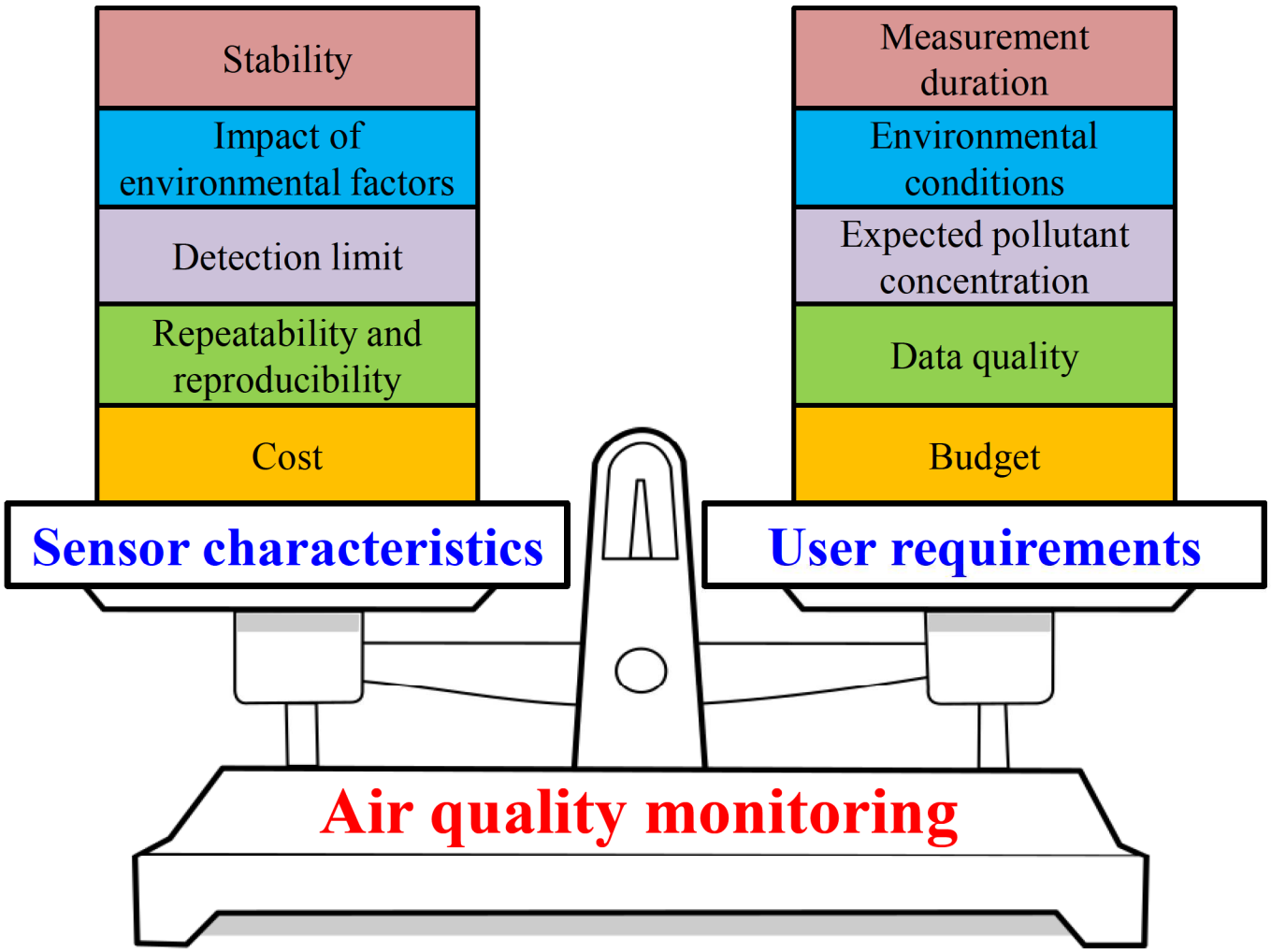
End-user perspective of low-cost sensors for outdoor air pollution monitoring



Graphical abstract

RESEARCH 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.

End-user Perspective of Low-cost Sensors for Outdoor Air Pollution Monitoring

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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 outlook for effectively deploying low-cost sensors, and maintaining data quality is 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.

KEYWORDS: Pollution exposure; Human health; Outdoor pollution sensing; Environmental sensing; Real-time exposure

LIST OF ACRONYMS

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 less than 2.5 μm in diameter

PM_{10} = PM less than 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

$t_{0\text{-}90}$ Time interval needed by a sensor to reach 90% of the final stable value

$t_{90\text{-}0}$: Time interval needed by a sensor to reach zero concentration

t_{90}: Mean of $t_{0\text{-}90}$ and $t_{90\text{-}0}$

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; Avnery et al., 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; Kumar et al., 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

92 concentrations of different air pollutants, which can be then utilised for a variety of air pollution
93 management tasks such as (i) supplementing conventional air pollution monitoring; (ii)
94 improving the link between pollutant exposure and human health; (iii) emergency response
95 management, hazardous leak detection, and source compliance monitoring; and (iv) increasing
96 community's awareness and engagement towards air quality issues.

97 Though there is no universally agreed definition of a "low-cost" sensor since anything costing
98 less than the instrumentation cost required for demonstrating compliance with the air quality
99 regulations can be termed as low-cost. However, the cost should be as low as possible to achieve
100 the above-mentioned aims of a sensor-based system for monitoring air pollution, so that
101 widespread deployment is commercially feasible. Thus, in this paper, the term low-cost sensor is
102 used either for designating sensors costing only a few 10's of US dollars or for sensing
103 kits/nodes/platforms costing a few 100's of US dollars. The higher cost of sensing kits is
104 expected since they typically include one or more sensors, microprocessor, data-logger, memory
105 card, battery, and display.

106 Several review articles have already addressed this emerging area of sensor-based air quality
107 monitoring (Table 1). A majority of these articles focus on the needs, benefits, challenges, and
108 future directions of a sensor-based pollution monitoring paradigm for different applications
109 (Castell et al., 2013; Kumar et al., 2016a; Kumar et al., 2015; Kumar et al., 2016b; Snyder et al.,
110 2013; White et al., 2012). A few others discuss emerging sensor technologies for monitoring
111 gaseous and/or particulate air pollutants (Aleixandre and Gerbolesb 2012; Bhanarkar et al., 2016;
112 White et al., 2012; Zhou et al., 2015). On-going air quality management campaigns using sensor
113 networks were reviewed in some other articles (Castell et al., 2013; Thompson 2016). However,

114 none of them have comprehensively addressed the crucial aspect of *performance assessment* of
115 low-cost sensors for monitoring different air pollutants vis-à-vis their more expensive
116 counterparts. Jovašević-Stojanović et al. (2015) provided some information about selecting low-
117 cost PM sensors based on their specifications and the monitoring objectives. However, they did
118 not include gaseous sensors, and several new research articles on performance assessment of PM
119 sensors have come up since then. Williams et al. (2014b) provided guidelines regarding sensor
120 selection but these guidelines are open ended and leave it for end-users to carefully review a
121 sensor's performance before purchasing it. Without a proper understanding of the performance
122 characteristics of the available low-cost sensors, the end-users cannot be expected to effectively
123 deploy them for achieving an effective sensor-based management of air pollution (Castell et al.,
124 2016; Jovašević-Stojanović et al., 2015; Judge and Wayland 2014; Lewis and Edwards 2016).
125 Addressing this crucial issue forms the motivation for this review article.

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

135 ## 2. LOW-COST SENSORS FOR MONITORING PARTICULATE MATTER

136 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 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

159 particles ≤2.5 μm in diameter to pass through the sensing zone, making it suitable for measuring
160 $PM_{2.5}$ (particles less than 2.5 μm in diameter). It is not known how the Plantower sensors (Table
161 2) perform size discrimination between particles. Thus, to monitor PM_{10} (particles less than 10
162 μm in diameter) or $PM_{2.5}$ any sensor given in Table 2 would be suitable if an appropriate
163 mechanism for size selection is used. The requirement for a size selection mechanism is not
164 stringent for monitoring PM_{10} since particles ≥10 μm are difficult to draw in the sensing zone
165 (Koehler and Peters 2015), meaning that the raw sensor output would roughly correspond to the
166 PM_{10} concentration.

