platform has already implemented correction factors for these effects. In this section, we analyse how the bias (computed as the difference between concentrations measured by the AQMesh node and the reference equipment) varies with temperature and relative humidity.

Fig. 3 shows the variation of the absolute bias with temperature for NO concentrations measured by co-located AQMesh nodes. It can be seen that the nodes' performance varies. For instance, node 688150 shows no significant bias, node 864150 shows increasing bias with temperature increase, and node 785150 shows higher bias when the temperature is below 5 °C or above 10 °C. This indicates that while the manufacturer adjustments work well for some nodes, they do not work as well for other nodes. Regarding relative humidity, the bias also varies from node to node (Fig. SI-6). For example, some nodes show high bias when the relative humidity is below 50% (e.g., node 862150), while other (e.g., node 688150) show negligible bias. Similar results were obtained for the other pollutants (CO, NO_2, O_3, PM_{10} and $PM_{2.5}$).

Our results show that the response of each sensor is unique, and that it is therefore necessary to evaluate each sensor node individually before deploying it in the field. In particular, the data supplied by the sensor manufacturers is insufficient for correcting the measurements under real-world conditions, where large temperature and relative humidity variations are encountered. Indeed, recent studies show the advantage

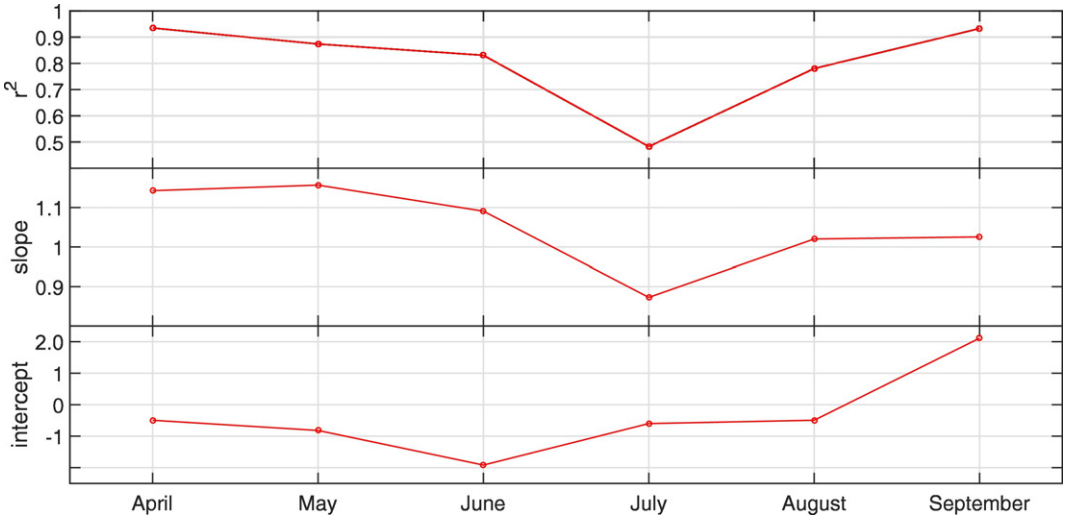

Fig. 2. Linear calibration parameters for NO concentrations measured by the node 715150. The node was co-located at Kirkeveien between April and September 2015.

