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Review

End-user perspective of low-cost sensors for outdoor air pollution monitoring

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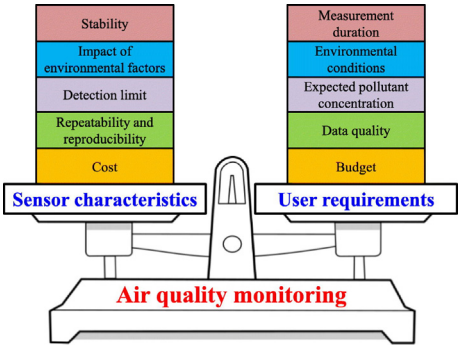
HIGHLIGHTS

- Low-cost sensors can enable high density monitoring of air pollutants.
- We review the performance of low-cost sensors for monitoring air pollution.
- Data quality is a major concern for the measurements from low-cost sensors.
- The sensors should be frequently calibrated under final deployment conditions.
- Sensor aging and manufacturing variability should be accounted during measurements.

GRAPHICAL ABSTRACT



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ABSTRACT

Low-cost sensor technology can potentially revolutionise the area of air pollution monitoring by providing high-density spatiotemporal pollution data. Such data can be utilised for supplementing traditional pollution monitoring, improving exposure estimates, and raising community awareness about air pollution. However, data quality remains a major concern that hinders the widespread adoption of low-cost sensor technology. Unreliable data may mislead unsuspecting users and potentially lead to alarming consequences such as reporting acceptable air pollutant levels when they are above the limits deemed safe for human health. This article provides scientific guidance to the end-users for effectively deploying low-cost sensors for monitoring air pollution and people's exposure, while ensuring reasonable data quality. We review the performance characteristics of several low-cost particle and gas monitoring sensors and provide recommendations to end-users for making proper sensor selection by summarizing the capabilities and limitations of such sensors. The challenges, best practices, and future

Abbreviations: CV, coefficient of variation; EC, electrochemical; EU, European Union; LOD, limit of detection; MOS, metal-oxide-semiconductor; nRMSE, normalised root mean square error; PM, particulate matter; $PM_{2.5}$, PM <2.5 μm in diameter; PM_{10}, PM <10 μm in diameter; R^2, coefficient of determination; R^2_{adj}, adjusted coefficient of determination; RH, relative humidity; RMSE, root mean square error; SD, standard deviation; SE, standard error; t_{lag}, time interval between a step change in input concentration and the first observable corresponding change in measurement response; t_{rise}, time interval between initial measurement response and 95% of final response after a step increase in input concentration; t_{0-90}, time interval needed by a sensor to reach 90% of the final stable value; t_{90-0}, time interval needed by a sensor to reach zero concentration; t_{90}, mean of t_{0-90} and t_{90-0}.

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outlook for effectively deploying low-cost sensors, and maintaining data quality are also discussed. For data quality assurance, a two-stage sensor calibration process is recommended, which includes laboratory calibration under controlled conditions by the manufacturer supplemented with routine calibration checks performed by the end-user under final deployment conditions. For large sensor networks where routine calibration checks are impractical, statistical techniques for data quality assurance should be utilised. Further advancements and adoption of sophisticated mathematical and statistical techniques for sensor calibration, fault detection, and data quality assurance can indeed help to realise the promised benefits of a low-cost air pollution sensor network.
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Contents

1. Introduction

Outdoor air pollution is a major problem in the 21st century, attributing to ~3.7 million deaths globally (WHO, 2014). Today, ~92% of the world's population lives in regions where air pollutant levels are higher than the WHO-specified limits (WHO, 2016). In addition, air pollution is also responsible for global climate change (Ramanathan and Feng, 2009) and environmental problems such as acid rain (Menz and Seip, 2004), haze (Li and Zhang, 2014; Xu et al., 2013), ozone depletion (Solomon, 1999; Solomon et al., 1986), and damage to crop (Avnery et al., 2011a, 2011b; Van Dingenen et al., 2009). Thus, there is a global drive to tackle this problem (Fenger, 2009).

Traditionally, air pollution is monitored by measuring concentrations of various pollutants such as carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), and particulate matter (PM) at fixed sites by using accurate and expensive instrumentation (Kumar et al., 2014; Mouzourides et al., 2015; Sharma et al., 2013). Monitoring sites in the EU are determined based on the EU Air Quality Directive 2008/50/EC, which clearly defines the minimum number of fixed monitoring stations for each target pollutant based on the air pollution levels, population, and coverage area. Such sites are generally spread in and around cities and provide temporal concentrations (typically hourly) of different pollutants. Cities in developed countries might contain one official monitoring station covering about 100,000 people as opposed to covering millions of people in cities of developing and highly polluted countries. For example, there are around 300 monitoring sites in the UK (DEFRA, 2011) and around 600 in India (CPCB, 2017). However, they are insufficient to provide accurate information about the spatial distribution of pollutants or identify pollution hotspots, and even more so for developing countries. Even though pollutant dispersion models can be used to address this issue, their accuracy is rather limited (Holmes and Morawska, 2006; Kumar et al., 2011, 2015; Vardoulakis et al., 2003).

Recent advancements in the field of sensors, digital electronics, and wireless communication technology have led to the emergence of a new paradigm for air pollution monitoring (Hagler et al., 2013; Kumar et al., 2015). This paradigm aims to gather high-resolution spatiotemporal air pollution data by using a ubiquitous network of low-cost sensors for monitoring real-time concentrations of different air pollutants, which can be then utilised for a variety of air pollution management tasks such as (i) supplementing conventional air pollution monitoring; (ii) improving the link between pollutant exposure and human health; (iii) emergency response management, hazardous leak detection, and source compliance monitoring; and (iv) increasing community's awareness and engagement towards air quality issues.

Though there is no universally agreed definition of a “low-cost” sensor, anything costing less than the instrumentation cost required for demonstrating compliance with the air quality regulations can be termed as low-cost. However, the cost should be as low as possible to achieve the above-mentioned aims of a sensor-based system for monitoring air pollution, so that widespread deployment is commercially feasible. Thus, in this paper, the term low-cost sensor is used either for designating sensors costing only a few 10's of US dollars or for sensing kits/nodes/platforms costing a few 100's of US dollars. The higher cost

of sensing kits is expected since they typically include one or more sensors, microprocessor, data-logger, memory card, battery, and display.

Several review articles have already addressed this emerging area of sensor-based air quality monitoring (Table 1). A majority of these articles focus on the needs, benefits, challenges, and future directions of a sensor-based pollution monitoring paradigm for different applications (Castell et al., 2013; Kumar et al., 2015, 2016a, 2016b; Snyder et al., 2013; White et al., 2012). A few others discuss emerging sensor technologies for monitoring gaseous and/or particulate air pollutants (Aleixandre and Gerbolesb, 2012; Bhanarkar et al., 2016; Koehler and Peters, 2015; White et al., 2012; Zhou et al., 2015). On-going air quality management campaigns using sensor networks were reviewed in some other articles (Castell et al., 2013; Thompson, 2016). However, none of them have comprehensively addressed the crucial aspect of *performance assessment* of low-cost sensors for monitoring different air pollutants vis-à-vis their more expensive counterparts. Jovašević-Stojanović et al. (2015) provided some information about selecting low-cost PM sensors based on their specifications and the monitoring objectives. However, they did not include gaseous sensors, and several new research articles on performance assessment of PM sensors have come up since then. Williams et al. (2014b) provided guidelines regarding sensor selection but these guidelines are open ended and leave it for end-users to carefully review a sensor's performance before purchasing it. Without a proper understanding of the performance characteristics of the available low-cost sensors, the end-users cannot be expected to effectively deploy them for achieving an effective sensor-based management of air pollution (Castell et al., 2017; Jovašević-Stojanović et al., 2015; Judge and Wayland, 2014; Lewis and Edwards, 2016). Addressing this crucial issue forms the motivation for this review article.

We recognise a need for providing scientific guidance to end-users in choosing appropriate low-cost sensors by matching user requirements with sensor performance. Through a comprehensive review of the scientific literature, we assessed the performance of several commercially available low-cost sensors for measuring PM and gaseous pollutants in the outdoor environment, i.e., CO, O_3 and NO_2. We could not review the low-cost sensors for measuring SO_2 due to a dearth of studies on their performance assessment. Additionally, we have provided recommendations for end-users in selecting low-cost sensors for monitoring outdoor air pollutants. Finally, we have outlined the challenges faced by the end-users in deploying low-cost sensors for monitoring air pollution and the future research directions to overcome them.

2. Low-cost sensors for monitoring particulate matter

The light scattering method is used in low-cost PM sensors since the sensors based on this principle are cheap to manufacture, have low power requirements, and quick response times (Wang et al., 2015). In this method, a light source illuminates the particles, and then the scattered light from the particles is measured by a photometer. For particles with diameters greater than ~0.3 μm, the amount of light scattered is roughly proportional to their mass/number concentration; however, particles smaller than ~0.3 μm in diameter do not scatter enough light, and cannot be detected by this method (Koehler and Peters, 2015; Thomas and Gebhart, 1994). The detectable particles (>0.3 μm in diameter) can be size-segregated by either using an algorithm on the signal obtained from the scattered light (Northcross et al., 2013) or by attaching an impactor/filter at the inlet (Sousan et al., 2016b).

2.1. Specifications and application areas

Low-cost PM sensors are available from several manufacturers, and their specifications are given in Table 2 as claimed by their respective makers. These sensors are roughly palm-sized, weigh a few 10's of grams (or 100's of grams for sensor kits), are battery operable, and cost around $10–100 (or $100–500 for the sensor kits). The typical range of measurement extends from a few μg/m^3 to about 100's of μg/m^3.

Some of the sensor models such as the GP2Y1010AU0F, DSM501A, PPD42NS, PPD60PV, and SDS198 (Table 2) cannot distinguish between particle sizes and typically report the concentration of particles with sizes greater than ~0.3 μm as a single value for the PM concentration in air. Other sensor models such as the Novafit sensors and Dylos (Table 2) rely on size discrimination by applying signal processing

Table 1
Summary of review articles focused on the applications of low-cost sensors for monitoring air pollution.

Author (year)	Study focus
Aleixandre and Gerbolesb (2012)	Reviewed available commercial sensors for gaseous pollutants and compared their detection ranges with those specified in the European Directive on air quality 2008/50/EC.
White et al. (2012)	Highlighted the synergistic opportunities available between the sensor and wireless communication technologies for reducing human exposure to air pollutants.
Castell et al. (2013)	Reviewed potential application areas of sensor technologies for air quality management. The article also provided a critical analysis of commercially available sensors for gas measurements and emphasised the need for performance assessment of emerging sensor technologies under real-world conditions. Finally, the article summarised 24 different air quality management campaigns based on emerging sensor technologies.
Snyder et al. (2013)	Discussed the changing paradigm of air pollution monitoring due to the emergence of portable air quality sensors. The paper also illustrates a few application areas for such sensors in managing air quality issues together with key challenges and possible solutions.
Jovašević-Stojanović et al. (2015)	Assessed low-cost sensors for monitoring PM, including their specifications and general performance characteristics. They also reported measurements and modelling results to show validation methodology of a particular low-cost PM sensors.
Koehler and Peters (2015)	Reviewed personal exposure assessment to particulate air pollution by using novel sensors developed over last 5–10 years. They also discussed new metrics (that go beyond traditional mass measurements) for evaluating the relationship between particulate matter and its health impacts.
Kumar et al. (2015)	Reviewed the emergence of low-cost sensing technologies for managing air pollution in cities with respect to its need, state-of-the-art, opportunities, challenges, and future directions.
Zhou et al. (2015)	Reviewed state of the art and future perspectives for different types of chemosensors for monitoring gases involved in environmental exhausts (CO_2, SO_2, NOx, VOCs), biological signalling (H_2S, NO, O_2), and toxic use (nerve gases, sulphur mustard).
Bhanarkar et al. (2016)	Reviewed the issues and challenges in the design and deployment of wireless sensor nodes for outdoor air pollution monitoring.
Kumar et al. (2016a)	Focused on solving the typical problem of deteriorating indoor air quality (IAQ) in building management programs aimed at conserving energy by proposing to use real-time sensing.
Kumar et al. (2016b)	Highlighted the needs, benefits, challenges, and future outlook of monitoring indoor air quality (IAQ) using real-time sensors. The review also critically analysed the currently available sensor technologies available for monitoring different types of gaseous and particulate air pollutants.
Thompson (2016)	Reviewed current and emerging areas of analytical chemistry and sensor technology suitable for the development of a low-cost sensing platform for monitoring air quality together with a summary of recent crowd-sourced sensing efforts.

Table 2
Specifications of the different PM sensors as given by their respective manufacturers.

