

Review of Sensors for Air Quality

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Abstract

1. Introduction

The introduction and diffusion of the micro-sensors technology for monitoring ambient air pollution (as emerging measuring devices) is contributing to the rapid adoption of low-cost sensors (LCS) for air quality monitoring for citizen science initiative and by public authorities³⁶. Low-cost in this context is typically referring to the cost of the hardware component needed to make a measurement. LCS can provide real time measurements at lower cost allowing higher spatial coverage than the current reference methods of measurements of air pollutants. Additionally, the monitoring of air pollution with reference measurements methods requires skilled operators for the maintenance and calibration of measuring devices that are described in detailed Standard Operational Procedures¹³⁻¹⁷. Conversely, it should be possible that LCS are operated without human intervention making it possible for unskilled users to be able to monitor air pollution without the need of important technical understanding.

However, a lot of LCS are becoming available whose performance regarding the agreement between LCS values and reference measurement can be of variable quality making it fundamental to evaluate LCS before choosing any LCS for routine measurements and case studies⁴⁰. As reported below, few independent tests are reported in academic publications. The rapid technological progress of LCS and the time needed to publish studies in academic journals makes publication of articles not the preferred route and the majority of the available information is found in grey literature, mainly of report types.

The major sources of information of LCS evaluation consist of AQ-SPEC², the US-EPA and the work carried out by the Joint Research Centre⁵⁷. (check in the article US-EPA workshop what do they say). Although a number of reviews of the suitability of sensors for ambient air quality have been published (Refs needed here), quantitative data for comparing and evaluating the agreement between sensors and reference data are mostly missing. Additionally, there is no commonly accepted protocol for the test of LCS, the metrics reported are generally diverse making it difficult to compare the performance of sensor between evaluation studies. The most common reported metrics consist of: the coefficient of determination, R^2 , the slope and intercept of regression line between sensor and

reference measurements, the Root mean square of Error, RMSE and the measurement uncertainty . Here after, the results of an exhaustive review of the existing literature on LCS evaluation are presented.

The purpose of this review is to identify LCSs whose comparison with reference measurements shows the highest correlation and accuracy. For this purpose, we performed a comprehensive review about the performance of commercial LCSs. We have aggregated summary statistics about the agreement between sensors and reference instruments. Although in Europe, the main metrics to evaluate the performance of measuring methods consists of the measurement uncertainty, this metrics could not be used in our study since the majority of studies do not report it (166 records out of 1290 total number of records reporting RMSE and other metrics for uncertainty) give the number of studies with this parameter?). Conversely, we had to rely on most common metrics, i. e., the coefficient of determination R^2 , the slope and intercept of linear regression line between sensor and reference measurement and, in few cases, the Root Mean Square of Error that were scrutinized and analyzed to identify sensors that could potentially be complementary to the reference methods of air quality monitoring.

The market of LCSs for ambient air monitoring only consists of a small number of sensor model types that are manufactured by a few companies. These LCSs, are usually known as Original Equipment Manufacturers (OEM).

As per definition, an **OEM** is a chemical cell or physical unit that produces an analytically useful signal by detecting or measuring the analyte. On the other hand a **Sensor System (SS)** or **sensor node** is an integrated set of hardware that uses one or more sensors to detect and/or measure a chemical concentration or quantity that is able to supply real time measurements. A sensor systems contain a number of common components in addition to the basic sensing/analytical element that is used for detection. Common core components and functions may include:

- Sensing element or detector (actually the sensor)
- Sampling capability (active or passive sampling)
- Power systems, including batteries
- Analogue to digital conversion
- Signal processing
- Local data storage
- Data transmission
- Remote calibration
- Housing/casing

OEMs use chemical and physical techniques phenomena to sense pollutant in ambient air. However, in order to simplify measurement operations, calibration and data transfer into a convenient sensor object, OEMs need be integrated into a sensor system (SS), consisting of electronic boards, software and protective box gathering the hardware, software and OEM sensors.