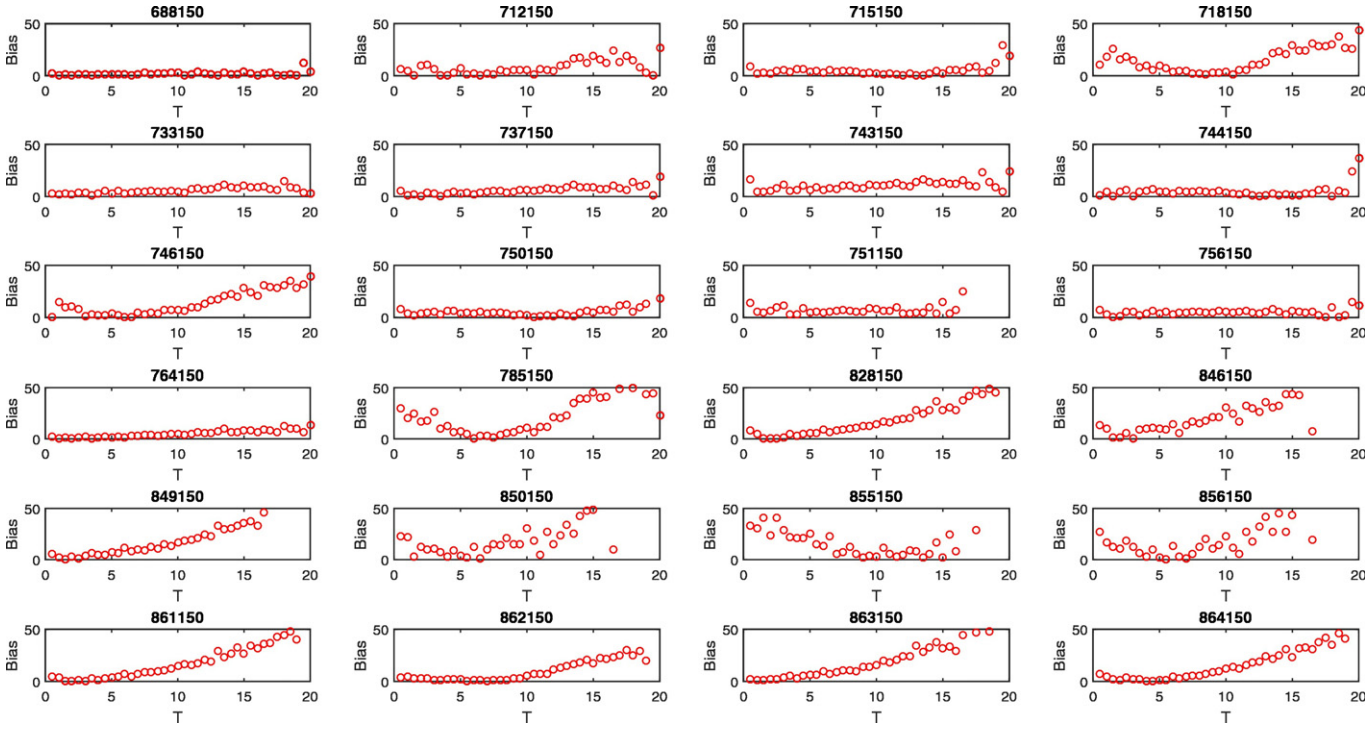

Fig. 3. Absolute bias (y-axis) for NO concentrations in relation to temperature (range: 0–20 °C) for AQMesh nodes co-located at Kirkeveien station, Oslo, Norway.

of applying post-processing methods, such as multiple regression, neural network and machine learning, to correct for the impact of environmental conditions on electrochemical sensors (Spinelle et al., 2015; Sun et al., 2016).

3.2.5. Dependence on the location

In order to evaluate the sensor performance in different urban environments the platforms were co-located during the period between 1st July–22nd September 2015, at 3 reference stations: Kirkeveien and Manglerud (near busy roads) and Åkebergveien (a calm street).

For NO_2 the results indicated poor correlations in all three locations, with all correlations < 0.7. For NO, the correlations were good at the three stations although lower at Åkebergveien AQM station (0.5–0.8) compared to the two urban AQM stations known to be affected by busy traffic (0.8–0.9; in Kirkeveien and Manglerud). This may be due to the lower NO_x concentrations at urban background AQM stations compared to stations close to dense traffic.

For particulate matter, the results show a better correlation at the station located in a calm street, with correlations of 0.7–0.8 for PM_{10} and of 0.8–0.9 for $PM_{2.5}$. At the traffic AQM stations, r was <0.4 for both PM_{10} and $PM_{2.5}$. It should be noted that the AQMesh node estimates the PM mass concentration based on OPC number measurements, using several assumptions discussed in Section 2. In AQM stations close to traffic, the particles are freshly emitted and their composition might differ from the particles found in background stations, due to aging and restructuring (Broday and Rosenzweig, 2011). In the case of the AQMesh nodes, the conversion factors used within the algorithm to obtain PM mass seem to be better tuned for background sites.

Table 4 reports calibration results obtained for node 688150 during laboratory and field tests. Field tests took place at a station close to a busy road (Kirkeveien, 13/04–24/06, 2015) and a station in a calm street (Åkebergveien, 01/07–22/09, 2015). Reference O_3 and CO gas analyzers were not available at Åkebergveien station. As already mentioned, the results show that the performance for the NO and NO_2 sensors was better at the traffic AQM station, probably due to the higher ambient NOx concentrations. For gaseous pollutants, the laboratory results were much better than the field results, i.e., the sensor performance under controlled laboratory conditions was better than in the field. For PM, the measurement is more reliable at the background AQM station than at the traffic AQM stations.