Model	Size (mm)	Weight (g)	Power supply	Maximum current consumption (mA)	Cost (US$)	Detectable particle size	Concentration range of measurement	Performance tested in scientific literature
Alphasense OPC-N2	75×64×60	105	5 V DC	175	~500	0.38–17 μm in 16 size bins	0.1–1,500,000 μg/m^3	Yes
Dylos DC 1100 Pro	178×114×76	544	110 V AC	NA	~300	0.5–2.5 μm and 0.5–10 μm in two size bins	0–106 particles/cm^3	Yes
Dylos DC 1700	178×114×76	544	110 V AC or battery	NA	~400	0.5–2.5 μm and 0.5–10 μm in two size bins	0–106 particles/cm^3	Yes
Novafitness SDL301	204×100×36	580	5 V DC	NA	~250	0.3–2.5 μm and 0.3–10 μm in two size bins	0–1000 μg/m^3	No
Novafitness SDL607	73×73×20	120	5 V DC	NA	~120	0.3–2.5 μm and 0.3–10 μm in two size bins	0–1000 μg/m^3	No
Novafitness SDS011	71×70×23	NA	5V DC	80	~35	0.3–2.5 μm and 0.3–10 μm in two size bins	0–1000 μg/m^3	No
Novafitness SDS018	59×45×20	NA	5 V DC	70	~40	0.3–2.5 μm and 0.3–10 μm in two size bins	0–1000 μg/m^3	No
Novafitness SDS021	42×32×24	NA	5 V DC	70	~35	0.3–2.5 μm and 0.3–10 μm in two size bins	0–1000 μg/m^3	No
Novafitness SDS198	71×70×23	NA	5 V DC	80	~80	1–100 μm	0–20000 μg/m^3	No
Plantower PMS 1003	65×42×23	NA	5 V DC	120	~ 20	0.3–1.0 μm, 1.0–2.5 μm, and 2.5–10 μm in three size bins	0–500 μg/m^3	Yes
Plantower PMS 3003	65×42×23	NA	5 V DC	120	~ 20	0.3–1.0 μm, 1.0–2.5 μm, and 2.5–10 μm in three size bins	NA	Yes
Samyoung DSM501A	59×45×20	25	5 V DC	90	~15	Greater than 1.0 μm	0–1400 μg/m^3	Yes
Sharp DN7C3CA006	50×44×20	52	5 V DC	180	~20	0.5–2.5μm	25–500 μg/m^3	Yes
Sharp GP2Y1010AU0F	46×30×18	15	5 V DC	20	~10	Greater than 0.5μm	0–600 μg/m^3	Yes
Shinyei PPD42NS	59×45×22	24	5 V DC	90	~15	Greater than 1.0 μm	0–28 particles/cm^3	Yes
Shinyei PPD60PV	88×60×20	36	5 V DC	NA	~250	Greater than 0.5 μm	0–70 particles/cm^3	Yes

NA stands for not available.

techniques on the photometer's output. However, this technique might result in significant misclassification of particles (Sousan et al., 2016b). We found that the DN7C3CA006 sensor is the only sensor equipped with a virtual impactor that allows only particles ≤2.5 μm in diameter to pass through the sensing zone, making it suitable for measuring $PM_{2.5}$ (particles <2.5 μm in diameter). It is not known how the Plantower sensors (Table 2) perform size discrimination between particles. Thus, to monitor PM_{10} (particles <10 μm in diameter) or $PM_{2.5}$ any sensor given in Table 2 would be suitable if an appropriate mechanism for size selection is used. The requirement for a size selection mechanism is not stringent for monitoring PM_{10} since particles ≥10 μm are difficult to draw in the sensing zone (Koehler and Peters, 2015), meaning that the raw sensor output would roughly correspond to the PM_{10} concentration.

Many of these sensors have already been used in air quality monitoring studies such as monitoring ambient wood smoke (Olivares and Edwards, 2015), risk husk in a rice mill (Zakaria et al., 2014), cigarette smoke in a garage (Rajasegarar et al., 2014), PM levels associated with source activities in homes (Olivares et al., 2012), and urban and rural backgrounds (Steinle et al., 2015). However, there is a huge gap in the scientific literature related to their calibration and performance assessment, which makes it challenging to evaluate the data quality obtained by the different investigations and make comparisons between them. Several PM sensors have not been tested by scientific investigations, making it infeasible to judge their performance (see Table 2). Thus, in the remainder of this paper, we focus only on those low-cost sensors (both for PM and gaseous pollutants) whose performance traits have been tested by at least one scientific investigation. Table S1 gives a summary of investigations focused on testing low-cost PM sensors along with the test conditions and reference instrumentation. Due to the lack of a standard calibration protocol specific for low-cost sensors, studies have used dissimilar calibration methods, including chamber and field testing against a variety of reference instruments, which again makes inter-comparison between them infeasible. Nevertheless, these studies provide crucial information about the performances of low-cost sensors under a variety of operating conditions, as discussed in the following sub-section.

2.2. Performance assessment

Table 3 gives a summary of the performance characteristics of the low-cost PM sensors tested by scientific studies; including their comparisons with reference measurements; repeatability and reproducibility characteristics, limit of detection (LOD); and dependence on particle composition, size, humidity, and temperature. These individual performance criteria are discussed in the subsequent text.

2.2.1. Comparisons with reference measurements

All the investigations sumarised in Table S1 compared the measurements from the low-cost PM sensors with relevant high-cost reference instruments. Fig. 1 shows the range of values for the coefficient of determination (R^2) between the low-cost PM sensors and the high-cost reference instruments obtained by using a simple linear function from the different investigations. Fig. 1 also shows that a simple linear function is generally adequate to calibrate the sensor response with the reference measurements, yielding moderate to high R^2 values. However, a few investigations have reported that the sensor response begins to saturate at high particle concentrations (higher than 50–100 μg/m^3) and that higher order polynomial or exponential functions are needed to capture this behaviour (Austin et al., 2015; Johnson et al., 2016; Kelly et al., 2017; Manikonda et al., 2016; Wang et al., 2015). Thus, it is necessary to select the appropriate response function for a particular sensor by calibrating it under the full range of expected PM concentrations.

Fig. 1 also suggests that the sensors typically performed better (with high R^2 values) under laboratory conditions compared with field conditions. This performance deterioration in real-world conditions is attributed to the changing conditions of particle compositions, sizes, and environmental factors, which can drastically impact a sensor's response as discussed below. Thus, on-site calibration of low-cost PM sensors is crucial, and laboratory calibrated sensors should not be directly used for real-world measurements. Furthermore, the sensors should be calibrated individually since even the sensors of the same type can give different outputs even under identical conditions (Austin et al., 2015; Olivares et al., 2012; Sousan et al., 2016b; Wang et al., 2015).

Table 3
A summary of performance characteristics of low-cost PM sensors.

Model	Comparison with reference measurements (R^2)	Repeatability and reproducibility	Limit of detection ($\mu g/m^3$)	Effect of particle composition on sensor output	Effect of particle size on sensor output	Effect of humidity on sensor output	Effect of temperature on sensor output
Alphasense OPC-N2	$R^2_{lab} = 0.94–0.99$[a]	$CV_{Rr} = 4.2–16\%$[a]	NA	$\delta_{PC} \approx 30$, estimated from Sousan et al. (2016a).	$\eta_d = 0.83–1.01$[a]	NA	NA
Dylos models 1100 Pro and 1700	$R^2_{lab} = 0.97–0.99$[b] $R^2_{lab} = 0.64–0.95$[c] $R^2_{lab} = 0.91–0.98$[d] $R^2_{fld} = 0.81–0.99$[b] $R^2_{fld} = 0.58–0.99$[e] $R^2_{fld} = 0.70–0.90$[f] $R^2_{fld} = 0.48–0.78$[g] $R^2_{fld} = 0.40–0.45$[h] $R^2_{fld} = 0.74–0.84$[i] $R^2_{fld} = 0.55$[j]	$CV_{Rr} = 1.4–8.0\%$[d] $R^2 = 0.67–0.98$[h] nRMSE = 13.4–46.1%[c]	<1[b]	$\delta_{PC} \leq 20$, estimated from Sousan et al. (2016b). $\delta_{PC} \leq 3$, estimated from Northcross et al. (2013). Did not seem to affect the sensor output under ambient conditions.[f]	$\eta_d = 0.6–1.1$, estimated from Sousan et al. (2016b). $\eta_d = 0.25–4.0$, estimated from Han et al. (2017).	$\eta_d = 0.5–4.8$, estimated from Han et al. (2017). Slight correlation between sensor output and humidity ($R^2 = 0.18$).[j] Seems affected by humidity.[h]	NA No correlation between sensor output and temperature ($R^2 = 0.03$).[j] Sensor response probably not dependent on temperature.[h]
Plantower PMS 1003	$R^2_{fld} = 0.82–0.93$[k] $R^2_{lab} = 0.69–0.99$[k]	$R^2 = 0.99$[k]	0.721–10.5[k]	NA	NA	Slight correlation between sensor output and humidity ($R^2 = 0.09–0.17$).[k]	No correlation between sensor output and temperature ($R^2 < 0.02$).[k]
Plantower PMS 3003	$R^2_{lab} = 0.73–0.97$[k]	NA	NA	NA	NA	NA	NA
Samyoung DSM501A	$R^2_{lab} = 0.88–0.90$[l] $R^2_{lab} \approx 0.50$[m] $R^2_{lab} = 0.58–0.97$[c] $R^2_{fld} = 0.07–0.46$[r]	$CV_{Rt} = 2–28\%$[l] nRMSE = 22.3–52.7%[c]	4.28–11.4[l] 10[r]	$\delta_{PC} \leq 8$, estimated from Wang et al. (2015).	$\delta_{PS} \leq 18$, estimated from Wang et al. (2015).	$\delta_{RH\text{-}PM} \leq 2.8$, estimated from Wang et al. (2015).	$\delta_{T\text{-}PM} \leq 1.2$, estimated from Wang et al. (2015).
Sharp DN7C3CA006	$R^2_{lab} = 0.98–0.99$[d]	$CV_{Rr} = 0.8–7.1\%$[d]	NA	$\delta_{PC} \leq 2$, estimated from Sousan et al. (2016b).	NA	NA	NA
Sharp GP2Y1010AU0F	$R^2_{lab} = 0.42–0.99$[c] $R^2_{lab} = 0.95–0.99$[d] $R^2_{lab} = 0.98–0.99$[l] $R^2_{lab} = 0.92–0.98$[m] $R^2_{fld} = 0.72$[n] $R^2_{fld} = 0.99$[o]	$CV_{Rt} = 5–25\%$[l] $CV_{Rr} = 0.9–5.9\%$[d] nRMSE = 2.6–118.2%[c]	26.1–26.9[l]	$\delta_{PC} \leq 6$, estimated from Wang et al. (2015). $\delta_{PC} \leq 4$, estimated from Sousan et al. (2016b).	$\delta_{PS} \leq 2.4$, estimated from Wang et al. (2015).	$\delta_{RH\text{-}PM} \leq 1.5$, estimated from Wang et al. (2015).	$\delta_{T\text{-}PM} \leq 1.5$, estimated from Wang et al. (2015). Baseline response linearly proportional to temperature.[o] Seems unaffected by temperature.[n]
Shinyei PPD42NS	$R^2_{lab} = 0.66–0.99$[p] $R^2_{lab} = 0.93–0.96$[l] $R^2_{fld} < 0.16$[h] $R^2_{fld} = 0.53–0.98$[q] $R^2_{fld} = 0.55–0.94$[e] $R^2_{lab} = 0.50–0.80$[k]	$CV_{Rt} = 4–28\%$[l] $R^2 = 0.91–0.94$[e] $R^2 = 0.25–0.44$[h]	4.59–6.44[l] 1[p]	$\delta_{PC} \leq 18$, estimated from Wang et al. (2015).	$\delta_{PS} \leq 24$, estimated from Wang et al. (2015). $\delta_{PS} \leq 13$, estimated from Austin et al. (2015).	$\delta_{RH\text{-}PM} \leq 8.0$, estimated from Wang et al. (2015). Seems affected by humidity.[q] Slight correlation between sensor output and humidity ($R^2 = 0.01–0.27$).[e]	$\delta_{T\text{-}PM} \leq 1.6$, estimated from Wang et al. (2015). Seems affected by temperature.[q] No correlation between sensor output and temperature ($R^2 = 0.01$).[e]
Shinyei PPD60PV	$R^2_{fld} = 0.43$[h]	$R^2 = 0.98–1.0$[h]	NA	NA	NA	Seems unaffected by humidity.[h]	Seems unaffected by temperature.[h]

R^2 and CV are the coefficients of determination and variance, respectively. The subscript is lab or fld when referring to comparison between sensor and reference measurements under laboratory or field conditions, respectively; subscript is Rt or Rr when referring to repeatability or reproducibility, respectively. nRMSE is the normalised root mean square error, which is define as $nRMSE = \frac{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_{Ai}-M_{Bi})^2}\right)}{\frac{1}{2n}\sum_{i=1}^{n}M_{Ai}+M_{Bi}}$, where M_{Ai} and M_{Bi} are the ith values measured by sensors A and B, respectively, and n is the number of measurements. δ_{PC}, δ_{PS}, $\delta_{RH\text{-}PM}$, $\delta_{T\text{-}PM}$ is the change in sensor response due to change in particle composition, particle size, relative humidity, and temperature, respectively, measured at the same mass concentration. It is defined as $\delta_x = y_{high}/y_{low}$, where the subscript x is PC, PS, RH-PM, and T-PM when refereeing to particle composition, particle size, relative humidity, or temperature, respectively. y_{high} and y_{low} are the different (high and low) sensor responses under different conditions. NA stands for not available. The alphabets refer to the following studies - a: (Sousan et al., 2016a), b: (Northcross et al., 2013), c: (Manikonda et al., 2016), d: (Sousan et al., 2016b), e: (Holstius et al., 2014), f: (Steinle et al., 2015), g: (Han et al., 2017), h: (Jiao et al., 2016), i: (Jovašević-Stojanović et al., 2015), j: (Williams et al., 2014a), k: (Kelly et al., 2017), l: (Wang et al., 2015), m: (Alvarado et al., 2015), n: (Olivares and Edwards, 2015), o: (Olivares et al., 2012), p: (Austin et al., 2015), q: (Gao et al., 2015), and r: (Zikova et al., 2016).