167 Many of these sensors have already been used in air quality monitoring studies such as
168 monitoring ambient wood smoke (Olivares and Edwards 2015), risk husk in a rice mill (Zakaria
169 et al., 2014), cigarette smoke in a garage (Rajasegarar et al., 2014), PM levels associated with
170 source activities in homes (Olivares et al., 2012), and urban and rural backgrounds (Steinle et al.,
171 2015). However, there is a huge gap in the scientific literature related to their calibration and
172 performance assessment, which makes it challenging to evaluate the data quality obtained by the
173 different investigations and make comparisons between them. Several PM sensors have not been
174 tested by scientific investigations, making it infeasible to judge their performance (see Table 2).
175 Thus, in the remainder of this paper, we focus only on those low-cost sensors (both for PM and
176 gaseous pollutants) whose performance traits have been tested by at least one scientific
177 investigation. Table S1 gives a summary of investigations focused on testing low-cost PM
178 sensors along with the test conditions and reference instrumentation. Due to the lack of a standard
179 calibration protocol specific for low-cost sensors, studies have used dissimilar calibration
180 methods, including chamber and field testing against a variety of reference instruments, which
181 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. Figure 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. Figure 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.

Figure 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).

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 $\mu g/m^3$ 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 1–27 $\mu g/m^3$. Figure 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 sensor reported by Wang et al. (2015) likely to rise 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 $\mu g/m^3$). 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; Sousan et al., 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; Sousan et al., 2016b; Wang et al., 2015), wood-smoke (Northcross et al., 2013), diesel exhaust (Sousan et al., 2016b), welding fumes (Sousan et al., 2016a; Sousan et al., 2016b) to road dust (Sousan et al., 2016a; Sousan et al., 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., 2016; Sousan et al., 2016a; Sousan et al., 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.

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).

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

318 **2.3 Recommendations for end-users**

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

331 It is also important to note that a few low-cost PM sensors (e.g., GP2Y1010AU0G and
332 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 greater than 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 1–27 $\mu g/m^3$, 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.

354 ## 3. LOW-COST SENSORS FOR MONITORING GASEOUS POLLUTANTS

355 ### 3.1 Specifications and application areas

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

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

365 The EC sensors are generally operated in an amperometric mode, wherein the electrochemical
366 reactions between the target gas and an electrolyte produce a current dependent on the gaseous
367 concentration (Stetter and Li 2008). The sensors typically consist of three electrodes, termed as
368 working, counter, and reference. The target gas undergoes electrolysis (oxidation or reduction) at
369 the working electrode and generates an electric current, which is balanced by the reaction at the
370 counter electrode. The measured electric current corresponds to the concentration of the gas, and
371 the response is either linear or logarithmic (Aleixandre and Gerbolesb 2012). The reference
372 electrode is typically employed in the sensor to ensure that the working electrode is maintained at
373 the correct operating potential. These sensors are claimed to have lower detection limits, power
374 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

Figure 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 0–110 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 5–6 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; Spinelle et al., 2015b) assessed the performances of two different EC sensors under chamber and field conditions. During the chamber study, the R^2 was greater than 0.99 for both the sensors (Spinelle et al., 2015a). However, when 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 0.67–0.81 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.

435 ***3.2.2 Repeatability, reproducibility, stability, limit of detection, and response times***

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

449 The reproducibility of MOS O_3 sensors has been quantified by a few studies (Moltchanov et al.,
450 2015; Piedrahita et al., 2014) through the computation of R^2 between the responses of several
451 identical sensors under similar conditions. Moltchanov et al. (2015) reported high reproducibility
452 between sensors (R^2 = 0.85–0.98), whereas Piedrahita et al. (2014) reported variable
453 reproducibility (R^2 = 0.21–0.98). We did not find studies that reported reproducibility
454 characteristics for the EC O_3 sensors.

455 The stability of four different MOS sensors and two different EC sensors was studied by Spinella
456 and co-workers under laboratory conditions (Spinelle et al., 2015a; Spinellea et al., 2016). They

457 reported that the sensor drifts ranged from −0.009 to 0.081 ppb O_3/day and 0.016 to 0.142 ppb
458 O_3/day for the MOS and EC sensors, respectively, during their six months testing. This translates
459 to −2 to 15 ppb and 3 to 26 ppb difference in sensor outputs for the MOS and EC sensors,
460 respectively, in six months. Thus, there does not seem to be a significant difference between the
461 stability characteristics of the MOS and EC O_3 sensor. However, the different models of the
462 EC/MOS sensors exhibit different drifts values, meaning that the sensor manufacturing process
463 might be playing a role in their stability.

464 A few field investigations have also reported the stability characteristics of the low-cost O_3
465 sensors. For the O3_3E1F EC sensor, Spinelle et al. (2015b) reported a significant decrease in R^2
466 values between the sensor response and the reference measurements from the calibration phase to
467 the validation phase, indicating poor stability. Moltchanov et al. (2015) reported that the
468 regression coefficients of the calibration curve of SM50 MOS sensor changed with time possibly
469 because of aging and/or dust accumulation in the sensors due to episodic events (e.g., rain and
470 dust storms). However, Jiao et al. (2016) did not find any association between the response of
471 SM50 sensor and the "days of use" during their field campaign, suggesting that episodic dust
472 accumulation might be the causing the response changes reported by Moltchanov et al. (2015).
473 For the S300 MOS sensor, Williams et al. (2013) reported their long-term stability characteristics
474 in monitoring campaigns conducted at several outdoor sites (Table 4). The sensor response was
475 generally stable over several months of operation; however, at a heavily industrial site, significant
476 sensor drift was observed due to dust accumulation at the inlet filter (Williams et al., 2009).
477 Clearly, sensor stability is an important consideration, if long term O_3 measurements are to be
478 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 (Figure 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 between 1–3 min and 2–8 min, respectively (Table 4). Thus, the t_{90} can be roughly calculated to be around 10 minutes (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

524 interference is a big problem for the EC sensors since the sensor response increases by 0.76–1.0
525 ppb of O_3 per 1 ppb of NO_2.

526 The other cross-sensitivities seem negligible at first glance. However, to fully understand their
527 impact on a sensor's response, we should know the concentration of the co-pollutant gas since the
528 sensor response is a product of the gaseous cross-sensitivity with its corresponding concentration.
529 Thus, we estimated the change in sensor response by multiplying the gaseous cross-sensitivities
530 with their corresponding ambient concentrations. For CO, NO_2, and SO_2 concentrations, we used
531 the EU specified limits; we used a representative value for background urban sites for CO_2 (400
532 ppb), NO (15 ppb), and NH_3 (30 ppb). The estimated changes in MOS sensor outputs were very
533 low (−2.4 ppb to 2.0 ppb) for interferences by CO_2, NO, NO_2, and NH_3. However, CO
534 interference caused a significant change in the MOS sensor outputs (−6.8 ppb to 20 ppb),
535 meaning that cross-sensitivity to CO could be important for such sensors. For EC sensors, the
536 estimated changes in outputs were low for interferences by CO, CO_2, NO, NH_3, and SO_2 (−3.77
537 ppb to 0.048 ppb); however, NO_2 interference causes a significant increase in sensor outputs (16–
538 21 ppb). We also found a few field investigation that reported the negligible influence of gaseous
539 cross-sensitivities on a MOS O_3 sensor under urban ambient concentrations (Bart et al., 2014; Lin
540 et al., 2015). However, under such conditions several co-pollutants will be present, meaning that
541 the overall sensor cross-sensitivity will a combination of the individual cross-sensitivities. If the
542 individual cross-sensitivities cancel each other, the sensor will appear to suffer from no cross-
543 sensitivities problems. Thus, we recommended that the sensor manufacturer/user should first
544 evaluate its cross-sensitivity coefficients (to anticipated levels of co-pollutants) under laboratory
545 conditions, and then perform field calibration under the conditions of actual deployment.