The linear calibration parameters were different when the node was located in traffic-saturated environment or at a traffic-calm environment. This highlights the importance of calibrating the nodes in an environment similar to the one in which they would be deployed (or better, to perform in-situ calibration at the deployment site).

3.3. Data Quality Objective results

The use of low-cost sensors as indicative measurements could reduce the cost of air pollution monitoring as well as allow larger spatial coverage, especially in remote areas where the use of traditional equipment is complicated. However, to be used for regulatory purposes, sensor platforms should comply with the Data Quality Objectives (DQOs) defined in the AQD (EU, 2008): 50% uncertainty for PM_{10} and $PM_{2.5}$, 30% uncertainty for O_3 and 25% uncertainty for CO, NO_x, NO_2 and SO_2.

Results for NO show that for some nodes the expanded uncertainty is <20% for concentrations above 50 ppb (Fig. 4, left panel) whereas for other nodes higher expanded uncertainties were obtained (40%–80%) even for high concentrations (Fig. 4, right panel). For CO, the

Table 4
Summary of the calibration of AQMesh node 688150 in the laboratory and at two locations in field: dense traffic (Kirkeveien) and calm traffic (Åkebergveien).

	CO	NO	NO_2	O_3	PM_{10}	$PM_{2.5}$
Coef. determination (r^2) lab	0.99	0.99	0.99	0.99	–	–
Coef. determination (r^2) field (dense traffic)	0.34	0.92	0.42	0.65	0.53	0.40
Coef. determination (r^2) field (calm traffic)	–	0.24	0.15	–	0.68	0.84
Slope lab	0.86	0.97	1.22	1.16	–	–
Slope field (dense traffic)	0.88	0.93	0.38	0.26	1.30	0.51
Slope field (calm traffic)	–	0.27	0.087	–	2.10	1.90
Intercept lab	0.07	−1.13	−1.02	−1.27	–	–
Intercept field (dense traffic)	166	−0.12	3.80	7.20	5.60	3.30
Intercept field (calm traffic)	–	4.20	6.90	–	−1.30	0.98

results show that the expanded uncertainties were about 100% for concentrations above 300 ppb, with higher expanded uncertainties observed for lower concentrations (Fig. SI-7). Expanded uncertainties for NO_2 (Fig. SI-8) and O_3 (Fig. SI-9) were also above 100% even at high concentrations. For PM_{10}, the expanded uncertainties are below or close to 50% for some of the nodes for concentrations above 75 μg/m^3 (Fig. SI-10). For $PM_{2.5}$ the expanded uncertainty is close to 50% for some of the nodes (Fig. SI-11). Thus, the evaluation of the sensors' expanded uncertainty as a measure of its suitability for indicative monitoring shows high variability and a largely expanded uncertainty that exceeds the DQO defined in the AQD for CO, NO_2 and O_3. The results are better for NO and PM, but still we observe variability from sensor to sensor.

3.4. Match score analysis

It is clear that for most citizen applications (e.g., awareness raising and education) data quality does not need to reach the same standards necessary for air quality management by authorities or for research (e.g., legislation compliance and health studies). We have computed the match score (see Section 2.4.3) for the 24 sensor nodes co-located at Kirkeveien AQM during the period between April and June 2015. The aim is to see to what extent the sensor platform is able to provide an indication of the air pollution levels, i.e., whether the air pollution is low, medium, or high. This is similar to the information that authorities offer to citizens based on an Air Quality Index (AQI), which aggregates information from the reference monitoring stations.

Table 5 shows the results of the match score analysis. NO and PM_{10} show very good results, with an average match score close of 0.8 and 0.9, respectively. For NO_2, CO, O_3 and $PM_{2.5}$ the match score is below 0.5, indicating that the agreement between the sensor platform and the station is not good.

Fig. 5 shows the daily variation for NO and PM_{10} concentrations. The sensor platform is capable of reproducing the time variation measured at the reference station. Thus, even if their data uncertainty is too high for use for legislative purposes, some sensors are still capable of offering interesting information to concerned citizens.

4. Conclusions

We have evaluated the performance of commercial low-cost sensors (AQMesh v3.5) measuring four gaseous pollutants (NO, NO_2, O_3, CO) and particulate matter (PM_{10} and $PM_{2.5}$). We performed the tests in the laboratory against traceable gas standards and controlled ambient conditions and in the field where 24 AQMesh nodes were co-located against reference instruments and tested under real-world conditions for 6 months (April to September 2015). We found high correlations for all the gaseous pollutants in the laboratory ($r > 0.9$) when the sensors were tested under steady temperature and relative humidity conditions, while in the field the correlations were significantly lower. Our results clearly show that a good performance in the laboratory is not indicative of a good performance under real-world conditions.