2.2.2. Repeatability, reproducibility, stability, and limit of detection

Repeatability and reproducibility are defined as the closeness between successive measurements of the same measurand carried out under identical and non-identical conditions of measurement, respectively (Taylor and Kuyatt, 1994). Thus, we use the terms sensor repeatability to denote the dispersion between consecutive measurements obtained from a given sensor, whereas reproducibility is used for designating dispersion between measurements obtained by using different sensors of the same model.

Repeatability is very difficult to measure for PM sensors due to difficulty in maintaining constant particle concentrations. Wang et al. (2015) reported repeatability characteristics for three different low-cost PM sensors, as measured by the coefficient of variation (CV), to lie between 2 and 28% (Table 3). The repeatability deteriorated at low PM concentrations, and all the sensors had CV in the 23–26% range at ~50 μg/m^3 PM concentration (Wang et al., 2015).

Regarding reproducibly, several investigations have pointed out that the sensors need to be calibrated individually, illustrating poor reproducibility for the raw sensor outputs. However, after calibration, their reproducibility characteristics get improved (Sousan et al., 2016b). To quantify reproducibility, a few investigations reported CV values ranging from 0.9–16% as given in Table 3 (Sousan et al., 2016a, 2016b), while some others reported the R^2 values (R^2 = 0.25 to 1.0 in Table 3) between sensors (Holstius et al., 2014; Jiao et al., 2016; Kelly et al., 2017). Manikonda et al. (2016) used the normalised root mean square error (nRMSE) value to quantify sensor reproducibility, and found that the reproducibly was much higher when the sensors were exposed to cigarette smoke (nRMSE = 2.6–22.3%) as compared to Arizona test dust (nRMSE = 46.1–118.2%). Sensor reproducibility could get deteriorated due to the accumulation of particles in the sensing zone, which seems more pronounced when the sensors were exposed to larger sized particles (Arizona test dust) as compared to smaller particles (cigarette smoke).

We define stability as a sensor's capability to maintain its performance characteristics over a sufficiently long duration (at least a few months). This is a crucial performance trait if low-cost sensors are to be deployed for long-term monitoring. However, only Jiao et al. (2016) have conducted measurements with low-cost PM sensors for a sufficiently long period (2–6 months). They reported an improvement in the adjusted-R^2 (R^2_{adj}) value from 0.45 to 0.56 for a sensor when "days of use" was added as a predictor in the regression model used for calibration. Thus, it seems possible that the sensor's response was changing with time due to sensor aging and/or dust accumulation; however, "days of use" could just have been a confounding variable also. Clearly, more investigations are required to address this crucial issue of sensor stability.

Limit of detection (LOD) for a sensor is defined as the lowest concentration of a pollutant that can be significantly differentiated from zero concentration. LOD can be estimated as three times the standard deviation of the sensor output obtained at zero pollutant concentration. It is desirable to have the LOD as low as possible since it determines the lowest detectable concentration. LOD values for the different PM sensors have only been evaluated by a few studies (Table 3) and lie between 1 and 27 μg/m^3. Fig. 2 shows the LOD for the different low-cost PM and gaseous sensors together with the pollutant concentrations (urban and background) typically found in EU countries and their corresponding limits. It is evident that the LOD for all the PM sensors (except GP2Y1010AU0F) is less than the EU specified limits for both $PM_{2.5}$ and PM_{10} and lie in the lower spectrum of the concentration ranges found in EU nations. Note that the high LOD values for the GP2Y1010AU0F

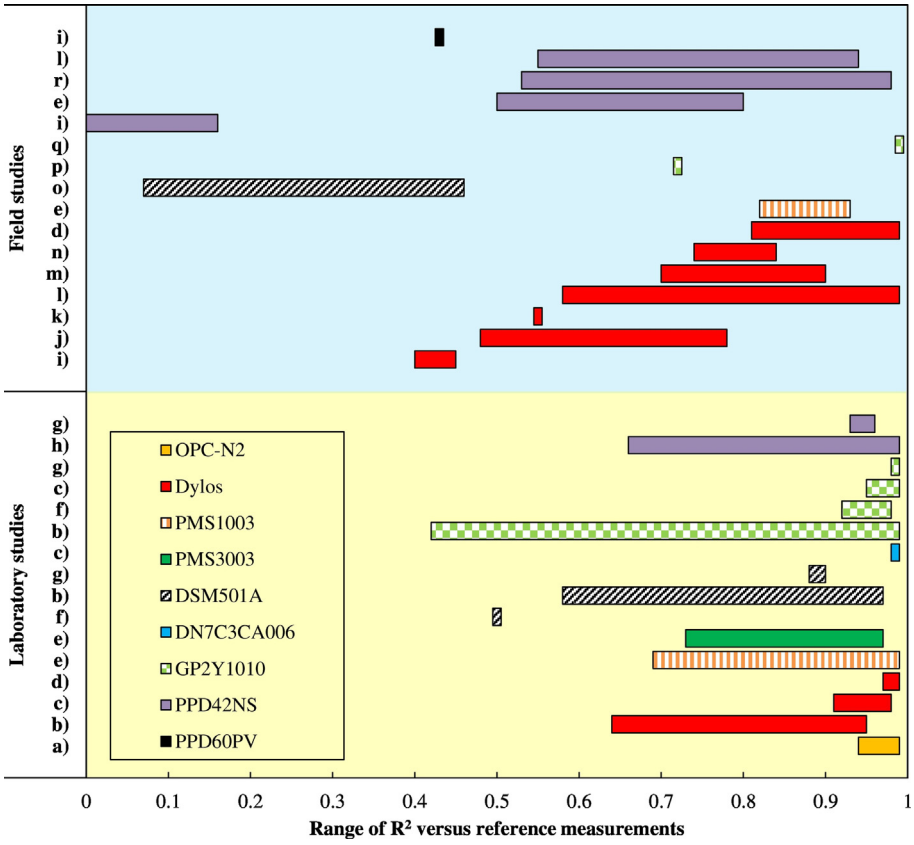

Fig. 1. Comparisons of the low-cost PM sensors with the reference instruments under laboratory and field conditions based on the R^2 (coefficient of determination) values. Note that the bars denote the range of R^2, as obtained in the studies referred by the alphabets on y-axis (given in Table S1) under laboratory and field conditions.

sensor reported by Wang et al. (2015) likely to occur since they probably did not account for the large intercept present in the sensor calibration curve while calculating its LOD. Generally, the PM sensors seem suitable for measuring both $PM_{2.5}$ and PM_{10} concentrations, unless the concentrations are very low (<10 μg/m^3). However, given that PM_{10} levels are always higher than $PM_{2.5}$ levels, the sensors would be better suited for monitoring PM_{10}.

2.2.3. Impact of particle characteristics on sensor output

The impact of particle composition on outputs of the low-cost PM sensors has been studied by a few laboratory investigations (Northcross et al., 2013; Sousan et al., 2016a, 2016b; Wang et al., 2015). This factor was found to affect the sensor outputs by as much as 30 times for the various sensors (Table 3). One field investigation reported that the output of Dylos sensor was unaffected by the change in aerosol composition from secondary inorganic aerosols to sea-salt dominated aerosols (Steinle et al., 2015). Since the chamber investigations have used aerosols with significantly different compositions ranging from polystyrene latex spheres (Northcross et al., 2013), sugar (Wang et al., 2015), salt (Northcross et al., 2013; Sousan et al., 2016a, 2016b; Wang et al., 2015), wood-smoke (Northcross et al., 2013), diesel exhaust (Sousan et al., 2016b), welding fumes (Sousan et al., 2016a, 2016b) to road dust (Sousan et al., 2016a, 2016b) compared with the field investigations, the high variability in sensor outputs during laboratory testing is reasonable. The difference in particle composition impacts the scattering and absorption of light by the sensors; thus, affecting their outputs. For example, organic materials tend to absorb a higher proportion of incident light as compared to inorganic materials. This means that the optical sensors will report a much higher concentration when measuring organic particles as compared to inorganic particles, even under identical concentrations (Wang et al., 2015).

Some investigations have studied the impact of particle size on the outputs of low-cost PM sensors as given in Table 3 (Austin et al., 2015; Han et al., 2017; Sousan et al., 2016a, 2016b; Wang et al., 2015). The sensor outputs are generally found to increase with the particle size since for the same mass concentration larger particles scatter more light, which results in higher reported concentrations (Wang et al., 2015). For example, Wang et al. (2015) reported that the output of the sensor with 900 nm size particles was as high as 2–24 times when compared to their outputs with 300 nm size particles at similar mass concentrations. All the low-cost PM sensors show similar dependence on particle size except for the OPC-N2, which seems relatively unaffected by particle sizes (Sousan et al., 2016a); however, the reason is unknown.

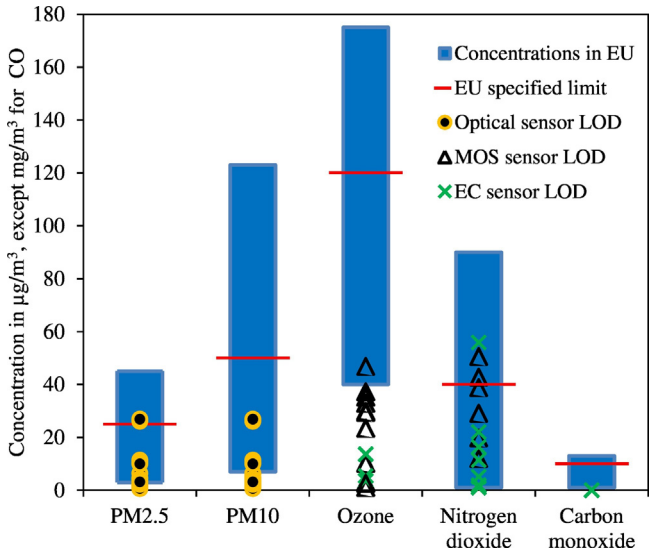

Fig. 2. Limit of detection (LOD values as presented in Tables 3–4 and S3–S4) of low-cost pollutant sensors along with the typical pollutant concentrations found in EU as well as the corresponding EU specified reference values (yearly averaged limit for $PM_{2.5}$ and NO_2, daily averaged limit for PM_{10}, maximum daily 8-hour averaged target for O_3, and maximum daily 8-hour averaged limit for CO). $PM_{2.5}$ and NO_2 ranges are computed from the minimum and maximum values of the annual mean concentrations reported by each EU member state (Guerreiro et al., 2016). Similarly, PM_{10} and O_3 ranges are computed from the minimum and maximum values of the 90.4 percentile of the daily mean concentration and 93.2 percentile of maximum daily 8-hour mean concentration, respectively (Guerreiro et al., 2016). Likewise, CO range is computed from the minimum and maximum values of the maximum daily 8-hour mean concentration (Guerreiro et al., 2013).

2.2.4. Impact of environmental factors on sensor output

The impact of environmental factors (relative humidity and temperature) has been assessed by several investigations (Table 3). For example, Wang et al. (2015) used an environmental chamber to study the effect of environmental factors on the performance of three different PM sensors by comparing their outputs under different relative humidity and temperature conditions, while maintaining similar PM mass concentrations. They found that the sensors outputs first increased, and then decreased as the relative humidity was increased from 20% to 90%. The ratios of the sensor outputs at different humidity conditions ranged from 1.5–8.0 (Table 3). However, the impact of temperature on sensor outputs was very less as compared to humidity, with the ratios of the sensor outputs ranging from 1.2–1.6 at different temperatures (5–32 °C). The effect of humidity on sensor outputs is attributed to a combination of factors: (i) absorption of radiation by water causing an overestimation of particle concentrations, (ii) unsuitability of the reference instrument used at high humidity conditions, and (iii) probable circuit failure in particle sensors at high relative humidity. Whereas light scattering and absorption are theoretically independent of temperature, which means that temperature variations should not affect an optical sensor's output.

Of the several field investigations that have looked into the effects of environmental factors on the outputs from different low-cost PM sensors, almost all have reported that the sensor outputs do not seem to be associated with humidity or temperature (Table 3). Olivares et al. (2012) reported that the baseline response of a PM sensor was linearly proportional to the temperature. However, the same lead author later reported that this linear relationship was probably because the temperature affects the measured particles, and not because it affects the sensor (Olivares and Edwards, 2015).

Overall, there seems to be a consensus between the field investigations that the low-cost PM sensor outputs are not affected by humidity or temperature variations. However, the laboratory investigation (Wang et al., 2015) discussed previously had a conflicting conclusion about the effect of humidity on sensor outputs. Laboratory investigations are preferred for such assessments since field investigations do not have a control over all the variables that can impact the output of a sensor, and it is not possible to deduce causal relationships. Thus, more laboratory studies are required to address this contradiction.

2.3. Recommendations for end-users

Several low-cost PM sensors are available in the market that measures the concentration of particles based on the light scattering method. This method is suitable only for measuring particles larger than ~0.3 μm in diameter since smaller particles do not scatter enough light. To use this technique for measuring $PM_{2.5}$ or PM_{10}, it should be ensured that the sensor is equipped with an impactor or filter at the air inlet that provides the appropriate cut-off diameter (2.5 μm and 10 μm for measuring $PM_{2.5}$ and PM_{10}, respectively). This feature is not provided in any of the sensors given in Table 2, expect for the DN7C3CA006 sensor that is equipped with a 2.5 μm virtual impactor. A few sensors (e.g. Dylos) utilise signal processing algorithms to categorise particles between $PM_{2.5}$ and PM_{10}; however, such algorithms may lead to significant misclassification (Sousan et al., 2016b). Thus, to measure

concentrations of $PM_{2.5}$ or PM_{10}, any optical sensor (Table 2) can be used in principle when combined with a suitable size cut-off mechanism.