546 **3.3 Performance assessment of NO_2 sensors**

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

549 ***3.3.1 Comparisons with reference measurements***

550 Figure 4 shows the R^2 values between the measurements from the MOS and EC NO_2 sensors and
551 reference instrumentation under laboratory and field conditions. Figure 4 is similar to Figure 3,
552 and the low-cost NO_2 sensors show excellent performance under laboratory conditions. However,
553 their performance gets significantly deteriorated under real-world conditions due to similar
554 reasons as discussed in the case of O_3 sensors. Furthermore, there is considerable variation in R^2
555 values, reported by the different field investigations. For example, the two studies that used MOS
556 NO_2 sensors have conflicting results. Jiao et al. (2016) obtained extremely poor performance (R^2
557 <0.1 between the sensor outputs and the reference measurements) from the MICS-2710 sensor,
558 which was a part of the Air Quality Egg platform. Conversely, Piedrahita et al. (2014) reported
559 reasonable measurement errors (RMSE = 6.9–9.5 ppb) with the same sensor by using a multiple
560 linear regression model for calibration that accounted for temperature and humidity effects on the
561 sensor's response.

562 Of the studies that tested EC NO_2 sensors, a few have reported R^2 ≈0.90 between the sensor
563 response and the reference measurements after applying correction algorithms for interference by
564 O_3 or humidity (Lin et al., 2015; Mead et al., 2013; Sun et al., 2016). Duvall et al. (2016)
565 reported R^2 = 0.01 for the CairClip NO_2 sensor; however, the poor sensor performance was
566 attributed to low NO_2 concentrations (5.5 ppb hourly averaged value). Castell et al. (2016) tested
567 24 EC NO_2 sensors as part of the AQMesh platform and reported R^2 = 0.04–0.52 during a

568 collocation campaign at a reference station. Their results clearly show that even for identical
569 sensor and platform, drastically different results can be obtained, calling for careful quality
570 control in the manufacturing process for both sensors and platforms.

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

584 From the above discussion, we conclude that the best performance under real-world conditions
585 has been achieved by performing on-site calibration of the sensors and accounting for the
586 different factors that affect their outputs, rather than relying on manufacturer's calibration. This is
587 because the calibration conditions used by the manufacturer might be drastically different from
588 the actual deployment conditions. Furthermore, sensor aging and manufacturing variability also

589 stand out as important factors that need to be accounted for when conducting measurements using
590 low-cost NO_2 sensors.

591 ***3.3.2 Repeatability, reproducibility, stability, limit of detection, and response times***

592 The repeatability characteristics of different MOS and EC NO_2 sensors have been studied by only
593 a few investigations (Table S3). The SD of repeated measurements ranged from 1.2–7.5 and 4.6–
594 23.3 for MOS and EC NO_2 sensors, respectively, as reported by Williams et al. (2014c) under
595 different chamber conditions. However, they have not reported the NO_2 concentration at which
596 the measurements were conducted, meaning the relative errors cannot be estimated. Spinelle et al.
597 (2015a) and Castell et al. (2016) have reported SD ranging from 0.8–2.9 for different EC NO_2
598 sensors at 100 ppb NO_2 concentration, meaning that 1–3% measurement error can be expected
599 even under ideal measurement conditions.

600 Regarding the reproducibility of the low-cost NO_2 sensor outputs, we noted in the previous sub-
601 section that the R^2 values ranged from 0.04–0.52, when 24 identical NO2-B4 EC sensors were
602 tested as part of the AQMesh platform by Castell et al. (2016). This demonstrates poor
603 reproducibility characteristics of this sensor platform. However, Mead et al. (2013) found good
604 reproducibility between two pairs of identical NO2-A1 EC sensors (R^2 = 0.94–0.95). Similarly,
605 Piedrahita et al. (2014) also reported good reproducibility (R^2 = 0.88–0.98) between
606 measurements from eight identical MICS-2710 MOS sensors. Overall, we found insufficient
607 investigations on sensor reproducibility, and further studies are required to better understand this
608 issue.

609 Sensor *stability* is a concern for low-cost NO_2 sensors, as demonstrated by Spinelle et al. (2015b)
610 for both EC and MOS sensors, and discussed in the previous sub-section. The sensor drifts for

611 EC NO_2 sensors are reported to be between −0.497 to −0.065 ppb/day (Table S3). This would
612 cause a significant decrease in the reported NO_2 concentration (by 12–89 ppb) for a six-month
613 monitoring campaign. Clearly, this effect needs to be considered when conducting long-term
614 campaigns with EC NO_2 sensors.

615 The LOD for the different MOS and EC sensors are plotted in Figure 2 along with the typical
616 NO_2 concentration in EU countries and its corresponding EU specified limit. Almost all the LOD
617 values lie above the minimum measured concentrations, showing that the sensors should not be
618 used in places with very low concentrations of NO_2 (<10 ppb or <20 $\mu g/m^3$). From the Figure 2,
619 it also appears that the LOD for the MOS sensors is higher than that for the EC sensors.
620 However, the LOD values for the MOS sensors have only been reported by Williams et al.
621 (2014c), who used a different method for estimating LOD as compared to that used by other
622 investigations, thereby reporting much higher values. This is also the reason for the outlier
623 present in EC sensors: NO2-A1 with LOD equals 12–29.4 ppb.

624 The sensor response times for the different MOS and EC NO_2 sensors are also given in Table S3.
625 For the MOS sensors, we can approximate t_{90} (as the sum of t_{lag} and t_{rise}) to vary between 6 and
626 34 min. For the NO2-A1 EC sensor, the t_{90} is estimated as 9–19 min. For the other EC sensors,
627 the t_{90} equals 1.3–1.6 min, except the abnormally high value for the CairPol CairClip sensor (t_{90} =
628 38.42 min) possibly due to the presence of an O_3 filter and/or a humidity buffer in that sensor.
629 The inter-comparison between the MOS and EC sensors is not feasible due to limited
630 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 12–32 °C for three different EC sensors. However, Sun et al. (2016) did not detect any influence of temperature (15–21°C) on the NO2-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 40–70% 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.

653 For the gaseous cross-sensitivities, both field and laboratory studies report that the responses
654 from MOS and EC NO_2 sensors are predominantly affected by O_3 concentration (about 1.0–1.5
655 ppb NO_2 reported by the sensor per ppb of O_3), unless the sensors are equipped with O_3 filters
656 (Table S3). Williams et al. (2014c) reported the cross-sensitivity to SO_2 for two different MOS
657 and one EC sensor; however, the SO_2 concentration in their study was very high (>200 ppb), and
658 unlikely to be found in the outdoor environment. For the other gaseous co-pollutants, cross-
659 sensitivity data is only available for EC NO_2 sensors. We computed the estimated change in
660 sensor response due to those cross-sensitivities by using the procedure described in the section on
661 gaseous cross-sensitivities for ozone. The outputs from EC sensors were estimated to change by
662 −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
663 these gaseous interferences can be neglected for EC NO_2 sensors.

664 **3.4 Performance assessment of CO sensors**

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

675 sensors, it seems that aging is also an important factor for MOS CO sensors, and should be
676 accounted for before making long-term measurements.

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

688 Figure 2 shows the LOD values for the EC CO sensors (LOD = 4–21 ppb from Table S4), which
689 lie well below the typical concentration range of CO in EU countries, meaning that these sensors
690 seem suitable for measuring ambient CO. Mead et al. (2013) reported high sensor-to-sensor
691 reproducibility for the CO-AF sensor (R^2 = 0.86–0.95). Sun et al. (2016) reported that the CO-B4
692 sensor was unaffected by humidity and temperature changes during chamber testing. Lewis et al.
693 (2016) reported that the CO-B4 sensor's response will increase by 0.532 ppb CO per percentage
694 point increase in humidity, meaning that the maximum variation in output would be 53.2 ppb
695 (when RH changes from 0 to 100%), which is quite low compared to typical CO concentrations
696 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.

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.

Improper 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; De Vito et al., 2009; De Vito et al., 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; Harkat et al., 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., 2016; Spinelle et al., 2015b; 2017). The sensors seem to perform better at high pollutant concentrations (Castell et al., 2016), which could present an

763 enhanced opportunity for using such sensors in highly polluted areas (developing countries);
764 however, more studies are required to test the sensors under such conditions.