The use of low-cost sensors is extensively interesting for citizen-science initiatives. Therefore, Small Medium Enterprises were able to sell sensor-systems which could be deployed by citizen who wanted to monitor air quality in a chosen environment. Up to date,

there are several sensor systems using sensors from the same OEM. However, outputs from these sensors system often differ from each other. The ideal candidate sensor system would show good agreement with reference measurements and, at the same time, provide sensor raw data allowing to be calibrated using open source correction algorithms. The number of air pollutants being measured was also a parameter taken into consideration. Finally, the price of a low cost-sensor was also taken into account.

2. Methods

2.1. Data sources

About 1290 records were systematically gathered from peer-reviewed studies of sensors for air quality and air pollution reported in the Scopus database, the World Wide Web, the AirMontech web site (<http://db-airmontech.jrc.ec.europa.eu/search.aspx>), ResearchGate and Google search. Overall, about a number of 61 independent studies were found from different sources from reports, peer-review papers and sensors manufacturers. The research was focused on sensors for Particulate Matter (*PM*), Ozone (*O₃*), Nitric Dioxide (*NO₂*) and Carbon Monoxide (*CO*). A few references were also included for nitrogen monoxide sensors (*NO*). We have started evaluating summary statistics from the correlation of sensors with reference measurements (validation).

The research covered the period between 2010 and 2018 (year of publication). Data gathered from sensor studies were reviewed according to criteria described in the following sections. Additionally, reviewed sensor data were used to populate a database that was used to generate summary statistics about characteristics and performances of sensors.

2.2. Data collection

Most of the reviewed studies reported regression parameters obtained from the comparison between sensors and reference measurements. Records from regression parameters were the result of both calibration and comparison of the sensor with a reference instrument. In the case of calibration, we identified four types of most used regression models: linear, multilinear (MLR), quadratic and logarithmic.

2.3. Evaluation criteria

We have carried out an extensive literature review of OEM sensors and sensor systems (SS) that were used to estimate concentration of air pollutants against a reference systems during field and laboratory tests. The purpose was to gather quantitative information about the performance of sensors according to the following criteria:

1. Agreement between sensor and reference measurements
2. Availability of raw data, transparency of data treatment and possibility of a-posteriori calibration
3. Capability to measure multiple pollutants
4. Affordability of sensor systems taking into consideration the number of provided sensors

5. Capacity to satisfy the requirement of interoperability of data according to the INSPIRE directive
6. Automatic data-transfer and website visualization of sensor data

The review was focused on available commercially available OEMs and sensor systems, even though a few non-commercial sensor were also considered, measuring concentrations of Particulate Matter ($PM_{2.5}$, PM_{10} , PM_1), Nitric Dioxide (NO_2), Nitrix Monoxide (NO), Carbon Monoxide (CO) and Ozone O_3 . **Table 1** reports the number of records, by pollutant and operating technology, gathered in literature about validation and testing of OEMs / sensor systems against a reference system. Records were collected from laboratory (135) and field tests (1155).

Table 1. Number of analyzed records for OEMs/Sensor Systems by pollutant and by type of technology.