It is also important to note that a few low-cost PM sensors (e.g., GP2Y1010AU0G and PPD42NS) are available as stand-alone sensors, and require integration into a data acquisition and storage system. However, other sensors (e.g., Dylos and Novafitness SDL301) are available as ready-to-use modules with their own data acquisition, storage, and display system. Based on the user's familiarity with these issues, an appropriate choice can be made.

A number of investigations have assessed the performance of low-cost PM sensors. However, the lack of a standardised method for performance assessment of low-cost PM sensors makes it difficult to make inter-comparisons between the results obtained from different studies. Nevertheless, the performance characteristics of the different sensors seem to be roughly similar (Table 3). The sensors generally demonstrate R^2 values >0.50 when compared with reference measurements. The CV value, which is generally used to characterise sensor repeatability and reproducibility, is in the 1–28% range. This means that even if the sensors work perfectly, 1–28% errors in PM concentrations can be expected. The LOD ranges from 1 to 27 μg/m^3, and generally lies at the lower spectrum of the $PM_{2.5}$ and PM_{10} concentration ranges in EU countries. It is also seen that the sensors' outputs are highly dependent on the particle composition and size. Environmental factors such as relative humidity and temperature might also influence PM sensors' response; however, further investigations are required to understand this influence. Sensor stability is another inadequately understood issue.

Thus, the end-users should be aware of the above-mentioned characteristics, performance traits, and limitations of the low-cost PM sensors when deploying them. Before performing any PM monitoring task, the sensors should be properly calibrated under conditions as close to the final deployment as possible. Furthermore, since the long-term (more than a week) performance of these low-cost sensors largely remains unknown, frequent calibration is recommended.

3. Low-cost sensors for monitoring gaseous pollutants

3.1. Specifications and application areas

To measure gaseous air pollutants, there are currently two types of low-cost sensors available in the market: (i) metal-oxide-semiconductor (MOS) sensors, and (ii) electrochemical (EC) sensors.

The MOS sensors employ a metal oxide that changes its electrical properties (typically resistance) when exposed to the target gas. This change can be easily measured and corresponds to the concentration of the gas (Fine et al., 2010). Such sensors are small in size (a few millimeters), light-weight (a few grams), inexpensive (~$10), have quick response times, low detection limits and power requirements (~100 mW) (Aleixandre and Gerbolesb, 2012; Piedrahita et al., 2014). However, they have a non-linear response curve; and suffer from sensitivity to changes in environmental conditions and interfering gases (Spinellea et al., 2016).

The EC sensors are generally operated in an amperometric mode, wherein the electrochemical reactions between the target gas and an electrolyte produce a current dependent on the gaseous concentration (Stetter and Li, 2008). The sensors typically consist of three electrodes, termed as working, counter, and reference. The target gas undergoes electrolysis (oxidation or reduction) at the working electrode and generates an electric current, which is balanced by the reaction at the counter electrode. The measured electric current corresponds to the concentration of the gas, and the response is either linear or logarithmic (Aleixandre and Gerbolesb, 2012). The reference electrode is typically employed in the sensor to ensure that the working electrode is maintained at the correct operating potential. These sensors are claimed to have lower detection limits, power requirements (~100 μW), and sensitivity to changes in environmental conditions and interfering gases than MOS sensors, but are also larger (few tens of millimeters in size), and more expensive (~$100) (Aleixandre and Gerbolesb, 2012; Piedrahita et al., 2014).

Low-cost gas sensors have been used in several air quality campaigns ranging from background pollutant measurements at rural and urban sites (Jiang et al., 2016; Spinelle et al., 2015b; Sun et al., 2016), measurements of road-side pollution (Mead et al., 2013; Popoola et al., 2016), mobile vehicular measurements (Hu et al., 2011; Suriano et al., 2015), source attribution (Heimann et al., 2015), and personal exposure monitoring (Jiang et al., 2011; Piedrahita et al., 2014). However, their performance characteristics are not well understood, and we found only a few studies focused on their performance assessment (Table S2). Based on those studies, we have evaluated the performance of low-cost sensors for O_3, NO_2, and CO in the following sub-sections.

3.2. Performance assessment of O_3 sensors

We found several MOS O_3 sensors and a few EC O_3 sensors that have been tested in scientific studies. Their key performance characteristics are summarised in Table 4 and discussed below.

3.2.1. Comparisons with reference measurements

Fig. 3 shows the comparisons between the outputs from the low-cost O_3 sensors and reference measurements, as quantified by the R^2 values during laboratory and field testing. Clearly, both EC and MOS sensors perform very well during laboratory tests ($R^2 > 0.90$); however, their performance gets deteriorated under real-world conditions ($R^2 = 0.01–0.94$). This performance deterioration is expected since these low-cost sensors are generally prone to sensitivities to environmental conditions, gaseous co-pollutants, and aging (Spinelle et al., 2015b, 2017).

The MOS O_3 sensors have been tested by a few studies under chamber conditions. Williams et al. (2014c) tested three different MOS sensors in an exposure chamber under four different conditions (normal, hot, humid, and cold). They generally found high R^2 values (0.88–0.99). However, it should be noted that the MICS-2611 sensor could not complete the tests under hot (temperature ≥ 50 °C) and humid (RH ≥ 85%) conditions since its response was found unstable under those conditions. Spinellea et al. (2016) tested four MOS O_3 sensors in an exposure chamber, and reported the residual values (reference concentration minus the sensor measured concentration) for those sensors. At O_3 concentrations ranging from 0 to 110 ppb, the residuals were quite low (2.0–4.2 ppb) for three sensors; however, the residual was as high as 13.3 ppb for the MICS-2610 sensor. Low standard errors (SE = 3–8 ppb) were reported by Williams et al. (2013) while testing the S300 sensor under chamber conditions.

Some studies have tested MOS O_3 sensors under real-world conditions. Like the chamber investigations, they have also reported moderate to excellent R^2 values (0.77–0.94); except for Borrego et al. (2016) who reported R^2 as 0.12 for the MICS 2610 sensor, which seems due to sensor malfunctioning. Interestingly, the same sensor model also perform poorly in the chamber investigation by Spinellea et al. (2016) as mentioned in the previous paragraph. Piedrahita et al. (2014) conducted a measurement campaign at an air quality monitoring station, and tested eight identical MOS sensors (MICS 2611), and reported that the median value of the root mean squared error (RMSE) was 6.1 ppb. The S300 sensor has also been evaluated under different outdoor conditions, and reported to have SE values between 5 and 6 ppb (Bart et al., 2014; Williams et al., 2013). Overall, the laboratory and field testing of the MOS O_3 sensors generally show good comparisons between the sensors and reference measurements.

The performances of EC O_3 sensors have been tested by a few investigation (Table 4). Spinelle and co-workers (Spinelle et al., 2015a, 2015b) assessed the performances of two different EC sensors under chamber and field conditions. During the chamber study, the R^2 was >0.99 for both the sensors (Spinelle et al., 2015a). However, when

Table 4
Performance characteristics of low-cost O_3 sensors.

Model (sensor type)	Comparison with reference measurements	Response time (t_{90}, t_{lag}, and t_{rise} in min)	Repeatability (SD in ppb)	LOD (ppb)	Cross sensitivity (in ppb of O_3/ppm for CO_2 and ppb of O_3/ppb for other gases, unless otherwise mentioned)	Effect of humidity on sensor output (δ_{RH} in ppb/%RH)	Effect of temperature on sensor output (δ_T in ppb/°C)	Stability (δ_{time} in ppb/day)
Aeroqual SM50 (MOS)	$R^2_{fld} = 0.82–0.94$[a] $R^2_{fld} = 0.77–0.94$[b]	NA	NA	NA	NA	Seems unaffected by humidity.[a]	Seems unaffected by temperature.[a]	Seems unaffected by usage duration.[a] Seems affected by usage duration.[b]
UnitecSens 3000 (MOS)	$Res_{lab} < 2.0$ ppb[c]	$t_{90} = 52$[c]	3.3[c]	2.3[c]	0.015 to NO_2, −0.061 to NO, 2.3×10^{-3} to CO, −0.076 to CO_2, and -1.1×10^{-3} to NH_3.[c]	$\delta_{RH} = -0.65$[c]	$\delta_T = -3.86$[c]	$\delta_{time} = 0.070$[c]
SGX MICS OZ-47 (MOS)	$Res_{lab} < 3.1$ ppb[c] $R^2_{fld} = 0.77$[d]	$t_{90} = 9.8$[c]	2.0[c]	1.5[c]	0.014 to NO_2, -1.9×10^{-3} to NO, -7.9×10^{-4} to CO, 2.2×10^{-3} to CO_2, and 8.0×10^{-4} to NH_3.[c]	$\delta_{RH} = -0.02$[c]	$\delta_T = -0.7$[c]	$\delta_{time} = 0.081$[c]
SGX MICS 2610 (MOS)	$Res_{lab} < 13.3$ ppb[c] $R^2_{fld} = 0.12$[d]	$t_{90} = 4.4$[c]	0.2[c]	0.5[c]	0.081 to NO_2, −0.016 to NO, -3.5×10^{-4} to CO, 1.9×10^{-3} to CO_2, and -1.0×10^{-3} to NH_3.[c]	$\delta_{RH} = 0.84$[c]	$\delta_T = -3.1$[c]	$\delta_{time} = -0.009$[c]
SGX MICS 2611 (MOS)	$R^2_{lab} = 0.88–0.95$[e] $RMSE_{fld} = 4.2–15.4$ ppb[l]	$t_{lag} = 1–3$[e] $t_{rise} = 5–8$[e]	6.5–46.2[e]	5.1–11.7[e]	Response equivalent to 0 ppb O_3 at >200 ppb of SO_2.[e]	NA	NA	NA
FIS SP-61 (MOS)	$Res_{lab} < 4.2$ ppb[c]	$t_{90} = 89$[c]	19.8[c]	n.a.	0.024 to NO_2, 0.13 to NO, 9.9×10^{-4} to CO, -1.2×10^{-2} to CO_2, and 3.0×10^{-2} to NH_3.[c]	$\delta_{RH} = -0.46$[c]	$\delta_T = -2.3$[c]	$\delta_{time} = -0.007$[c]
AGT Environmental Sensor (MOS)	$R^2_{lab} > 0.98$[e]	$t_{lag} = 1$[e] $t_{rise} = 3–6$[e]	2.6–13.6[e]	15–23.4[e]	Response equivalent to 7.5 ppb O_3 at >200 ppb of SO_2.[e]	NA	NA	NA
Dynamo Sensor (MOS)	$R^2_{lab} > 0.97$[e]	$t_{lag} = 1$[e] $t_{rise} = 2–5$[e]	3.3–7[e]	15–17.6[e]	Response equivalent to 2.9 ppb and 15.6 ppb of O_3 at >200 ppb of SO_2 and NO_2, respectively.[e]	NA	NA	NA
Aeroqual S500 (MOS)	$R^2_{fld} = 0.91$[f]	NA	NA	NA	Seems unaffected by ambient gaseous species.[f]	Seems unaffected by humidity.[f]	Seems unaffected by temperature.[f]	NA
Alphasense O3B4 (EC)	$R^2_{lab} > 0.99$[g] $R^2_{fld} = 0.02$[h] $R^2_{fld} = 0.13–0.70$[d]	$t_{90} = 1.4$[g]	0.4[g]	6.8[g]	0.92 to NO_2, −0.042 to NO, -6.6×10^{-5} to CO, 2×10^{-4} to CO_2, and 2.5×10^{-4} to NH_3.[g] No cross-sensitivity to NO, and CO.[i]	$\delta_{RH} = 0.40$[g]	$\delta_T = 0$[g]	$\delta_{time} < 0.016$[g]
Citytech O3_3E1F (EC)	$R^2_{lab} > 0.99$[g] $R^2_{fld} = 0.84–0.88$[h]	$t_{90} = 1.80$[g]	0.6[g]	2.7[g]	0.76 to NO_2, −0.011 to NO, 7.0×10^{-8} to CO, 3.5×10^{-3} to CO_2, and 1.6×10^{-3} to NH_3.[g]	$\delta_{RH} = -0.022$[g] Seems unaffected by humidity.[h]	$\delta_T = 1.3$[g] Seems unaffected by temperature.[h]	$\delta_{time} < 0.142$[h] Seems affected by usage duration.[h]
Alphasense OX-B421 (EC)	$R^2_{lab} = 0.99$[i] $R^2_{fld} = 0.01–0.66$[i]	NA	1.9[i]	1.8[i]	1.0 to NO_2, −0.251 to NO, 0 to CO, 0.22 to CO_2, and −0.036 to SO_2, estimated from Lewis et al. (2016). No cross-sensitivity to NO and CO.[i]	1.28, estimated from Lewis et al. (2016).	NA	NA
Aeroqual S300 (MOS)	$SE_{lab} = 3–8$ ppb[j] $SE_{fld} = 5$ ppb[j] $SE_{fld} = 6$ ppb[k]	NA	NA	NA	Unaffected by ambient NO.[k]	Slightly affected by humidity.[k]	NA	$\delta_{time} < 0.06$[j] Stable response for 4 months.[j] Significant sensor drift within 2 months.[j]

R^2 is the coefficient of determination, Res the residual (sensor measured value minus reference value), SE the standard error, RMSE the room mean squared error, t_{90} the mean of $t_{0–90}$ (the time needed for a sensor to reach 90% of the final stable value) and $t_{90–0}$ (the time needed by a sensor to reach zero concentration) t_{lag} the time interval between a step change in input concentration and the first observable corresponding change in measurement response, t_{rise} the time interval between the initial measurement response and 95% of final response after a step increase in input concentration, SD the standard deviation of repeated measurements, δ_{RH} the change in sensor response in ppb per percentage point increase in relative humidity, δ_T the change in sensor response in ppb per °C increase in temperature, and δ_{time} the change in sensor response in ppb per day. The subscript is lab or fld when referring to comparison between sensor and reference measurements under laboratory or field conditions, respectively. MOS stands for metal-oxide-semiconductor sensor, EC for electrochemical sensor, LOD for limit of detection, RH for relative humidity, and NA for not available. The alphabets refer to the following studies - a: (Jiao et al., 2016), b: (Moltchanov et al., 2015), c: (Spinellea et al., 2016), d: (Borrego et al., 2016), e: (Williams et al., 2014c), f: (Lin et al., 2015), g: (Spinelle et al., 2015a), h: (Spinelle et al., 2015b), i: (Castell et al., 2017), j: (Williams et al., 2013), k: (Bart et al., 2014), and l: (Piedrahita et al., 2014).