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769 **REFERENCES**

770 Alavi-Shoshtari, M.; Williams, D.E.; Salmond, J.A.; Kaipio, J.P. Detection of malfunctions in
771 sensor networks. Environmetrics 2013;24:227-236
772 Aleixandre, M.; Gerbolesb, M. Review of Small Commercial Sensors for Indicative Monitoring
773 of Ambient Gas. Chemical Engineering Transactions 2012;30
774 Alvarado, M.; Gonzalez, F.; Fletcher, A.; Doshi, A. Towards the development of a low cost
775 airborne sensing system to monitor dust particles after blasting at open-pit mine sites.
776 Sensors (Basel) 2015;15:19667-19687
777 Austin, E.; Novosselov, I.; Seto, E.; Yost, M.G. Laboratory evaluation of the Shinyei PPD42NS
778 low-cost particulate matter sensor. PloS one 2015;10:e0137789
779 Avnery, S.; Mauzerall, D.L.; Liu, J.; Horowitz, L.W. Global crop yield reductions due to surface
780 ozone exposure: 1. Year 2000 crop production losses and economic damage. Atmospheric
781 Environment 2011a;45:2284-2296
782 Avnery, S.; Mauzerall, D.L.; Liu, J.; Horowitz, L.W. Global crop yield reductions due to surface
783 ozone exposure: 2. Year 2030 potential crop production losses and economic damage under
784 two scenarios of O_3 pollution. Atmospheric Environment 2011b;45:2297-2309
785 Bart, M.; Williams, D.E.; Ainslie, B.; McKendry, I.; Salmond, J.; Grange, S.K.; Alavi-Shoshtari,
786 M.; Steyn, D.; Henshaw, G.S. High-density ozone monitoring using gas sensitive semi-
787 conductor sensors in the Lower Fraser Valley, British Columbia. Environmental Science &
788 Technology 2014;48:3970-3977
789 Bhanarkar, M.K.; Godase, S.M.; Korake, P.M.; Navarkhele, V.V. Review on WSN based outdoor
790 air pollution monitoring system. International Journal Series in Engineering Science
791 (IJSES)(ISSN: 2455-3328) 2016:1-13
792 Borrego, C.; Costa, A.M.; Ginja, J.; Amorim, M.; Coutinho, M.; Karatzas, K.; Sioumis, T.;
793 Katsifarakis, N.; Konstantinidis, K.; De Vito, S.; Esposito, E.; Smith, P.; André, N.; Gérard,
794 P.; Francis, L.A.; Castell, N.; Schneider, P.; Viana, M.; Minguillón, M.C.; Reimringer, W.;
795 Otjes, R.P.; von Sicard, O.; Pohle, R.; Elen, B.; Suriano, D.; Pfister, V.; Prato, M.; Dipinto,
796 S.; Penza, M. Assessment of air quality microsensors versus reference methods: The
797 EuNetAir joint exercise. Atmospheric Environment 2016;147:246-263

798 Castell, N.; Dauge, F.R.; Schneider, P.; Vogt, M.; Lerner, U.; Fishbain, B.; Broday, D.;
799 Bartonova, A. Can commercial low-cost sensor platforms contribute to air quality
800 monitoring and exposure estimates? Environment International 2016;
801 Castell, N.; Viana, M.; Minguillón, M.C.; Guerreiro, C.; Querol, X. Real-world application of
802 new sensor technologies for air quality monitoring. ETC/ACM Technical Paper 2013;16
803 CPCB. Central Pollution Control Pollution Board Network. Available from:
804 http://www.cpcb.nic.in/Network.php/ (accessed 05 June 2017)
805 De Vito, S.; Massera, E.; Piga, M.; Martinotto, L.; Di Francia, G. On field calibration of an
806 electronic nose for benzene estimation in an urban pollution monitoring scenario. Sensors
807 and Actuators B: Chemical 2008;129:750-757
808 De Vito, S.; Piga, M.; Martinotto, L.; Di Francia, G. CO, NO2 and NOx urban pollution
809 monitoring with on-field calibrated electronic nose by automatic bayesian regularization.
810 Sensors and Actuators B: Chemical 2009;143:182-191
811 De Vito, S.; Veneri, P.D.; Esposito, E.; Salvato, M.; Bright, V.; Jones, R.; Popoola, O. Dynamic
812 multivariate regression for on-field calibration of high speed air quality chemical multi-
813 sensor systems. AISEM Annual Conference, 2015 XVIII: IEEE; 2015
814 DEFRA. https://uk-air.defra.gov.uk/networks/ (accessed 31 October 2016). 2011
815 Duvall, R.M.; Long, R.W.; Beaver, M.R.; Kronmiller, K.G.; Wheeler, M.L.; Szykman, J.J.
816 Performance Evaluation and Community Application of Low-Cost Sensors for Ozone and
817 Nitrogen Dioxide. Sensors (Basel) 2016;16
818 Esposito, E.; De Vito, S.; Salvato, M.; Bright, V.; Jones, R.L.; Popoola, O. Dynamic neural
819 network architectures for on field stochastic calibration of indicative low cost air quality
820 sensing systems. Sensors and Actuators B: Chemical 2016;231:701-713
821 Fenger, J. Air pollution in the last 50 years–From local to global. Atmospheric Environment
822 2009;43:13-22
823 Fine, G.F.; Cavanagh, L.M.; Afonja, A.; Binions, R. Metal oxide semi-conductor gas sensors in
824 environmental monitoring. Sensors (Basel) 2010;10:5469-5502
825 Gao, M.; Cao, J.; Seto, E. A distributed network of low-cost continuous reading sensors to
826 measure spatiotemporal variations of PM2.5 in Xi'an, China. Environ Pollut 2015;199:56-
827 65
828 Guerreiro, C.; de Leeuw, F.; Foltescu, V. Air quality in Europe – 2013 report
829 http://www.eea.europa.eu/publications/air-quality-in-europe-2013 (accessed 18 January
830 2017). European Environment Agency; 2013
831 Guerreiro, C.; Ortiz, A.G.; de Leeuw, F.; Viana, M.; Horálek, J. Air quality in Europe – 2016
832 report http://www.eea.europa.eu/publications/air-quality-in-europe-2016 (accessed 18
833 January 2017). European Environment Agency; 2016
834 Hagler, G.S.W.; Solomon, P.A.; Hunt, S.W. New technology for low-cost, real-time air
835 monitoring. EM Magazine - Air & Waste Management Association; 2013
836 Han, I.; Symanski, E.; Stock, T.H. Feasibility of using low-cost portable particle monitors for
837 measurement of fine and coarse particulate matter in urban ambient air. J Air Waste Manag
838 Assoc 2016;
839 Harkat, M.-F.; Mourot, G.; Ragot, J. An improved PCA scheme for sensor FDI: Application to an
840 air quality monitoring network. Journal of Process Control 2006;16:625-634