pollutant	type	n. records	references
CO	electrochemical	64	AQ-SPEC[2], Jiao[31], Sun[65], Marjovi[44], Gerboles[27], Mead[45], Popoola[53], Borrego[9], Castell[11], Cross[21], Gerboles[26], Wei[72], Gillooly[28], Zimmerman[77], Spinnelle[59]
CO	MOs	23	AQ-SPEC[2], Piedrahita[51], Spinnelle[59]
NO	electrochemical	47	Jiao[31], Bigi[7], Gerboles[27], Mead[45], Popoola[53], AQ-SPEC[2], Castell[11], Borrego[9], Cross[21], Gillooly[28], Spinnelle[60], Gerboles[26], Wei[72]
NO_2	electrochemical	134	AQ-SPEC[2], Jiao[31], Williams[74], Sun[65], Mijling[46], Vaughn[69], Spinnelle[58], Mueller[47], Bigi[7], Marjovi[44], Cordero[19], Gerboles[27], Mead[45], Popoola[53], Borrego[9], Castell[11], Cross[21], Spinnelle[56], Duvall[23], Gillooly[28], Gerboles[26], Wei[72], Sun[66], Zimmerman[77], Lin[41]
NO_2	MOs	34	AQ-SPEC[2], Vaughn[69], Williams[74], US-EPA[68], Borrego[9], Piedrahita[51], Spinnelle[58]
O_3	electrochemical	61	AQ-SPEC[2], Jiao[31], Spinnelle[56], Spinnelle[58], Mueller[47], Marjovi[44], Gerboles[27], Borrego[9], Castell[11], Cross[21], Duvall[23], Feinberg[24], Gerboles[26], Wei[72]
O_3	MOs	55	AQ-SPEC[2], Jiao[31], Spinnelle[57], Borrego[9], Feinberg[24]
O_3	UV	10	Sun[65], AQ-SPEC[2]
$PM_{2.5}$	Electrical	6	AQ-SPEC[2]
$PM_{2.5}$	nephelometer	216	AQ-SPEC[2], Borghi[8], Jiao[31], Feinberg[24], US-EPA[68], Williams[73], Manikonda[43], Zikova[76], Wang[71], Alvarado[1], Chakrabarti[18], Sousan[54], Borrego[9], Olivares[50], Sun[65], Pillarisetti[52], Holstius[30], Austin[3], Gao[25], Kelly[34], Karagulian[33], Badura[4]
$PM_{2.5}$	OPC	355	AQ-SPEC[2], Mukherjee[48], Feinberg[24], Jiao[31], Cavaliere[12], Borrego[9], Viana[70], Williams[73], Manikonda[43], Northcross[49], Holstius[30], Steinle[64], Han[29], Jovasevic[32], Dacunto[22], Gillooly[28], Sousan[55], Crilley[20], Badura[4], Kelly[34], Zheng[75], Laquai[38], Budde[10], Liu[42]
PM_1	Electrical	6	AQ-SPEC[2]
PM_1	OPC	92	AQ-SPEC[2], Williams[73], Sousan[55], Crilley[20]
PM_{10}	nephelometer	32	AQ-SPEC[2], Borrego[9], Alvarado[1]
PM_{10}	OPC	155	AQ-SPEC[2], Cavaliere[12], Borrego[9], Feinberg[24], Manikonda[43],

Most of laboratory and field tests were collected results published and between the year 2010 and 2018. As reported in **Figure 1**, only few preliminary works were published from 2010 to 2014. On 2015 we recorded the highest number of references with 16 different works publishing results about performances of sensors for air quality monitoring. Since 2015, the number of references publishing works on sensors with about 10 - 12 publications per year.