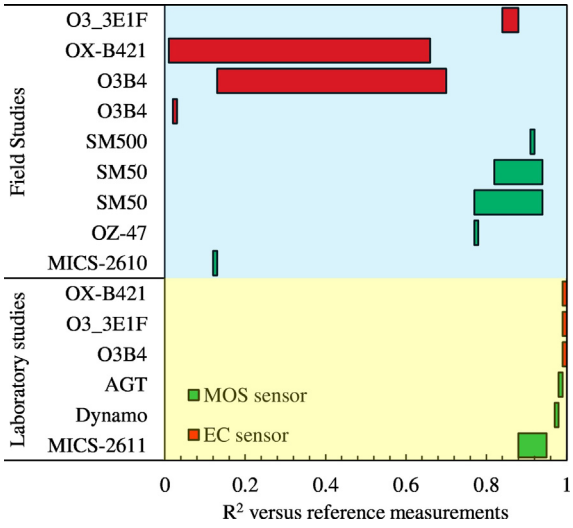

Fig. 3. Comparisons of the low-cost ozone sensors with the reference instruments under laboratory and field conditions based on the R^2 (coefficient of determination) values. Note that the y-axis refers to the different sensor models and the bars denote the range of R^2, as obtained by the different studies given in Table 4.

those sensors were calibrated under field conditions, the R^2 was 0.02 and 0.84–0.88 for the O3B4 and O3_3E1F sensors, respectively (Spinelle et al., 2015b). Thus, it seems that the O3B4 sensor was faulty, and we don't discuss additional results for this sensor obtained by Spinelle et al. (2015b). To better calibrate the O3_3E1F sensor, they used multiple linear regression models by including the concentration of NO_2 as an additional predictor, which improved the R^2 values (0.85–0.94). The linear models were then tested for 4.5 months of field deployment of the O3_3E1F sensor in the validation phase of the study. During this phase, the sensor performance deteriorated significantly, and the R^2 was between 0.67 and 0.81 and 0.58–0.82 with the simple and multiple linear regression models, respectively. This indicates that the response curves of the sensors were time variable possibly due to sensor aging and/or dust accumulation. Borrego et al. (2016) reported R^2 = 0.13–0.70 during field testing of the O3B4 sensor when it was deployed as a part of three different platforms under identical conditions. The different sensor platforms might use distinct signal processing techniques for converting the raw sensor response to the O_3 concentration, which might be the reason for the high variations in the R^2 values.

3.2.2. Repeatability, reproducibility, stability, limit of detection, and response times

The repeatability characteristics of different MOS and EC O_3 sensors have been studied by a few chamber investigations, by quantifying the standard deviations (SD) of their outputs obtained under identical conditions (Table 4). Spinellea et al. (2016) reported good repeatability characteristics for three different MOS sensors at 100 ppb O_3 (SD = 0.2–3.3 ppb); however the SP-61 MOS sensor was found to have poor repeatability (SD = 19.8 ppb) under similar conditions. Williams et al. (2014c) found variable repeatability characteristics (SD = 2.6–46.2 ppb) for different MOS sensors depending upon the sensor model, O_3 concentration, humidity, and temperature. However, they did not report the O_3 concentration range under which the different values were obtained, which makes it difficult to judge the relative measurement uncertainties. For the EC O_3 sensors, the SD values range from 0.4–1.9 ppb at 100 ppb O_3 (Table 4). Overall, it appears that both MOS and EC O_3 sensors have similar repeatability traits, and the measurement uncertainty would typically be <5% at 100 ppb O_3 concentration if the sensors worked perfectly.

The reproducibility of MOS O_3 sensors has been quantified by a few studies (Moltchanov et al., 2015; Piedrahita et al., 2014) through the computation of R^2 between the responses of several identical sensors under similar conditions. Moltchanov et al. (2015) reported high reproducibility between sensors (R^2 = 0.85–0.98), whereas Piedrahita et al. (2014) reported variable reproducibility (R^2 = 0.21–0.98). We did not find studies that reported reproducibility characteristics for the EC O_3 sensors.

The stability of four different MOS sensors and two different EC sensors was studied by Spinella and co-workers under laboratory conditions (Spinelle et al., 2015a; Spinellea et al., 2016). They reported that the sensor drifts ranged from −0.009 to 0.081 ppb O_3/day and 0.016 to 0.142 ppb O_3/day for the MOS and EC sensors, respectively, during their six months testing. This translates to −2 to 15 ppb and 3 to 26 ppb difference in sensor outputs for the MOS and EC sensors, respectively, in six months. Thus, there does not seem to be a significant difference between the stability characteristics of the MOS and EC O_3 sensor. However, the different models of the EC/MOS sensors exhibit different drifts values, meaning that the sensor manufacturing process might be playing a role in their stability.

A few field investigations have also reported the stability characteristics of the low-cost O_3 sensors. For the O3_3E1F EC sensor, Spinelle et al. (2015b) reported a significant decrease in R^2 values between the sensor response and the reference measurements from the calibration phase to the validation phase, indicating poor stability. Moltchanov et al. (2015) reported that the regression coefficients of the calibration curve of SM50 MOS sensor changed with time possibly because of aging and/or dust accumulation in the sensors due to episodic events (e.g., rain and dust storms). However, Jiao et al. (2016) did not find any association between the response of SM50 sensor and the "days of use" during their field campaign, suggesting that episodic dust accumulation might be the causing the response changes reported by Moltchanov et al. (2015). For the S300 MOS sensor, Williams et al. (2013) reported their long-term stability characteristics in monitoring campaigns conducted at several outdoor sites (Table 4). The sensor response was generally stable over several months of operation; however, at a heavily industrial site, significant sensor drift was observed due to dust accumulation at the inlet filter (Williams et al., 2009). Clearly, sensor stability is an important consideration, if long term O_3 measurements are to be conducted.

The LOD for different MOS and EC O_3 sensors were reported by a few investigations (Table 4). For the MOS sensors, the LOD values reported by Spinellea et al. (2016) were 0.5–2.3 ppb, which are much lower than the LOD values (5.1–23.4 ppb) reported by Williams et al. (2014c), due to the different methods employed for computing those values by the two investigations. For the EC sensors, the LOD ranges from 1.8–6.8 ppb, as obtained by a method identical to Spinellea et al. (2016). Thus, the LODs for the EC and MOS O_3 sensors seem comparable when same estimation method is used. Furthermore, the LODs are much lower than the typical ambient O_3 concentrations found in EU countries (Fig. 2), meaning that the sensors seem suitable for measuring ambient O_3.

The response times of four different MOS and two different EC O_3 sensors were reported by Spinellea and co-workers (Spinelle et al., 2015a; Spinellea et al., 2016). They reported the t_{90} values, which is defined as the mean of t_{0-90} (the time needed by a sensor to reach 90% of the final stable value) and t_{90-0} (the time needed by a sensor to reach zero concentration). The t_{90} was 4.4–89 min and 1.4–1.8 min for the different MOS and EC sensors, respectively. Williams et al. (2014c) reported the t_{lag} (time interval between a step change in input concentration and the first observable corresponding change in measurement response) and t_{rise} (time interval between the initial measurement response and 95% of final response after a step increase in input concentration) times for three different MOS sensors. The t_{lag} and t_{rise} were 1–3 min and 2–8 min, respectively (Table 4). Thus, the t_{90} can be roughly calculated to be around 10 min (by summing the t_{lag} and t_{rise}) for the different sensors, which is within the range of values reported by Spinellea et al. (2016) for the MOS sensors. Overall, the response

times of the MOS O_3 sensors seem to be about 5–10 times that of EC sensors, meaning that EC sensors are preferable if the high temporal resolution is required in O_3 measurements.

3.2.3. Impact of environmental factors and gaseous cross-sensitivities on sensor output

Environmental factors such as temperature and relative humidity have been found to significantly affect the outputs from MOS and EC O_3 sensors (Table 4). During the chamber testing by Spinellea et al. (2016), responses of the four different MOS sensors were found to decrease by 0.7–3.86 ppb O_3 per 1 °C increase at temperatures ranging from 12 to 32 °C. In those chamber tests, relative humidity was also found to impact the response of the MOS sensors with the change being −0.65 to 0.84 ppb O_3 per percentage point increase in relative humidity. However, during field testing negligible/little association has been observed between the responses from three different MOS sensors and temperature or humidity (Bart et al., 2014; Jiao et al., 2016; Lin et al., 2015).

Environmental factors were found to affect outputs of EC O_3 sensors with the responses of different sensors changing by −0.022 to 1.28 ppb O_3 per percentage point increase in relative humidity and by 0 to 1.3 ppb O_3 per 1 °C increase in temperature under laboratory testing (Lewis et al., 2016; Spinelle et al., 2015a). However, Spinelle et al. (2015a) did not find any influence of humidity or temperature on the response of EC sensors during their field campaign. The differences between field and chamber measurements are attributed to the inability of field measurements in isolating the effect of a particular factor (such as temperature) on the sensor's response from other confounding factors (e.g., gaseous interferences and sensor aging).

Gaseous cross-sensitivity refers to the false response obtained from a sensor because of its sensitivity to gaseous co-pollutants that commonly exist with the target pollutant. We found a few chamber investigations that reported the cross-sensitivities to CO, CO_2, NO, NO_2, SO_2, and NH_3 for different MOS and EC O_3 sensors (Table 4). From the table, it is clear that NO_2 interference is a big problem for the EC sensors since the sensor response increases by 0.76–1.0 ppb of O_3 per 1 ppb of NO_2.

The other cross-sensitivities seem negligible at first glance. However, to fully understand their impact on a sensor's response, we should know the concentration of the co-pollutant gas since the sensor response is a product of the gaseous cross-sensitivity with its corresponding concentration. Thus, we estimated the change in sensor response by multiplying the gaseous cross-sensitivities with their corresponding ambient concentrations. For CO, NO_2, and SO_2 concentrations, we used the EU specified limits; we used a representative value for background urban sites for CO_2 (400 ppb), NO (15 ppb), and NH_3 (30 ppb). The estimated changes in MOS sensor outputs were very low (−2.4 ppb to 2.0 ppb) for interferences by CO_2, NO, NO_2, and NH_3. However, CO interference caused a significant change in the MOS sensor outputs (−6.8 ppb to 20 ppb), meaning that cross-sensitivity to CO could be important for such sensors. For EC sensors, the estimated changes in outputs were low for interferences by CO, CO_2, NO, NH_3, and SO_2 (−3.77 ppb to 0.048 ppb); however, NO_2 interference causes a significant increase in sensor outputs (16–21 ppb). We also found a few field investigation that reported the negligible influence of gaseous cross-sensitivities on a MOS O_3 sensor under urban ambient concentrations (Bart et al., 2014; Lin et al., 2015). However, under such conditions several co-pollutants will be present, meaning that the overall sensor cross-sensitivity will a combination of the individual cross-sensitivities. If the individual cross-sensitivities cancel each other, the sensor will appear to suffer from no cross-sensitivities problems. Thus, we recommended that the sensor manufacturer/user should first evaluate its cross-sensitivity coefficients (to anticipated levels of co-pollutants) under laboratory conditions, and then perform field calibration under the conditions of actual deployment.

3.3. Performance assessment of NO_2 sensors

We found that three MOS and five EC NO_2 sensors have been tested by scientific studies. Their performance traits are summarised in Table S3 and discussed below.

3.3.1. Comparisons with reference measurements

Fig. 4 shows the R^2 values between the measurements from the MOS and EC NO_2 sensors and reference instrumentation under laboratory and field conditions. Fig. 4 is similar to Fig. 3, and the low-cost NO_2 sensors show excellent performance under laboratory conditions. However, their performance gets significantly deteriorated under real-world conditions due to similar reasons as discussed in the case of O_3 sensors. Furthermore, there is considerable variation in R^2 values, reported by the different field investigations. For example, the two studies that used MOS NO_2 sensors have conflicting results. Jiao et al. (2016) obtained extremely poor performance ($R^2 < 0.1$ between the sensor outputs and the reference measurements) from the MICS-2710 sensor, which was a part of the Air Quality Egg platform. Conversely, Piedrahita et al. (2014) reported reasonable measurement errors (RMSE = 6.9–9.5 ppb) with the same sensor by using a multiple linear regression model for calibration that accounted for temperature and humidity effects on the sensor's response.