841 Harkat, M.F.; Mourot, G.; Ragot, J. Sensor fault detection and isolation of an air quality
842 monitoring network using non linear principal component analysis. 16th IFAC World
843 Congress, Prague, Czech Republic; 2005
844 Hasenfratz, D.; Saukh, O.; Thiele, L. On-the-Fly Calibration of Low-Cost Gas Sensors. in: Picco
845 G.P., Heinzelman W., eds. Wireless Sensor Networks: 9th European Conference, EWSN
846 2012, Trento, Italy, February 15-17, 2012 Proceedings. Berlin, Heidelberg: Springer Berlin
847 Heidelberg; 2012
848 Heimann, I.; Bright, V.B.; McLeod, M.W.; Mead, M.I.; Popoola, O.A.M.; Stewart, G.B.; Jones,
849 R.L. Source attribution of air pollution by spatial scale separation using high spatial density
850 networks of low cost air quality sensors. Atmospheric Environment 2015;113:10-19
851 Holmes, N.S.; Morawska, L. A review of dispersion modelling and its application to the
852 dispersion of particles: An overview of different dispersion models available. Atmospheric
853 Environment 2006;40:5902-5928
854 Holstius, D.M.; Pillarisetti, A.; Smith, K.R.; Seto, E. Field calibrations of a low-cost aerosol
855 sensor at a regulatory monitoring site in California. Atmospheric Measurement Techniques
856 2014;7:1121-1131
857 Hu, S.-C.; Wang, Y.-C.; Huang, C.-Y.; Tseng, Y.-C. Measuring air quality in city areas by
858 vehicular wireless sensor networks. Journal of Systems and Software 2011;84:2005-2012
859 Jiang, Q.; Kresin, F.; Bregt, A.K.; Kooistra, L.; Pareschi, E.; Van Putten, E.; Volten, H.;
860 Wesseling, J. Citizen sensing for improved urban environmental monitoring. Journal of
861 Sensors 2016;2016
862 Jiang, Y.; Li, K.; Tian, L.; Piedrahita, R.; Yun, X.; Mansata, O.; Lv, Q.; Dick, R.P.; Hannigan,
863 M.; Shang, L. MAQS: a personalized mobile sensing system for indoor air quality
864 monitoring. Proceedings of the 13th International conference on Ubiquitous computing:
865 ACM; 2011
866 Jiao, W.; Hagler, G.; Williams, R.; Sharpe, R.; Brown, R.; Garver, D.; Judge, R.; Caudill, M.;
867 Rickard, J.; Davis, M. Community Air Sensor Network (CAIRSENSE) project: evaluation
868 of low-cost sensor performance in a suburban environment in the southeastern United
869 States. Atmospheric Measurement Techniques 2016;9:5281-5292
870 Johnson, K.K.; Bergin, M.H.; Russell, A.G.; Hagler, G.S.W. Using low-cost sensors to measure
871 ambient particulate matter concentrations and on-road emissions factors. Atmospheric
872 Measurement Techniques Discussions 2016:1-22
873 Jovašević-Stojanović, M.; Bartonova, A.; Topalović, D.; Lazović, I.; Pokrić, B.; Ristovski, Z. On
874 the use of small and cheaper sensors and devices for indicative citizen-based monitoring of
875 respirable particulate matter. Environmental Pollution 2015;206:696-704
876 Judge, R.; Wayland, R.A. Regulatory Considerations of Lower Cost Air Pollution Sensor Data
877 Performance. EM Magazine - Air & Waste Management Association; 2014
878 Kelly, K.E.; Whitaker, J.; Petty, A.; Widmer, C.; Dybwad, A.; Sleeth, D.; Martin, R.; Butterfield,
879 A. Ambient and laboratory evaluation of a low-cost particulate matter sensor. Environ
880 Pollut 2017;221:491-500
881 Koehler, K.A.; Peters, T.M. New methods for personal exposure monitoring for airborne
882 particles. Current Environmental Health Reports 2015;2:399-411

883 Kumar, P.; Ketzel, M.; Vardoulakis, S.; Pirjola, L.; Britter, R. Dynamics and dispersion
884 modelling of nanoparticles from road traffic in the urban atmospheric environment—A
885 review. Journal of Aerosol Science 2011;42:580-603
886 Kumar, P.; Martani, C.; Morawska, L.; Norford, L.; Choudhary, R.; Bell, M.; Leach, M. Indoor
887 air quality and energy management through real-time sensing in commercial buildings.
888 Energy and Buildings 2016a;111:145-153
889 Kumar, P.; Morawska, L.; Birmili, W.; Paasonen, P.; Hu, M.; Kulmala, M.; Harrison, R.M.;
890 Norford, L.; Britter, R. Ultrafine particles in cities. Environment International 2014;66:1-10
891 Kumar, P.; Morawska, L.; Martani, C.; Biskos, G.; Neophytou, M.; Di Sabatino, S.; Bell, M.;
892 Norford, L.; Britter, R. The rise of low-cost sensing for managing air pollution in cities.
893 Environment International 2015;75:199-205
894 Kumar, P.; Skouloudis, A.N.; Bell, M.; Viana, M.; Carotta, M.C.; Biskos, G.; Morawska, L.
895 Real-time sensors for indoor air monitoring and challenges ahead in deploying them to
896 urban buildings. Science of the Total Environment 2016b;560-561:150-159
897 Lewis, A.; Edwards, P. Validate personal air-pollution sensors. Nature 2016;535:29-31
898 Lewis, A.C.; Lee, J.D.; Edwards, P.M.; Shaw, M.D.; Evans, M.J.; Moller, S.J.; Smith, K.R.;
899 Buckley, J.W.; Ellis, M.; Gillot, S.R. Evaluating the performance of low-cost chemical
900 sensors for air pollution research. Faraday Discussions 2016;189:85-103
901 Li, M.; Zhang, L. Haze in China: current and future challenges. Environ Pollut 2014;189:85-86
902 Lin, C.; Gillespie, J.; Schuder, M.D.; Duberstein, W.; Beverland, I.J.; Heal, M.R. Evaluation and
903 calibration of Aeroqual series 500 portable gas sensors for accurate measurement of
904 ambient ozone and nitrogen dioxide. Atmospheric Environment 2015;100:111-116
905 Manikonda, A.; Zíková, N.; Hopke, P.K.; Ferro, A.R. Laboratory assessment of low-cost PM
906 monitors. Journal of Aerosol Science 2016;102:29-40
907 Mead, M.I.; Popoola, O.A.M.; Stewart, G.B.; Landshoff, P.; Calleja, M.; Hayes, M.; Baldovi,
908 J.J.; McLeod, M.W.; Hodgson, T.F.; Dicks, J.; Lewis, A.; Cohen, J.; Baron, R.; Saffell,
909 J.R.; Jones, R.L. The use of electrochemical sensors for monitoring urban air quality in
910 low-cost, high-density networks. Atmospheric Environment 2013;70:186-203
911 Menz, F.C.; Seip, H.M. Acid rain in Europe and the United States: an update. Environmental
912 Science & Policy 2004;7:253-265
913 Miskell, G.; Salmond, J.; Alavi-Shoshtari, M.; Bart, M.; Ainslie, B.; Grange, S.; McKendry, I.G.;
914 Henshaw, G.S.; Williams, D.E. Data Verification Tools for Minimizing Management Costs
915 of Dense Air-Quality Monitoring Networks. Environmental Science & Technology
916 2016;50:835-846
917 Moltchanov, S.; Levy, I.; Etzion, Y.; Lerner, U.; Broday, D.M.; Fishbain, B. On the feasibility of
918 measuring urban air pollution by wireless distributed sensor networks. Science of the Total
919 Environment 2015;502:537-547
920 Mouzourides, P.; Kumar, P.; Neophytou, M.K.-A. Assessment of long-term measurements of
921 particulate matter and gaseous pollutants in South-East Mediterranean. Atmospheric
922 Environment 2015;107:148-165
923 Northcross, A.L.; Edwards, R.J.; Johnson, M.A.; Wang, Z.M.; Zhu, K.; Allen, T.; Smith, K.R. A
924 low-cost particle counter as a real-time fine-particle mass monitor. Environmental Science
925 Processes & Impacts 2013;15:433-439

Olivares, G.; Edwards, S. The Outdoor Dust Information Node (ODIN) – development and performance assessment of a low-cost ambient dust sensor. Atmospheric Measurement Techniques Discussions 2015;8:7511-7533

Olivares, G.; Longley, I.; Coulson, G. 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; 2012

Piedrahita, R.; Xiang, Y.; Masson, N.; Ortega, J.; Collier, A.; Jiang, Y.; Li, K.; Dick, R.; Lv, Q.; Hannigan, M. The next generation of low-cost personal air quality sensors for quantitative exposure monitoring. Atmospheric Measurement Techniques 2014;7:3325-3336

Popoola, O.A.M.; Stewart, G.B.; Mead, M.I.; Jones, R.L. Development of a baseline-temperature correction methodology for electrochemical sensors and its implications for long-term stability. Atmospheric Environment 2016;147:330-343

Rajasegarar, S.; Zhang, P.; Zhou, Y.; Karunasekera, S.; Leckie, C.; Palaniswami, M. 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; 2014

Ramanathan, V.; Feng, Y. Air pollution, greenhouse gases and climate change: Global and regional perspectives. Atmospheric Environment 2009;43:37-50