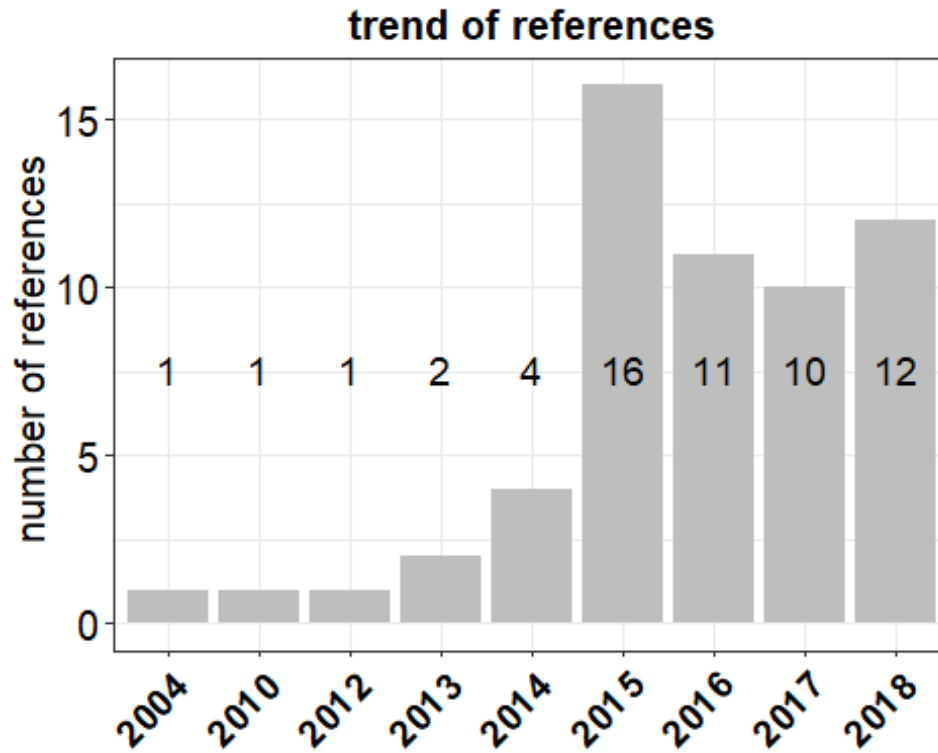


Figure 1. Number of references per year of publication.

Overall, we found 31 references reporting field tests with sensors co-located at urban sites, 8 references for rural sites and, 8 references for traffic sites. Most of the laboratory and field tests reported hourly averages with about 591 records obtained for over 85 models of OEMs and sensor systems. On the other hand, we found about 249 records from tests performed over an averaging time of 24 hours and 5 minutes with about 42 models of sensors (**Table S1**). Therefore, 1 hour averaged measurements were considered statistically more significative to represent most of the scrutinized 105 models of OEMs and sensor systems.

For the evaluation of sensors against reference systems we considered the metrics that were more frequently reported in the reviewed works about the evaluation of the sensor

performance both in field and/or laboratory tests. The coefficient of determination R^2 is usually used as indication of “usefulness” or “goodness” of fit obtained from regression models comparing sensor measurements with reference measurements **Table S2**. However, R^2 is a partial measures of how sensors data agree with reference measurements according to a regression model⁵. A larger R^2 reflects an increase in the predictive precision of the regression model but it ignores the loss in information due to possible loss in degrees of freedom. A significance test is therefore suggested in this case. Alternatively, R^2 can be viewed as a measure of goodness of fit (how close evaluation data is to the reference measurements) and the slope of the regression as level of accuracy. However, if the goodness of fit about the regression is fixed, then the slope will increase and consequently also the R^2 . Therefore, when it happens to calibrate different datasets, calibration using slope and R^2 values close to 1.0 might be less precise than calibration using smaller values of slope and R^2 . As shown in **Table 2**, most of the works reported coefficients of determination R^2 as well as the *slope* of regression line mainly from field tests. Root mean square error (*RMSE*) and the uncertainty (*U*), were mostly calculated as value of standard deviation and only reported in few works (23). Therefore, for the purpose of this work, we only focused on the analysis of the comparisons of R^2 and *slope* of laboratory and field tests of sensors.

Table 2. Number of records gathered by metric used in this work.

metrics	n. Field Tests	n. Laboratory Tests
	1155	135
R^2 from calibrations	213	64
R^2 from comparisons	1033	70
slope of reg. line	933	53
RMSE	162	5
Uncertainty (U)	45	29