Of the studies that tested EC NO_2 sensors, a few have reported $R^2 \approx 0.90$ between the sensor response and the reference measurements after applying correction algorithms for interference by O_3 or humidity (Lin et al., 2015; Mead et al., 2013; Sun et al., 2016). Duvall et al. (2016) reported $R^2 = 0.01$ for the CairClip NO_2 sensor; however, the poor sensor performance was attributed to low NO_2 concentrations (5.5 ppb

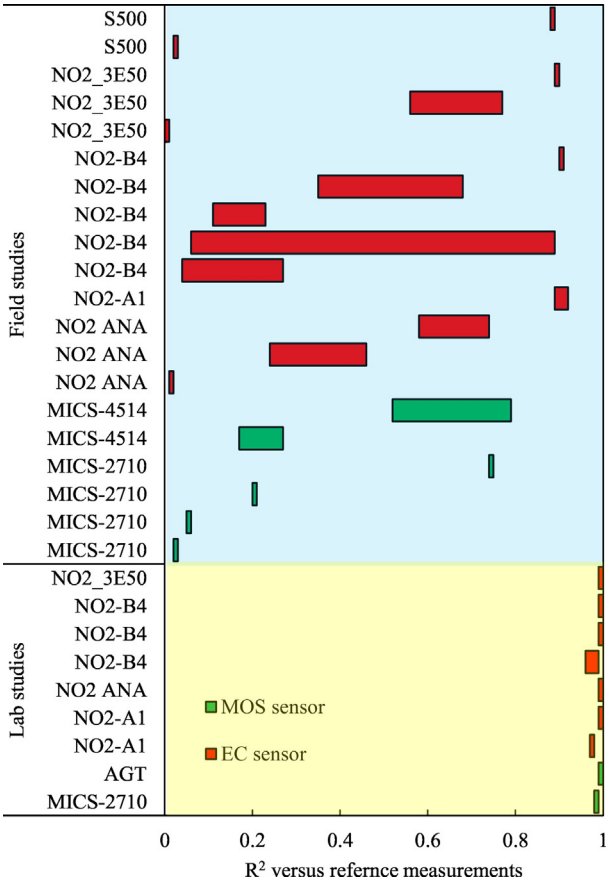

Fig. 4. Comparisons of the low-cost nitrogen dioxide sensors with the reference instruments under laboratory and field conditions based on the R^2 (coefficient of determination) values. Note that the y-axis refers to the different sensor models and the bars denote the range of R^2, as obtained by the different studies given in Table S3.

hourly averaged value). Castell et al. (2017) tested 24 EC NO_2 sensors as part of the AQMesh platform and reported $R^2 = 0.04–0.52$ during a collocation campaign at a reference station. Their results clearly show that even for identical sensor and platform, drastically different results can be obtained, calling for careful quality control in the manufacturing process for both sensors and platforms.

We found a few field investigations that have simultaneously tested MOS and EC NO_2 sensors. The investigation by Borrego et al. (2016) tested one MOS sensor and two EC sensors as part of six different sensor platforms. The MOS sensor performed poorly with $R^2 < 0.1$ between the sensor and the reference measurements, whereas the performance of EC sensors was variable with $R^2 = 0.06–0.89$ depending on the sensor and platform models. Spinelle et al. (2015b) performed a long-term assessment of two MOS and three EC NO_2 sensors. They reported low R^2 for the MOS (0.20–0.21) and EC sensors (0.00–0.46), by using a linear regression model for calibration. However, the R^2 could be considerably improved ($R^2 = 0.52–0.79$ and $R^2 = 0.35–0.77$ for the MOS and EC sensors, respectively) by using multiple linear regression models with additional predictors such as the concentrations of co-pollutants, humidity, and temperature. Those models were then tested for 4.5 months during the validation period. It was found that the performances of both the simple and multiple linear regression models were very poor during the validation period with $R^2 < 0.2$ for all the sensors probably due to sensor aging.

From the above discussion, we conclude that the best performance under real-world conditions has been achieved by performing on-site calibration of the sensors and accounting for the different factors that affect their outputs, rather than relying on manufacturer's calibration. This is because the calibration conditions used by the manufacturer might be drastically different from the actual deployment conditions. Furthermore, sensor aging and manufacturing variability also stand out as important factors that need to be accounted for when conducting measurements using low-cost NO_2 sensors.

3.3.2. Repeatability, reproducibility, stability, limit of detection, and response times

The repeatability characteristics of different MOS and EC NO_2 sensors have been studied by only a few investigations (Table S3). The SD of repeated measurements ranged from 1.2–7.5 and 4.6–23.3 for MOS and EC NO_2 sensors, respectively, as reported by Williams et al. (2014c) under different chamber conditions. However, they have not reported the NO_2 concentration at which the measurements were conducted, meaning the relative errors cannot be estimated. Spinelle et al. (2015a) and Castell et al. (2017) have reported SD ranging from 0.8–2.9 for different EC NO_2 sensors at 100 ppb NO_2 concentration, meaning that 1–3% measurement error can be expected even under ideal measurement conditions.

Regarding the reproducibility of the low-cost NO_2 sensor outputs, we noted in the previous sub-section that the R^2 values ranged from 0.04–0.52, when 24 identical NO_2-B4 EC sensors were tested as part of the AQMesh platform by Castell et al. (2017). This demonstrates poor reproducibility characteristics of this sensor platform. However, Mead et al. (2013) found good reproducibility between two pairs of identical NO_2-A1 EC sensors ($R^2 = 0.94–0.95$). Similarly, Piedrahita et al. (2014) also reported good reproducibility ($R^2 = 0.88–0.98$) between measurements from eight identical MICS-2710 MOS sensors. Overall, we found insufficient investigations on sensor reproducibility, and further studies are required to better understand this issue.

Sensor *stability* is a concern for low-cost NO_2 sensors, as demonstrated by Spinelle et al. (2015b) for both EC and MOS sensors, and discussed in the previous sub-section. The sensor drifts for EC NO_2 sensors are reported to be between −0.497 to −0.065 ppb/day (Table S3). This would cause a significant decrease in the reported NO_2 concentration (by 12–89 ppb) for a six-month monitoring campaign. Clearly, this effect needs to be considered when conducting long-term campaigns with EC NO_2 sensors.

The LOD for the different MOS and EC sensors are plotted in Fig. 2 along with the typical NO_2 concentration in EU countries and its corresponding EU specified limit. Almost all the LOD values lie above the minimum measured concentrations, showing that the sensors should not be used in places with very low concentrations of NO_2 (<10 ppb or <20 μg/m^3). From the Fig. 2, it also appears that the LOD for the MOS sensors is higher than that for the EC sensors. However, the LOD values for the MOS sensors have only been reported by Williams et al. (2014c), who used a different method for estimating LOD as compared to that used by other investigations, thereby reporting much higher values. This is also the reason for the outlier present in EC sensors: NO_2-A1 with LOD equals 12–29.4 ppb.

The sensor response times for the different MOS and EC NO_2 sensors are also given in Table S3. For the MOS sensors, we can approximate t_{90} (as the sum of t_{lag} and t_{rise}) to vary between 6 and 34 min. For the NO_2-A1 EC sensor, the t_{90} is estimated as 9–19 min. For the other EC sensors, the t_{90} equals 1.3–1.6 min, except the abnormally high value for the CairPol CairClip sensor ($t_{90} = 38.42$ min) possibly due to the presence of an O_3 filter and/or a humidity buffer in that sensor. The inter-comparison between the MOS and EC sensors is not feasible due to limited investigations that have studied this sensor trait.

3.3.3. Impact of environmental factors and gaseous cross-sensitivities on sensor output

As discussed above, some field investigations have reported improvements in R^2 values between sensor outputs and reference measurements, if factors such as humidity, temperature, and gaseous co-pollutants are included in the calibration equation. However, there are also others that show insignificant improvements in R^2, when those factors are included in the calibration equations (Table S3). As previously mentioned, field investigations are unreliable to draw such conclusions, and chamber investigations are preferred.

The effects of environmental factors on EC NO_2 sensor outputs have been reported by a few chamber investigations; however, no such investigations were found for the MOS sensors. Spinelle et al. (2015a) found that the sensor response increased by 0.093–0.47 ppb of NO_2 per °C increase in temperature from 12 to 32 °C for three different EC sensors. However, Sun et al. (2016) did not detect any influence of temperature (15–21 °C) on the NO_2-B4 sensor's response. Their temperature range is only 6 °C, and we can estimate an increase in the sensor output by only 2.8 ppb based on 0.47 ppb NO_2 per °C, reported by Spinelle et al. (2015a), which was probably left undetected by Sun et al. (2016). The impact of humidity on EC sensor outputs was reported to be between −0.057 to 0.13 ppb of NO_2 per % RH increase in humidity (40–80% RH) for three different sensors by Spinelle et al. (2015a). Sun et al. (2016) also found that humidity ranging from 40 to 70% RH increased the sensor output for the NO_2-B4 sensor; however, Lewis et al. (2016) did not observe any influence of humidity for the same sensor model. Overall, we find conflicting results regarding the effects of humidity and temperature on the response of low-cost NO_2 sensors, which might be arising due to differences in sensor models or manufacturing variations between same sensor types.

For the gaseous cross-sensitivities, both field and laboratory studies report that the responses from MOS and EC NO_2 sensors are predominantly affected by O_3 concentration (about 1.0–1.5 ppb NO_2 reported by the sensor per ppb of O_3), unless the sensors are equipped with O_3 filters (Table S3). Williams et al. (2014c) reported the cross-sensitivity to SO_2 for two different MOS and one EC sensor; however, the SO_2 concentration in their study was very high (>200 ppb), and unlikely to be found in the outdoor environment. For the other gaseous co-pollutants, cross-sensitivity data is only available for EC NO_2 sensors. We computed the estimated change in sensor response due to those cross-sensitivities by using the procedure described in the section on gaseous cross-sensitivities for ozone. The outputs from EC sensors were estimated to change by −3.3 to 1.3 ppb NO_2 due to cross-sensitivities to CO, CO_2,

NO, NH_3, and SO_2. Thus, it seems that these gaseous interferences can be neglected for EC NO_2 sensors.

3.4. Performance assessment of CO sensors

We found that only two MOS CO sensors have been tested by the scientific community. The MICS-5525 CO sensor was tested by two investigations, and both reported poor comparisons between the sensor output and reference measurements (Table S4). Piedrahita et al. (2014) also reported that the MICS-5525 sensor's response decreased linearly when the temperature was increased from 19 °C to 40 °C during chamber testing. The MICS-5525 sensor's reproducibility was moderate with R^2 between 0.38 and 0.60 (Piedrahita et al., 2014). Another MOS sensor (model MICS-4514) was tested by Spinelle et al. (2017) under field conditions. They reported good agreement ($R^2 = 0.76–0.78$) between sensor response and reference measurements when it was calibrated by using simple or multiple linear regression models. However, the same models performed poorly during the 4.5 months validation phase ($R^2 < 0.1$). Like low-cost O_3 and NO_2 sensors, it seems that aging is also an important factor for MOS CO sensors, and should be accounted for before making long-term measurements.

Three different EC CO sensors have been tested in both chamber and field conditions. In chamber conditions, there is an excellent agreement between the sensor output and reference measurements with $R^2 > 0.99$ (Castell et al., 2017; Mead et al., 2013; Sun et al., 2016). However, the field investigations report significant deterioration and variations in sensor performances (Fig. 5). Two field studies reported moderate to excellent R^2 values (0.53–0.97) for the CO-B4 sensor (Borrego et al., 2016; Sun et al., 2016). However, two other field studies have reported poor R^2 values (0.17–0.45) for the CO-B4 and TGS-5042 sensors, when calibrating them with reference measurements (Castell et al., 2017; Spinelle et al., 2017). The differences in sensor performances could be attributed to the differences in testing conditions and methods. Note that sensor aging is also important for EC CO sensors since the sensor calibration curve can change significantly over time (Castell et al., 2017; Spinelle et al., 2017).

Fig. 2 shows the LOD values for the EC CO sensors (LOD = 4–21 ppb from Table S4), which lie well below the typical concentration range of CO in EU countries, meaning that these sensors seem suitable for measuring ambient CO. Mead et al. (2013) reported high sensor-to-sensor reproducibility for the CO-AF sensor ($R^2 = 0.86–0.95$). Sun et al. (2016) reported that the CO-B4 sensor was unaffected by humidity and temperature changes during chamber testing. Lewis et al. (2016) reported that the CO-B4 sensor's response will increase by 0.532 ppb CO per percentage point increase in humidity, meaning that the maximum variation in output would be 53.2 ppb (when RH changes from 0 to 100%), which is quite low compared to typical CO concentrations in Europe. Popoola et al. (2016) found that the CO-AF sensor's baseline response was slightly affected by temperature during chamber tests. Thus, it seems that humidity and temperature influences might not be important for EC CO sensors. We computed that the cross-sensitivities to NO_2, O_3, NO, CO_2, and SO_2 would only change the response of the CO-B4 sensor by −1.7 to 1.8 ppb from the data given by Lewis et al. (2016) by following the procedure discussed previously. The other investigations (Table S4) also show that the response from EC CO sensors does not seem influenced by gaseous co-pollutants.