Sharma, P.; Sharma, P.; Jain, S.; Kumar, P. An integrated statistical approach for evaluating the exceedence of criteria pollutants in the ambient air of megacity Delhi. Atmospheric Environment 2013;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. The changing paradigm of air pollution monitoring. Environmental Science & Technology 2013;47:11369-11377

Solomon, S. Stratospheric ozone depletion: A review of concepts and history. Reviews of Geophysics 1999;37:275-316

Solomon, S.; Garcia, R.R.; Rowland, F.S.; Wuebbles, D.J. On the depletion of Antarctic ozone. Nature 1986;321:755-758

Sousan, S.; Koehler, K.; Hallett, L.; Peters, T.M. Evaluation of the Alphasense optical particle counter (OPC-N2) and the Grimm portable aerosol spectrometer (PAS-1.108). Aerosol Science and Technology 2016a;50:1352-1365

Sousan, S.; Koehler, K.; Thomas, G.; Park, J.H.; Hillman, M.; Halterman, A.; Peters, T.M. Inter-comparison of low-cost sensors for measuring the mass concentration of occupational aerosols. Aerosol Science and Technology 2016b;50:462-473

Spinelle, L.; Gerboles, M.; Aleixandre, M. Performance Evaluation of Amperometric Sensors for the Monitoring of O_3 and NO_2 in Ambient Air at ppb Level. Procedia Engineering 2015a;120:480-483

Spinelle, L.; Gerboles, M.; Villani, M.G.; Aleixandre, M.; Bonavitacola, F. Field calibration of a cluster of low-cost available sensors for air quality monitoring. Part A: Ozone and nitrogen dioxide. Sensors and Actuators B: Chemical 2015b;215:249-257

Spinelle, L.; Gerboles, M.; Villani, M.G.; Aleixandre, M.; Bonavitacola, F. Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. Sensors and Actuators B: Chemical 2017;238:706-715

Spinellea, L.; Gerbolesa, M.; Aleixandreb, M.; Bonavitacolac, F. Evaluation of metal oxides sensors for the monitoring of O3 in ambient air at ppb level. Chemical Engineering Transactions 2016;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. Personal exposure monitoring of PM2.5 in indoor and outdoor microenvironments. Science of the Total Environment 2015;508:383-394

Stetter, J.R.; Li, J. Amperometric gas sensors a review. Chemical reviews 2008;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. Development and Application of a Next Generation Air Sensor Network for the Hong Kong Marathon 2015 Air Quality Monitoring. Sensors (Basel) 2016;16:211

Suriano, D.; Prato, M.; Pfister, V.; Cassano, G.; Camporeale, G.; Dipinto, S.; Penza, M. Stationary and Mobile Low-Cost Gas Sensor Systems for Air Quality Monitoring Applications. Fourth Scientific Meeting EuNetAir. Linkoping University, Linkoping, Sweden; 2015

Talampas, M.C.R.; Low, K.-S. Maximum likelihood estimation of ground truth for air quality monitoring using vehicular sensor networks. TENCON 2012-2012 IEEE Region 10 Conference: IEEE; 2012

Taylor, B.N.; Kuyatt, C.E. Guidelines for Evaluating and Expressing the Uncertainty of NIST Measurement Results. https://www.nist.gov/sites/default/files/documents/pml/pubs/tn1297/tn1297s.pdf (accessed 25 October 2016). Gaithersburg, MD 20899-0001: National Institute of Standards and Technology; 1994

Thomas, A.; Gebhart, J. Correlations between gravimetry and light scattering photometry for atmospheric aerosols. Atmospheric Environment 1994;28:935-938

Thompson, J.E. Crowd-sourced air quality studies: A review of the literature & portable sensors. Trends in Environmental Analytical Chemistry 2016;11:23-34

Van Dingenen, R.; Dentener, F.J.; Raes, F.; Krol, M.C.; Emberson, L.; Cofala, J. The global impact of ozone on agricultural crop yields under current and future air quality legislation. Atmospheric Environment 2009;43:604-618

Vardoulakis, S.; Fisher, B.E.; Pericleous, K.; Gonzalez-Flesca, N. Modelling air quality in street canyons: a review. Atmospheric Environment 2003;37:155-182

Wang, Y.; Li, J.; Jing, H.; Zhang, Q.; Jiang, J.; Biswas, P. Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement. Aerosol Science and Technology 2015;49:1063-1077

Weissert, L.F.; Salmond, J.A.; Miskell, G.; Alavi-Shoshtari, M.; Grange, S.K.; Henshaw, G.S.; Williams, D.E. 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. The Science of the Total Environment 2017;575:67-78

White, R.M.; Paprotny, I.; Doering, F.; Cascio, W.E.; Solomon, P.A.; Gundel, L.A. Sensors and 'apps' for community-based atmospheric monitoring. EM: Air and Waste Management Association's Magazine for Environmental Managers 2012; 5:36-40.

WHO. Burden of disease from Ambient Air Pollution for 2012. http://www.who.int/phe/health_topics/outdoorair/databases/AAP_BoD_results_March2014.pdf (accessed 31 October 2016). World Health Organization; 2014

WHO. 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 (accessed 31 October 2016). World Health Organization; 2016

Williams, D.E.; Henshaw, G.S.; Bart, M.; Laing, G.; Wagner, J.; Naisbitt, S.; Salmond, J.A. Validation of low-cost ozone measurement instruments suitable for use in an air-quality monitoring network. Measurement Science and Technology 2013;24:065803

Williams, D.E.; Henshaw, G.S.; Wells, B.; Ding, G.; Wagner, J.; Wright, B.; Yung, Y.F.; Salmond, J. Development of Low-Cost Ozone Measurement Instruments Suitable for Use in an Air Quality Monitoring Network. Chemistry in New Zealand 2009;73:27-33

Williams, R.; Kaufman, A.; Hanley, T.; Joann, R.; Garvey, S. Evaluation of Field-deployed Low Cost PM Sensors. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=297517 (accessed 13 January 2017). U.S. Environmental Protection Agency; 2014a

Williams, R.; Kilaru, V.; Snyder, E.; Kaufman, A.; Dye, T.; Rutter, A.; Russell, A.; Hafner, H. Air Sensor Guidebook. U.S. Environmental Protection Agency. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277996 (accessed 31 October 2016); 2014b

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. Sensor Evaluation Report. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277270 (accessed 31 October 2016). U.S. Environmental Protection Agency; 2014c

Xu, P.; Chen, Y.; Ye, X. Haze, air pollution, and health in China. The Lancet 2013;382:2067

Zakaria, N.; Abdullah, J.; Yusof, A.; Azizan, M.; Kimpol, N. A study of rice husk total suspended particles (TSP) level using optical sensor in a rice mill factory. International Journal of Energy and Power Engineering Research 2014;2:29-33

Zhou, X.; Lee, S.; Xu, Z.; Yoon, J. Recent progress on the development of chemosensors for gases. Chemical Reviews 2015;115:7944-8000

Zikova, N.; Hopke, P.K.; Ferro, A.R. Evaluation of new low-cost particle monitors for PM 2.5 concentrations measurements. Journal of Aerosol Science 2016;105:24–34

LIST OF FIGURES

Figure 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.

Figure 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).

Figure 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.

Figure 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.

Figure 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.

1071 *Table 1: Summary of review articles focused on the applications of low-cost sensors for*
1072 *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.

1073

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
Sharp GP2Y1010AU0F	46×30×18	15	5 V DC	20	~10	Greater than 0.5µm	0–600 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
Samyoung DSM501A	59×45×20	25	5 V DC	90	~15	Greater than 1.0 µm	0–1400 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
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
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
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 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 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 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 SDS198	71×70×23	NA	5 V DC	80	~80	1–100 µm	0–20000 µg/m^3	No
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
Alphasense OPC-N2	75×64×60	105	5 V DC	175 mA	~500	0.38–17 µm in 16 size bins	0.1–1500,000 µg/m^3	Yes

NA stand for not available.