Particulate matter measurements were only evaluated in the field. Our results show better agreement at sites with low traffic than at high traffic sites. This might be related to the conversion factors employed by the AQMesh platform manufacturer to the OPC data, when converting the measured particle number concentrations to mass concentrations. Use of realistic conversion factors adapted to the location (background or traffic) might help to improve this issue.

In carrying out this evaluation, we identified a main technical challenge associated with current commercial low-cost sensors, regarding the sensor robustness and measurement repeatability. Our results show that laboratory calibration is not able to correct for real world conditions and that it is necessary to perform a field calibration for each sensor individually. Moreover, the calibration parameters might change over time depending on the meteorological conditions and the location, i.e., once the nodes are deployed it will be difficult to determine if they are under-or over-estimating the pollutant concentrations. Thus, it is necessary to evaluate rigorously low-cost sensor platforms under diverse environmental conditions.

The evaluation of the sensors' uncertainty revealed that for some pollutants and nodes, as NO, PM_{10} and $PM_{2.5}$, the expanded uncertainty meets the DQO criteria as defined in the Air Quality Directive. However, other pollutants, e.g., CO, NO_2 and O_3, show a highly expanded uncertainty that exceeded the DQO for indicative methods. The high sensor-to-sensor variability of the performance measures and the major

Table 5
Summary of the match score results for the 24 AQMesh nodes co-located at Kirkeveien station during April to June 2015.

	CO	NO	NO_2	O_3	PM_{10}	$PM_{2.5}$
Average	0.44	0.79	0.46	0.32	0.91	0.48
Max	0.50	0.92	0.52	0.54	0.93	0.52
Min	0.33	0.47	0.37	0.13	0.87	0.39

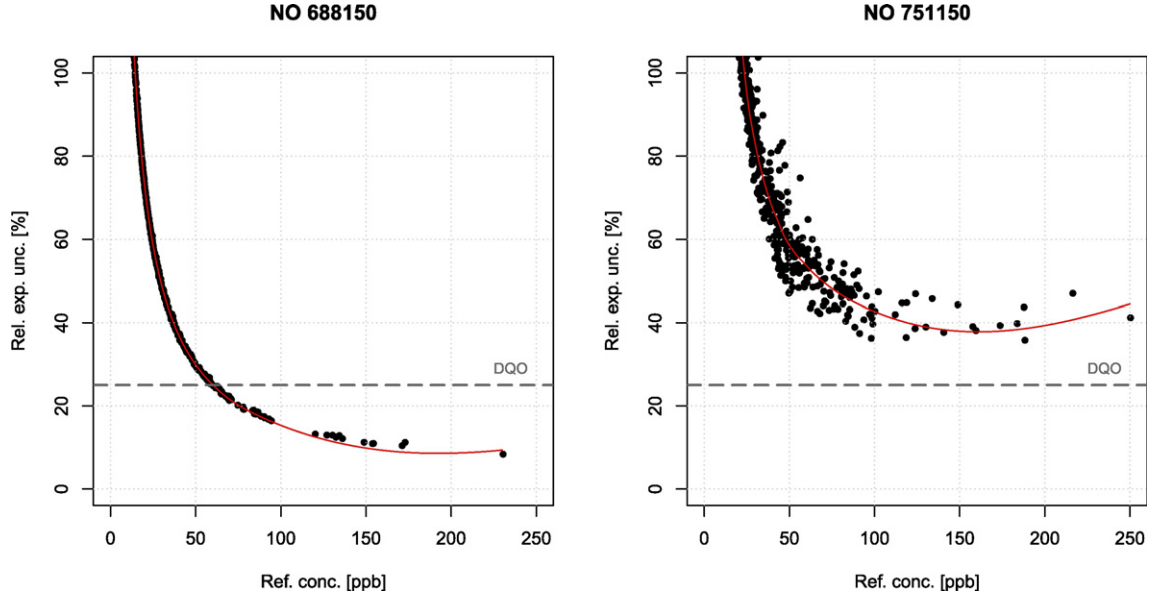

Fig. 4. Relative expanded uncertainty of AQMesh nodes 688150 and 751150 against reference NO concentrations.