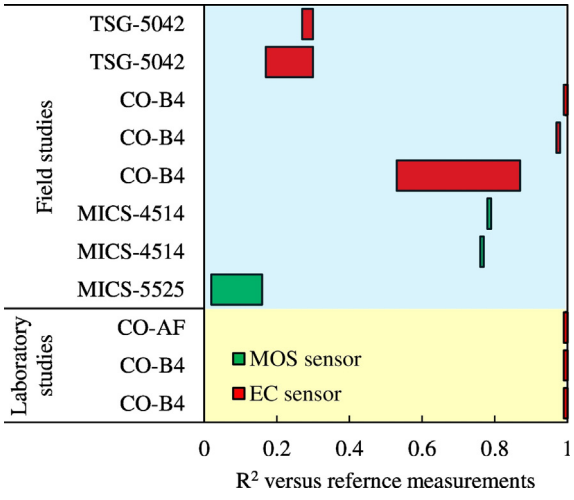

Fig. 5. Comparisons of the low-cost carbon monoxide sensors with the reference instruments under laboratory and field conditions based on the R^2 (coefficient of determination) values. Note that the y-axis refers to the different sensor models and the bars denote the range of R^2, as obtained by the different studies given in Table S4.

3.5. Recommendations for end-users

Two types of low-cost sensors are available in the market for measuring gaseous air pollutants: EC sensors and MOS sensors. From the above discussion, we find that both the sensor types seem to share many performance traits; however, a few significant differences also exist (Table S5). MOS sensors are typically cheaper than EC sensors; however, they also consume much higher power. For O_3 measurements, MOS sensors are preferable over EC sensors since they seem to provide better agreement with reference measurements, and do not suffer from a significant cross-sensitivity to NO_2. However, note that the EC O_3 sensors seem to have a faster response time, meaning they can achieve higher temporal resolution. For NO_2 and CO measurements, both sensor types seem to provide similar levels of comparisons with reference measurements. However, we did not find enough studies that compared the two sensor types for other performance characteristics. Thus, recommending a particular sensor type is not feasible at this stage for NO_2 and CO measurements.

Like the low-cost PM sensors, the gaseous sensors are also available as stand-alone sensors or sensor kits such as AQMesh and Air Quality Egg, and an appropriate choice can be made depending on the end user's expertise in data-handling tasks. Note that a few sensor kits (such as AQMesh) have a proprietary data processing algorithm, and caution must be exercised while using them since they have not been calibrated and tested for the end user's test conditions. Thus, to judge the data quality obtained from such kits, it is essential to compare their outputs with the corresponding reference measurements under deployment conditions. For the stand-alone sensors and user-calibrated sensor kits, it is recommended to calibrate them under conditions as close to final deployment as possible. Furthermore, frequent calibration is recommended depending on the sensor's stability.

4. Conclusions and future outlook

The most important hindrance in deploying low-cost sensors at a large scale is regarding quality control of the data. While many scientific studies have utilised low-cost PM and gaseous sensors in a variety of air pollution monitoring activities, only a few have reported sensor performance characteristics and the associated data quality. To further exacerbate the matter, performance assessments have been done by using different experimental setups, reference equipment, and environmental conditions, making it extremely difficult to make inter-comparisons between them and draw generalised conclusions regarding the data quality. Thus, to deploy a large-scale sensor network and meaningfully use the plethora of data generated, it is imperative to formulate standard guidelines for assessing the short and long-term performance of low-cost sensors, which can be used by all. The onus should ideally be on sensor manufacturers to provide the end-user with information about the data quality expected from a sensor since the manufacturers are best positioned to ensure standardisation of the sensor manufacturing and calibration process.

Inadequate sensor calibration seems to be another issue plaguing the data quality. The sensor response is largely impacted by environmental conditions, particle characteristics (for PM sensors), and gaseous cross-sensitivities (for gas sensors). Thus, calibration methods that don't include these factors are bound to produce erroneous data. The sensor manufacturer should ideally provide a calibration equation by using laboratory testing and identify the major factors that affect their sensor's response. The calibration curve can then be improved by the end-user through testing the sensor under actual conditions of deployment (Williams et al., 2013). Advanced calibration techniques such as neural networks could also be considered since they might be more effective than regression modelling (De Vito et al., 2008, 2009, 2015; Esposito et al., 2016; Spinelle et al., 2015b, 2017).

In the case of large sensor networks that might be used for making high-resolution spatiotemporal air pollution maps, frequent in-situ calibration might not be practically possible. In such scenarios, advanced statistical techniques for sensor fault detection and data quality verification could be utilised. These include using data consistency checks (Bart et al., 2014), principal components analysis (Harkat et al., 2006, 2005), network correlations (Alavi-Shoshtari et al., 2013), and algorithm-based mobile quality checks (Hasenfratz et al., 2012; Talampas and Low, 2012), some of which have been successfully exploited for managing large-scale ozone sensor networks (Bart et al., 2014; Miskell et al., 2016; Weissert et al., 2017).

Once the data obtained from low-cost sensors has met the expected quality criteria (such as the ones specified in the EU Air Quality Directive 2008/50/EC or a user-specified criteria), it can be utilised for its intended purpose. Currently, the sensors are unsuitable for indicative monitoring purpose in EU since they generally cannot meet the data quality objectives as specified in the 2008/50/EC directive (Castell et al., 2017; Spinelle et al., 2015b, 2017). The sensors seem to perform better at high pollutant concentrations (Castell et al., 2017), which could present an enhanced opportunity for using such sensors in highly polluted areas (developing countries); however, more studies are required to test the sensors under such conditions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2017.06.266.

References

Alavi-Shoshtari, M., Williams, D.E., Salmond, J.A., Kaipio, J.P., 2013. Detection of malfunctions in sensor networks. Environmetrics 24, 227–236.
Aleixandre, M., Gerbolesb, M., 2012. Review of small commercial sensors for indicative monitoring of ambient gas. Chem. Eng. Trans. 30.
Alvarado, M., Gonzalez, F., Fletcher, A., Doshi, A., 2015. Towards the development of a low cost airborne sensing system to monitor dust particles after blasting at open-pit mine sites. Sensors (Basel) 15, 19667–19687.
Austin, E., Novosselov, I., Seto, E., Yost, M.G., 2015. Laboratory evaluation of the Shinyei PPD42NS low-cost particulate matter sensor. PLoS One 10, e0137789.
Avnery, S., Mauzerall, D.L., Liu, J., Horowitz, L.W., 2011a. Global crop yield reductions due to surface ozone exposure: 1. Year 2000 crop production losses and economic damage. Atmos. Environ. 45, 2284–2296.
Avnery, S., Mauzerall, D.L., Liu, J., Horowitz, L.W., 2011b. Global crop yield reductions due to surface ozone exposure: 2. Year 2030 potential crop production losses and economic damage under two scenarios of O_3 pollution. Atmos. Environ. 45, 2297–2309.
Bart, M., Williams, D.E., Ainslie, B., McKendry, I., Salmond, J., Grange, S.K., Alavi-Shoshtari, M., Steyn, D., Henshaw, G.S., 2014. High-density ozone monitoring using gas sensitive semi-conductor sensors in the Lower Fraser Valley, British Columbia. Environ. Sci. Technol. 48, 3970–3977.
Bhanarkar, M.K., Godase, S.M., Korake, P.M., Navarkhele, V.V., 2016. Review on WSN based outdoor air pollution monitoring system. Int. J. Ser. Eng. Sci. 1–13 (ISSN: 2455-3328).
Borrego, C., Costa, A.M., Ginja, J., Amorim, M., Coutinho, M., Karatzas, K., Sioumis, T., Katsifarakis, N., Konstantinidis, K., De Vito, S., Esposito, E., Smith, P., André, N., Gérard, P., Francis, L.A., Castell, N., Schneider, P., Viana, M., Minguillón, M.C., Reimringer, W., Otjes, R.P., von Sicard, O., Pohle, R., Elen, B., Suriano, D., Pfister, V., Prato, M., Dipinto, S., Penza, M., 2016. Assessment of air quality microsensors versus reference methods: the EuNetAir joint exercise. Atmos. Environ. 147, 246–263.
Castell, N., Viana, M., Minguillón, M.C., Guerreiro, C., Querol, X., 2013. Real-world application of new sensor technologies for air quality monitoring. ETC/ACM Technical Paper. 16.
Castell, N., Dauge, F.R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., Bartonova, A., 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 99, 293–302.
CPCB, 2017. Central Pollution Control Pollution Board Network.Available from:. http://www.cpcb.nic.in/Network.php/ (accessed 05 June 2017).
De Vito, S., Massera, E., Piga, M., Martinotto, L., Di Francia, G., 2008. On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario. Sensors Actuators B Chem. 129, 750–757.
De Vito, S., Piga, M., Martinotto, L., Di Francia, G., 2009. CO, NO_2 and NOx urban pollution monitoring with on-field calibrated electronic nose by automatic Bayesian regularization. Sensors Actuators B Chem. 143, 182–191.
De Vito, S., Veneri, P.D., Esposito, E., Salvato, M., Bright, V., Jones, R., Popoola, O., 2015. Dynamic multivariate regression for on-field calibration of high speed air quality chemical multi-sensor systems. AISEM Annual Conference, 2015 XVIII. IEEE.
DEFRA, 2011. Department for Environment, Food & Rural Affairs. https://uk-air.defra.gov.uk/networks/ (accessed 31 October 2016).
Duvall, R.M., Long, R.W., Beaver, M.R., Kronmiller, K.G., Wheeler, M.L., Szykman, J.J., 2016. Performance evaluation and community application of low-cost sensors for ozone and nitrogen dioxide. Sensors (Basel) 16.
Esposito, E., De Vito, S., Salvato, M., Bright, V., Jones, R.L., Popoola, O., 2016. Dynamic neural network architectures for on field stochastic calibration of indicative low cost air quality sensing systems. Sensors Actuators B Chem. 231, 701–713.
Fenger, J., 2009. Air pollution in the last 50 years–from local to global. Atmos. Environ. 43, 13–22.
Fine, G.F., Cavanagh, L.M., Afonja, A., Binions, R., 2010. Metal oxide semi-conductor gas sensors in environmental monitoring. Sensors (Basel) 10, 5469–5502.
Gao, M., Cao, J., Seto, E., 2015. A distributed network of low-cost continuous reading sensors to measure spatiotemporal variations of PM2.5 in Xi'an, China. Environ. Pollut. 199, 56–65.
Guerreiro, C., de Leeuw, F., Foltescu, V., 2013. Air Quality in Europe – 2013 Report. http://www.eea.europa.eu/publications/air-quality-in-europe-2013 European Environment Agency (accessed 18 January 2017).
Guerreiro, C., Ortiz, A.G., de Leeuw, F., Viana, M., Horálek, J., 2016. Air Quality in Europe – 2016 Report. http://www.eea.europa.eu/publications/air-quality-in-europe-2016 European Environment Agency (accessed 18 January 2017).
Hagler, G.S.W., Solomon, P.A., Hunt, S.W., 2013. New Technology for Low-cost, Real-time Air Monitoring. EM Magazine - Air & Waste Management Association.
Han, I., Symanski, E., Stock, T.H., 2017. Feasibility of using low-cost portable particle monitors for measurement of fine and coarse particulate matter in urban ambient air. J. Air Waste Manage. Assoc. 67, 330–340.
Harkat, M.F., Mourot, G., Ragot, J., 2005. Sensor fault detection and isolation of an air quality monitoring network using nonlinear principal component analysis. 16th IFAC World Congress, Prague, Czech Republic.
Harkat, M.-F., Mourot, G., Ragot, J., 2006. An improved PCA scheme for sensor FDI: application to an air quality monitoring network. J. Process Control 16, 625–634.
Hasenfratz, D., Saukh, O., Thiele, L., 2012. In: Picco, G.P., Heinzelman, W. (Eds.), On-the-fly calibration of low-cost gas sensors. Wireless Sensor Networks: 9th European Conference, EWSN 2012, Trento, Italy, February 15–17, 2012 Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg.
Heimann, I., Bright, V.B., McLeod, M.W., Mead, M.I., Popoola, O.A.M., Stewart, G.B., Jones, R.L., 2015. Source attribution of air pollution by spatial scale separation using high spatial density networks of low cost air quality sensors. Atmos. Environ. 113, 10–19.
Holmes, N.S., Morawska, L., 2006. A review of dispersion modelling and its application to the dispersion of particles: an overview of different dispersion models available. Atmos. Environ. 40, 5902–5928.
Holstius, D.M., Pillarisetti, A., Smith, K.R., Seto, E., 2014. Field calibrations of a low-cost aerosol sensor at a regulatory monitoring site in California. Atmos. Meas. Tech. 7, 1121–1131.
Hu, S.-C., Wang, Y.-C., Huang, C.-Y., Tseng, Y.-C., 2011. Measuring air quality in city areas by vehicular wireless sensor networks. J. Syst. Softw. 84, 2005–2012.
Jiang, Y., Li, K., Tian, L., Piedrahita, R., Yun, X., Mansata, O., Lv, Q., Dick, R.P., Hannigan, M., Shang, L., 2011. MAQS: a personalized mobile sensing system for indoor air quality monitoring. Proceedings of the 13th International Conference on Ubiquitous Computing: ACM.
Jiang, Q., Kresin, F., Bregt, A.K., Kooistra, L., Pareschi, E., Van Putten, E., Volten, H., Wesseling, J., 2016. Citizen sensing for improved urban environmental monitoring. J. Sens. 2016.
Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D., Judge, R., Caudill, M., Rickard, J., Davis, M., 2016. Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. Atmos. Meas. Tech. 9, 5281–5292.
Johnson, K.K., Bergin, M.H., Russell, A.G., Hagler, G.S.W., 2016. Using low-cost sensors to measure ambient particulate matter concentrations and on-road emissions factors. Atmos. Meas. Tech. Discuss. 1–22.
Jovašević-Stojanović, M., Bartonova, A., Topalović, D., Lazović, I., Pokrić, B., Ristovski, Z., 2015. On the use of small and cheaper sensors and devices for indicative citizen-based monitoring of respirable particulate matter. Environ. Pollut. 206, 696–704.