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 (µg/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).	η_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].	η_d = 0.6–1.1, estimated from Sousan et al., (2016b). η_d = 0.25–4.0 , estimated from Han et al., (2016).	η_d = 0. 5–4.8, estimated from Han et al., (2016). 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 $\text{nRMSE} = \frac{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_{Ai}-M_{Bi})^2}\right)}{\frac{1}{2n}\sum_{i=1}^{n}M_{Ai}+M_{Bi}}$, where M_{Ai} and M_{Bi} are the i^{th} 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., 2016), 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).

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].	δ_{RH} = −0.65 [c]	δ_T = −3.86 [c]	δ_{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].	δ_{RH} = −0.02 [c]	δ_T = −0.7 [c]	δ_{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].	δ_{RH} − 0.84 [c]	δ_T − 3.1 [c]	δ_{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].	δ_{RH} = −0.46 [c]	δ_T = −2.3 [c]	δ_{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].	δ_{RH} = 0.40 [g]	δ_T = 0 [g]	δ_{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].	δ_{RH} = −0.022 g. Seems unaffected by humidity [h].	δ_T = 1.3 [g] Seems unaffected by temperature [h].	δ_{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	δ_{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., 2016), j: (Williams et al., 2013), k: (Bart et al., 2014), and l: (Piedrahita et al., 2014).

Figure

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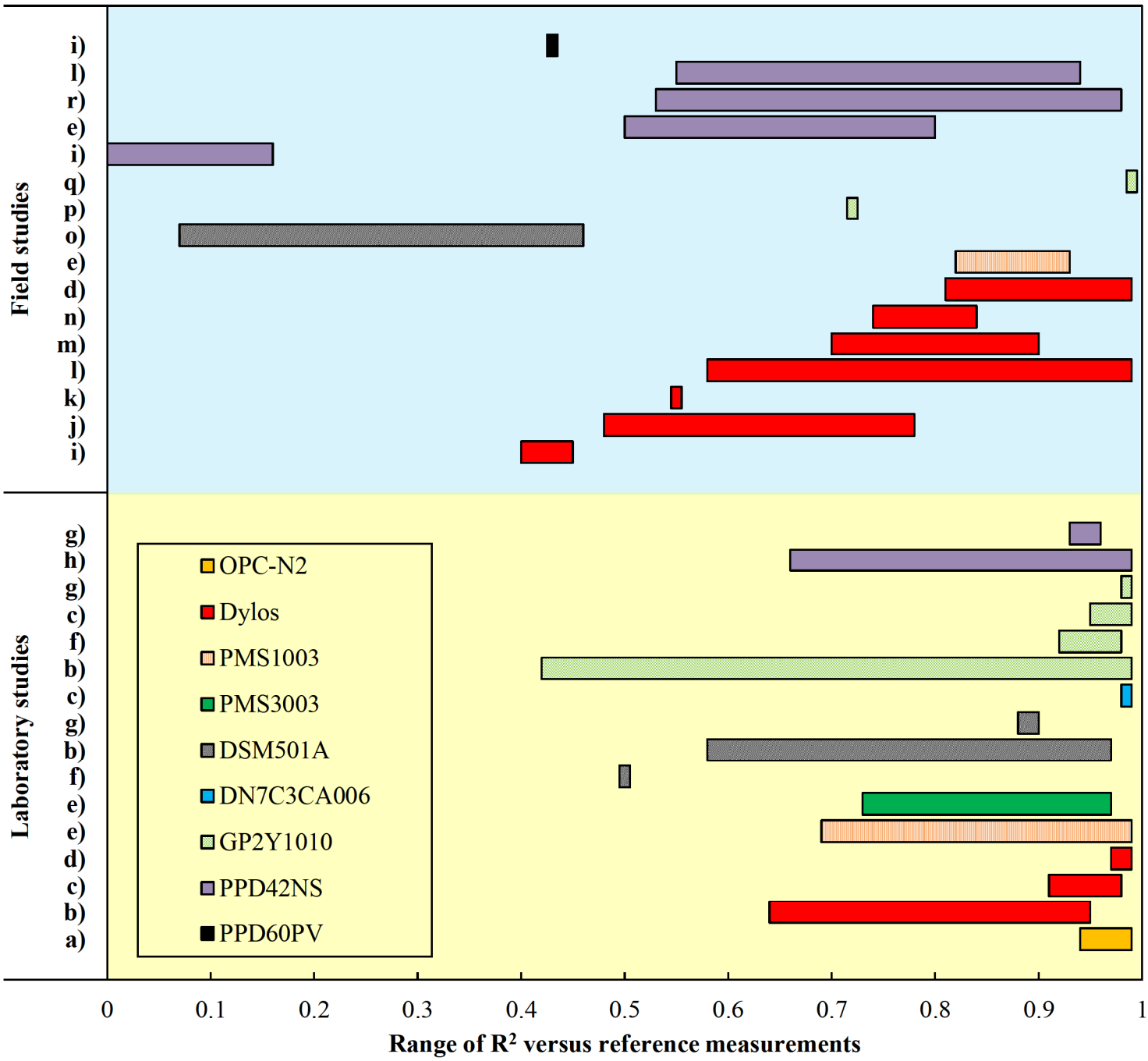
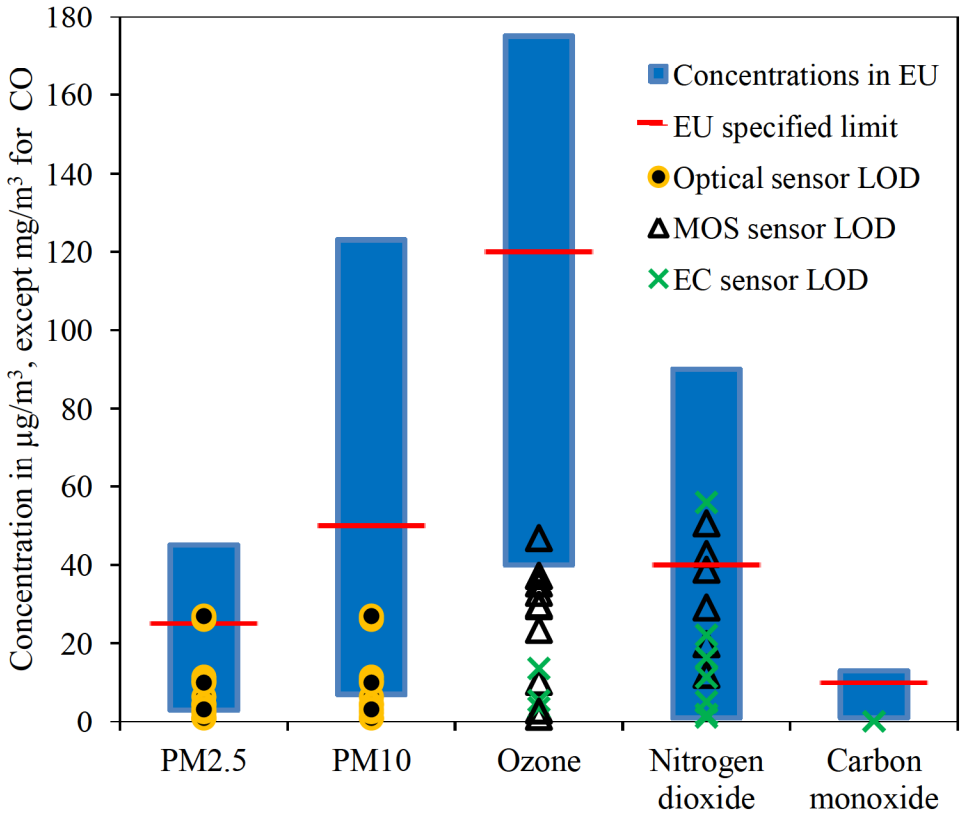