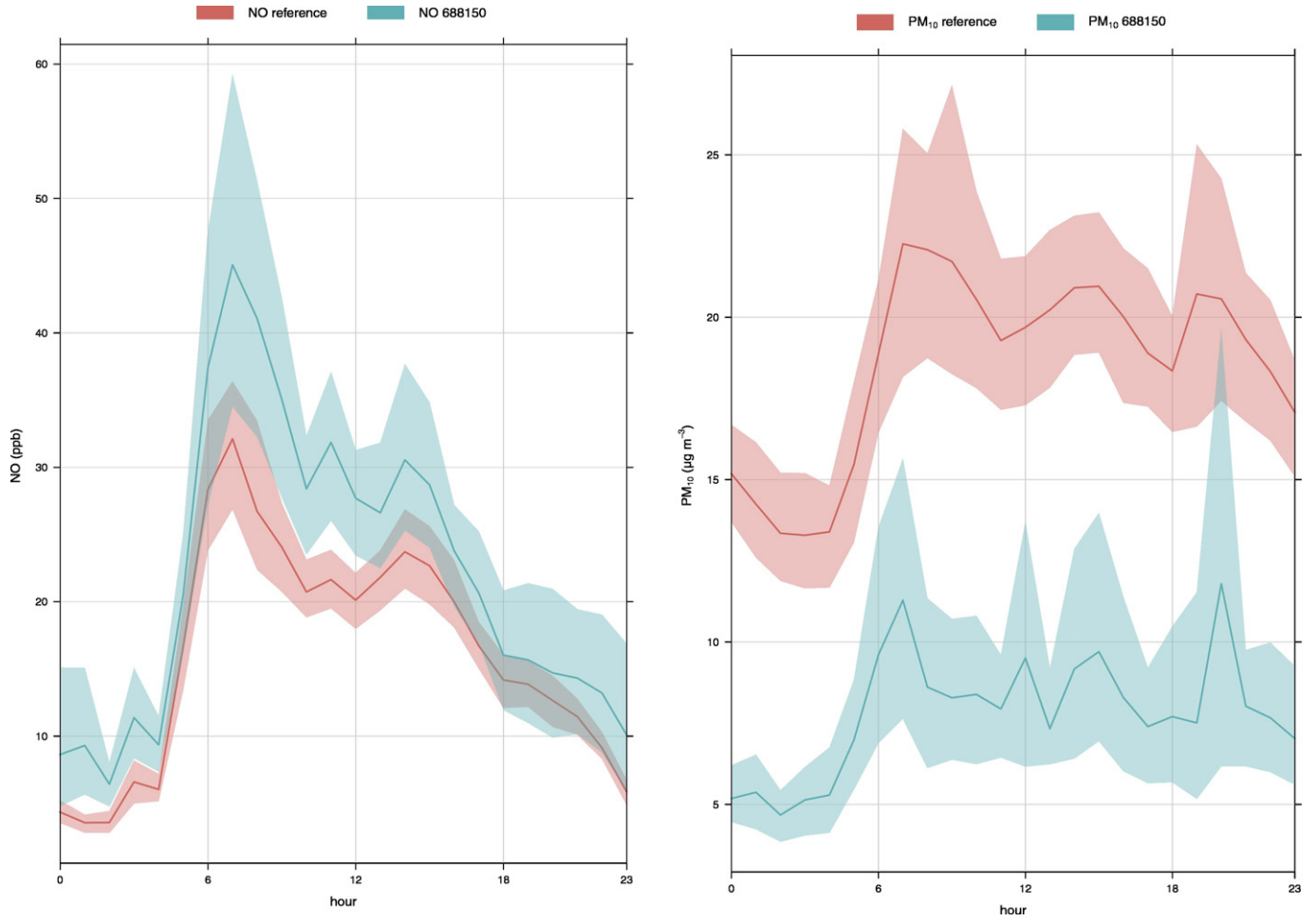

Fig. 5. Daily concentration cycle averaged during April–September 2015, for NO (left) and PM_{10} (right) by sensor node 688150 (blue) and the reference instrument (red). The shaded areas represent the 95% confidence interval.

variations in the nodes' response to the varying weather conditions or emission patterns make them currently unsuitable for air quality legislative compliance applications or applications that require high accuracy, precision and reliability, such as scientific evaluations of exposure estimates. However, recent studies show that the application of field calibrations based on machine learning techniques can reduce the expanded uncertainty.

The outlook for commercial low-cost sensors is promising, and our results show that currently some sensors, i.e., NO and PM_{10}, are already capable of offering coarse information about air quality, indicating if the air quality is good, moderate or if the air is heavily polluted. This type of information could be suitable for applications that aim to raise awareness, or engage the community by monitoring local air quality, as such applications do not require the same accuracy as scientific or regulative monitoring.

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Appendix A. Supplementary information

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