Judge, R., Wayland, R.A., 2014. Regulatory Considerations of Lower Cost Air Pollution Sensor Data Performance. EM Magazine - Air & Waste Management Association.
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. Environ. Pollut. 221, 491–500.
Koehler, K.A., Peters, T.M., 2015. New methods for personal exposure monitoring for airborne particles. Curr. Environ. Health Rep. 2, 399–411.
Kumar, P., Ketzel, M., Vardoulakis, S., Pirjola, L., Britter, R., 2011. Dynamics and dispersion modelling of nanoparticles from road traffic in the urban atmospheric environment—a review. J. Aerosol Sci. 42, 580–603.
Kumar, P., Morawska, L., Birmili, W., Paasonen, P., Hu, M., Kulmala, M., Harrison, R.M., Norford, L., Britter, R., 2014. Ultrafine particles in cities. Environ. Int. 66, 1–10.
Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., Bell, M., Norford, L., Britter, R., 2015. The rise of low-cost sensing for managing air pollution in cities. Environ. Int. 75, 199–205.
Kumar, P., Martani, C., Morawska, L., Norford, L., Choudhary, R., Bell, M., Leach, M., 2016a. Indoor air quality and energy management through real-time sensing in commercial buildings. Energ. Buildings 111, 145–153.
Kumar, P., Skouloudis, A.N., Bell, M., Viana, M., Carotta, M.C., Biskos, G., Morawska, L., 2016b. Real-time sensors for indoor air monitoring and challenges ahead in deploying them to urban buildings. Sci. Total Environ. 560–561, 150–159.
Lewis, A., Edwards, P., 2016. Validate personal air-pollution sensors. Nature 535, 29–31.
Lewis, A.C., Lee, J.D., Edwards, P.M., Shaw, M.D., Evans, M.J., Moller, S.J., Smith, K.R., Buckley, J.W., Ellis, M., Gillot, S.R., 2016. Evaluating the performance of low-cost chemical sensors for air pollution research. Faraday Discuss. 189, 85–103.
Li, M., Zhang, L., 2014. Haze in China: current and future challenges. Environ. Pollut. 189, 85–86.
Lin, C., Gillespie, J., Schuder, M.D., Duberstein, W., Beverland, I.J., Heal, M.R., 2015. Evaluation and calibration of Aeroqual series 500 portable gas sensors for accurate measurement of ambient ozone and nitrogen dioxide. Atmos. Environ. 100, 111–116.
Manikonda, A., Zíková, N., Hopke, P.K., Ferro, A.R., 2016. Laboratory assessment of low-cost PM monitors. J. Aerosol Sci. 102, 29–40.
Mead, M.I., Popoola, O.A.M., Stewart, G.B., Landshoff, P., Calleja, M., Hayes, M., Baldovi, J.J., McLeod, M.W., Hodgson, T.F., Dicks, J., Lewis, A., Cohen, J., Baron, R., Saffell, J.R., Jones, R.L., 2013. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. Atmos. Environ. 70, 186–203.
Menz, F.C., Seip, H.M., 2004. Acid rain in Europe and the United States: an update. Environ. Sci. Pol. 7, 253–265.
Miskell, G., Salmond, J., Alavi-Shoshtari, M., Bart, M., Ainslie, B., Grange, S., McKendry, I.G., Henshaw, G.S., Williams, D.E., 2016. Data verification tools for minimizing management costs of dense air-quality monitoring networks. Environ. Sci. Technol. 50, 835–846.
Moltchanov, S., Levy, I., Etzion, Y., Lerner, U., Broday, D.M., Fishbain, B., 2015. On the feasibility of measuring urban air pollution by wireless distributed sensor networks. Sci. Total Environ. 502, 537–547.
Mouzourides, P., Kumar, P., Neophytou, M.K.-A., 2015. Assessment of long-term measurements of particulate matter and gaseous pollutants in South-East Mediterranean. Atmos. Environ. 107, 148–165.
Northcross, A.L., Edwards, R.J., Johnson, M.A., Wang, Z.M., Zhu, K., Allen, T., Smith, K.R., 2013. A low-cost particle counter as a real-time fine-particle mass monitor. Environ. Sci.: Processes Impacts 15, 433–439.
Olivares, G., Edwards, S., 2015. The Outdoor Dust Information Node (ODIN) – development and performance assessment of a low-cost ambient dust sensor. Atmos. Meas. Tech. Discuss. 8, 7511–7533.
Olivares, G., Longley, I., Coulson, G., 2012. Development of a Low-cost Device for Observing Indoor Particle Levels Associated With Source Activities in the Home. Proceedings of the International Society of Exposure Science Conference, Seattle, WA, USA.
Piedrahita, R., Xiang, Y., Masson, N., Ortega, J., Collier, A., Jiang, Y., Li, K., Dick, R., Lv, Q., Hannigan, M., 2014. The next generation of low-cost personal air quality sensors for quantitative exposure monitoring. Atmos. Meas. Tech. 7, 3325–3336.
Popoola, O.A.M., Stewart, G.B., Mead, M.I., Jones, R.L., 2016. Development of a baseline-temperature correction methodology for electrochemical sensors and its implications for long-term stability. Atmos. Environ. 147, 330–343.
Rajasegarar, S., Zhang, P., Zhou, Y., Karunasekera, S., Leckie, C., Palaniswami, M., 2014. High resolution spatio-temporal monitoring of air pollutants using wireless sensor networks. Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2014 IEEE Ninth International Conference on. IEEE.
Ramanathan, V., Feng, Y., 2009. Air pollution, greenhouse gases and climate change: global and regional perspectives. Atmos. Environ. 43, 37–50.
Sharma, P., Sharma, P., Jain, S., Kumar, P., 2013. An integrated statistical approach for evaluating the exceedence of criteria pollutants in the ambient air of megacity Delhi. Atmos. Environ. 70, 7–17.
Snyder, E.G., Watkins, T.H., Solomon, P.A., Thoma, E.D., Williams, R.W., Hagler, G.S., Shelow, D., Hindin, D.A., Kilaru, V.J., Preuss, P.W., 2013. The changing paradigm of air pollution monitoring. Environ. Sci. Technol. 47, 11369–11377.
Solomon, S., 1999. Stratospheric ozone depletion: a review of concepts and history. Rev. Geophys. 37, 275–316.
Solomon, S., Garcia, R.R., Rowland, F.S., Wuebbles, D.J., 1986. On the depletion of Antarctic ozone. Nature 321, 755–758.
Sousan, S., Koehler, K., Hallett, L., Peters, T.M., 2016a. Evaluation of the Alphasense optical particle counter (OPC-N2) and the Grimm portable aerosol spectrometer (PAS-1.108). Aerosol Sci. Technol. 50, 1352–1365.
Sousan, S., Koehler, K., Thomas, G., Park, J.H., Hillman, M., Halterman, A., Peters, T.M., 2016b. Inter-comparison of low-cost sensors for measuring the mass concentration of occupational aerosols. Aerosol Sci. Technol. 50, 462–473.
Spinelle, L., Gerboles, M., Aleixandre, M., 2015a. Performance evaluation of amperometric sensors for the monitoring of O_3 and NO_2 in ambient air at ppb level. Procedia Eng. 120, 480–483.
Spinelle, L., Gerboles, M., Villani, M.G., Aleixandre, M., Bonavitacola, F., 2015b. Field calibration of a cluster of low-cost available sensors for air quality monitoring. Part a: ozone and nitrogen dioxide. Sensors Actuators B Chem. 215, 249–257.
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 CO_2. Sensors Actuators B Chem. 238, 706–715.
Spinellea, L., Gerbolesa, M., Aleixandreb, M., Bonavitacolac, F., 2016. Evaluation of metal oxides sensors for the monitoring of O_3 in ambient air at ppb level. Chem. Eng. Trans. 54, 319–324.
Steinle, S., Reis, S., Sabel, C.E., Semple, S., Twigg, M.M., Braban, C.F., Leeson, S.R., Heal, M.R., Harrison, D., Lin, C., Wu, H., 2015. Personal exposure monitoring of PM2.5 in indoor and outdoor microenvironments. Sci. Total Environ. 508, 383–394.
Stetter, J.R., Li, J., 2008. Amperometric gas sensors a review. Chem. Rev. 108, 352–366.
Sun, L., Wong, K.C., Wei, P., Ye, S., Huang, H., Yang, F., Westerdahl, D., Louie, P.K., Luk, C.W., Ning, Z., 2016. Development and application of a next generation air sensor network for the Hong Kong marathon 2015 air quality monitoring. Sensors (Basel) 16, 211.
Suriano, D., Prato, M., Pfister, V., Cassano, G., Camporeale, G., Dipinto, S., Penza, M., 2015. Stationary and mobile low-cost gas sensor systems for air quality monitoring applications. Fourth Scientific Meeting EuNetAir. Linkoping University, Linkoping, Sweden.
Talampas, M.C.R., Low, K.-S., 2012. Maximum likelihood estimation of ground truth for air quality monitoring using vehicular sensor networks. TENCON 2012-2012 IEEE Region 10 Conference. IEEE.
Taylor, B.N., Kuyatt, C.E., 1994. Guidelines for Evaluating and Expressing the Uncertainty of NIST Measurement Results. https://www.nist.gov/sites/default/files/documents/pml/pubs/tn1297/tn1297s.pdf National Institute of Standards and Technology, Gaithersburg, MD 20899-0001 (accessed 25 October 2016).
Thomas, A., Gebhart, J., 1994. Correlations between gravimetry and light scattering photometry for atmospheric aerosols. Atmos. Environ. 28, 935–938.
Thompson, J.E., 2016. Crowd-sourced air quality studies: a review of the literature & portable sensors. Trends Environ. Anal. Chem. 11, 23–34.
Van Dingenen, R., Dentener, F.J., Raes, F., Krol, M.C., Emberson, L., Cofala, J., 2009. The global impact of ozone on agricultural crop yields under current and future air quality legislation. Atmos. Environ. 43, 604–618.
Vardoulakis, S., Fisher, B.E., Pericleous, K., Gonzalez-Flesca, N., 2003. Modelling air quality in street canyons: a review. Atmos. Environ. 37, 155–182.
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 Sci. Technol. 49, 1063–1077.
Weissert, L.F., Salmond, J.A., Miskell, G., Alavi-Shoshtari, M., Grange, S.K., Henshaw, G.S., Williams, D.E., 2017. Use of a dense monitoring network of low-cost instruments to observe local changes in the diurnal ozone cycles as marine air passes over a geographically isolated urban centre. Sci. Total Environ. 575, 67–78.
White, R.M., Paprotny, I., Doering, F., Cascio, W.E., Solomon, P.A., Gundel, L.A., 2012. Sensors and 'apps' for community-based atmospheric monitoring. EM: Air and Waste Management Association's Magazine for Environmental Managers. 5, pp. 36–40.
WHO, 2014. Burden of Disease From Ambient Air Pollution for 2012. http://www.who.int/phe/health_topics/outdoorair/databases/AAP_BoD_results_March2014.pdf World Health Organization (accessed 31 October 2016).
WHO, 2016. Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease. http://apps.who.int/iris/bitstream/10665/250141/1/9789241511353-eng.pdf?ua=1 World Health Organization (accessed 31 October 2016).
Williams, D.E., Henshaw, G.S., Wells, B., Ding, G., Wagner, J., Wright, B., Yung, Y.F., Salmond, J., 2009. Development of low-cost ozone measurement instruments suitable for use in an air quality monitoring network. Chem. N. Z. 73, 27–33.
Williams, D.E., Henshaw, G.S., Bart, M., Laing, G., Wagner, J., Naisbitt, S., Salmond, J.A., 2013. Validation of low-cost ozone measurement instruments suitable for use in an air-quality monitoring network. Meas. Sci. Technol. 24, 065803.
Williams, R., Kaufman, A., Hanley, T., Joann, R., Garvey, S., 2014a. Evaluation of Field-deployed Low Cost PM Sensors. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=297517 U.S. Environmental Protection Agency (accessed 13 January 2017).
Williams, R., Kilaru, V., Snyder, E., Kaufman, A., Dye, T., Rutter, A., Russell, A., Hafner, H., 2014b. Air Sensor Guidebook. U.S. Environmental Protection Agency https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277996 (accessed 31 October 2016).
Williams, R., Long, R., Beaver, M., Kaufman, A., Zeiger, F., Heimbinder, M., Hang, I., Yap, R., Acharya, B., Ginwald, B., Kupcho, K., Robinson, S., Zaouak, O., Aubert, B., Hannigan, M., Piedrahita, R., Masson, N., Moran, B., Rook, M., Heppner, P., Cogar, C., Nikzad, N., Griswold, W., 2014c. Sensor Evaluation Report. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277270 U.S. Environmental Protection Agency (accessed 31 October 2016).
Xu, P., Chen, Y., Ye, X., 2013. Haze, air pollution, and health in China. Lancet 382, 2067.
Zakaria, N., Abdullah, J., Yusof, A., Azizan, M., Kimpol, N., 2014. A study of rice husk total suspended particles (TSP) level using optical sensor in a rice mill factory. Int. J. Energy Power Eng. Res. 2, 29–33.
Zhou, X., Lee, S., Xu, Z., Yoon, J., 2015. Recent progress on the development of chemosensors for gases. Chem. Rev. 115, 7944–8000.
Zikova, N., Hopke, P.K., Ferro, A.R., 2016. Evaluation of new low-cost particle monitors for PM 2.5 concentrations measurements. J. Aerosol Sci. 105, 24–34.

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