Figure 1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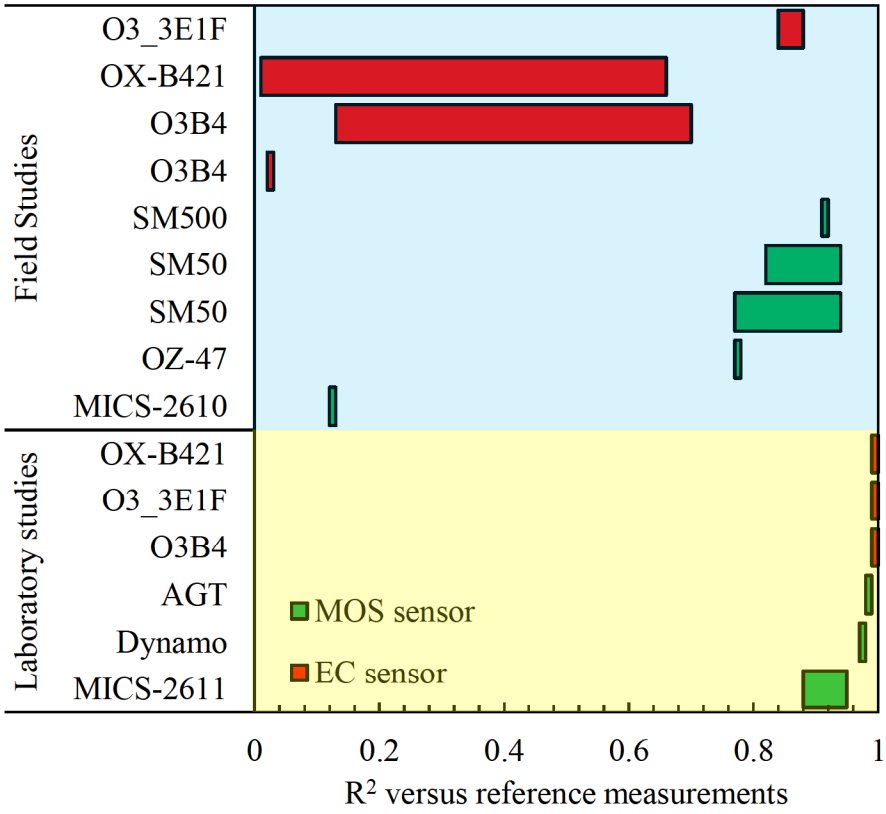
Carbon monoxide
Concentrations in EU
EU specified limit
Optical sensor LOD
MOS sensor LOD
EC sensor LOD

Figure 2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O3_3E1F
O3B4
AGT
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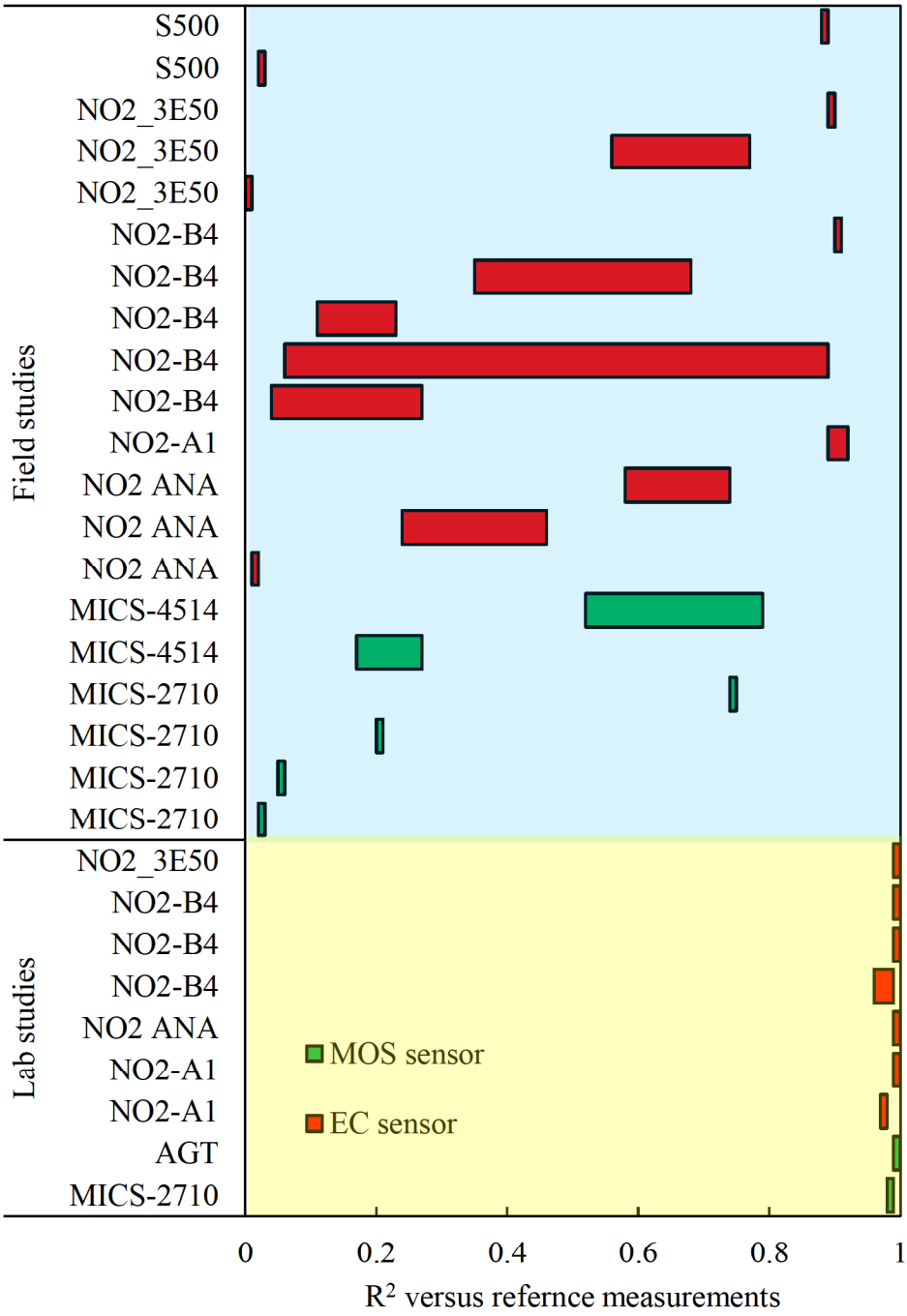
R2 versus reference measurements

Figure 3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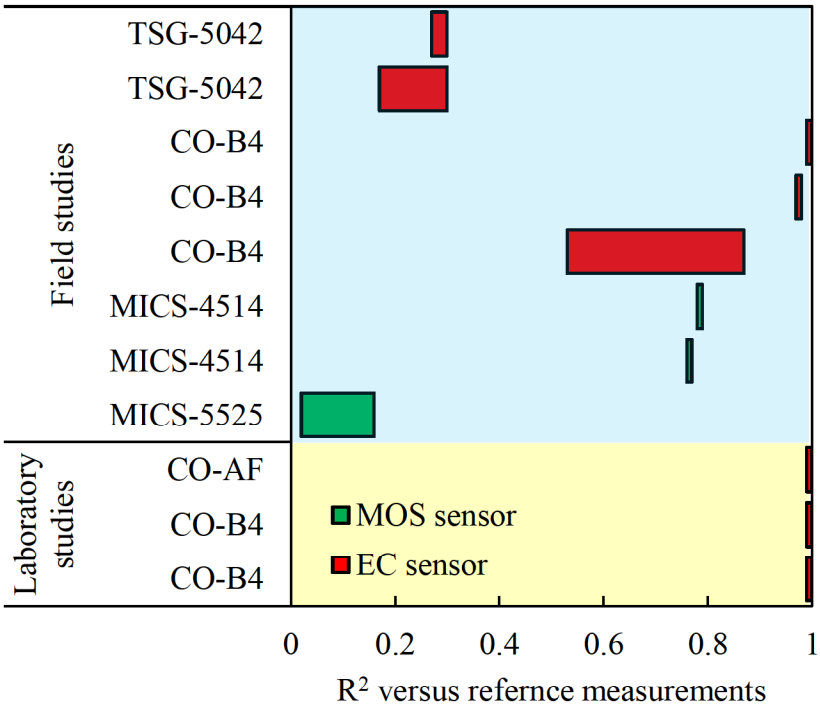
R² versus refernce measurements

Figure 4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Laboratory studies
MOS sensor
EC sensor
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0.8
1
R² versus refernce measurements

Figure 5