3. Classification of sensors

For each model of sensor system we identified the manufacturer of OEM sensor and the manufacturer of the sensor system itself including the sensors, protective box, internal hardware and software for data acquisition, data treatment and data transfer. Each database record describing the laboratory or field performance of a sensors was considered valuable only if it reported information about laboratory tests and/or field comparison against a reference measurement at a reference monitoring station. Overall, we found 105 models of sensors including both OEMs (38) and sensor systems (67) manufactured by 71 manufacturers (16 OEM and 55 SS). In addition, we identified 18 projects about the evaluation of OEMs/sensor systems under different operational conditions (Air Quality Egg, Air Quality Station, AirCasting,^{2,8,24,48}, Carnegie Mellon^{24,75}, CitiSense⁷³, Cairsense³¹, Developer Kit², HKEPD/14-02771⁶⁴, making-sense.eu⁴⁶, communitysensing.org⁶⁸, MacPoll.eu⁵⁸, OpenSense II^{7,47}, Proof of Concept AirSenseEUR²⁷,

SNAQ Heathrow^{45,53}). Out of 1290 records collected from literature, we identified 1155 records (341 OEM and 814 SS) from 86 **alive** sensors (33 OEM and 53 SS) and 135 records (28 OEM and 107 SS) from 19 “non active” (or **discontinued**) sensors (5 OEM and 14 SS).

Commonly speaking, “low-cost” refers to the cost of a sensor system compared to the cost of a reference instrument measuring the air pollutant³⁹. More recently, ultra-affordable OEMs are starting to appear on the market for PM monitoring. Many of them are designed to be integrated in the Internet of things (IoT) network of devices. Currently, for the detection of $PM_{2.5}$, it is possible to purchase optical sensor at prices of few hundreds euros to few tens of euros from devices manufactured in emerging economies such as the Republic of China and Republic of Korea⁶⁶. For the detection of $PM_{2.5}$, some of these sensors are starting achieving performances comparable to low-cost OEMs manufactured in the Western world.

3.1. Raw data and traceability of data treatment

The data treatment of measurements of OEM sensors and sensor systems can be classified in two distinct categories:

- 1) Data acquisition and data processing of sensor data that are operated by an “**open source**” software tuned according to different calibration parameters and environmental conditions. All data treatments from data acquisition until the conversion to pollutant concentration levels is known to the user. Among 38 sensors, we identified 401 records from OEMs (335) and sensor systems (66) using an open source software for data management. Usually, outputs from these sensor were already in the same measurement units as the reference measurements. In this category, sensor devices are generally connected to a custom-made data acquisition system to acquire sensor raw data. Generally, users are expected to set a calibration function in order to convert sensor raw data to validate against reference measurements. In this category, the sensor only consists of OEMs integrated in data acquisition system, in most cases with a posteriori data treatment.
- 2) Sensor systems with integrated built-in OEM sensors, data acquisition system and calibration algorithms whose data treatment is unknown and without the possibility to change any parameter have been identified as “**black box**”. This is because of the impossibility for the user to accurately know the whole chain of data treatment and to tune the sensor itself. Among 72 sensors, we identified 889 records among OEMs (34) and sensor systems (855) not using an open source software for data management. In most cases, the sensor system was previously calibrated against a reference system or, the calibration parameters were remotely adjusted by the manufacturer.

Clear definitions and examples of the principle of operations used by the different type of sensor (electrochemical, metal oxides, optical particulate counter, optical sensors) are reported in a recent work by WMO³⁹. This work also reports the several limitation of each type of sensor such as, interference by meteorological parameters, cross-sensitivities to other pollutants, drifts and aging effect. At the date, there is a larger number of active and

commercially available sensors (**Figure 2**). However, while most of the OEM sensors are open sources, allowing end-users to integrate them into sensors systemes, most of the sensor systems themselves were found to be “black-box” devices. This represents a limitation when the sensor system might need further re-calibration other then the one provided by the manufacturer.

Sensor are also classified according to their commercial availability. Sensor were assigned to the “Commercial” category if they could be purchased and operated by any user without the need for another service for data treatment or reporting activating (as a consultant service for example). Sensors fell under category non-commercial when it was non possible to find any supplier for purchasing. Typically this type of sensor are used for research and publication while it is difficult for any user to repeat the same sensor setup.

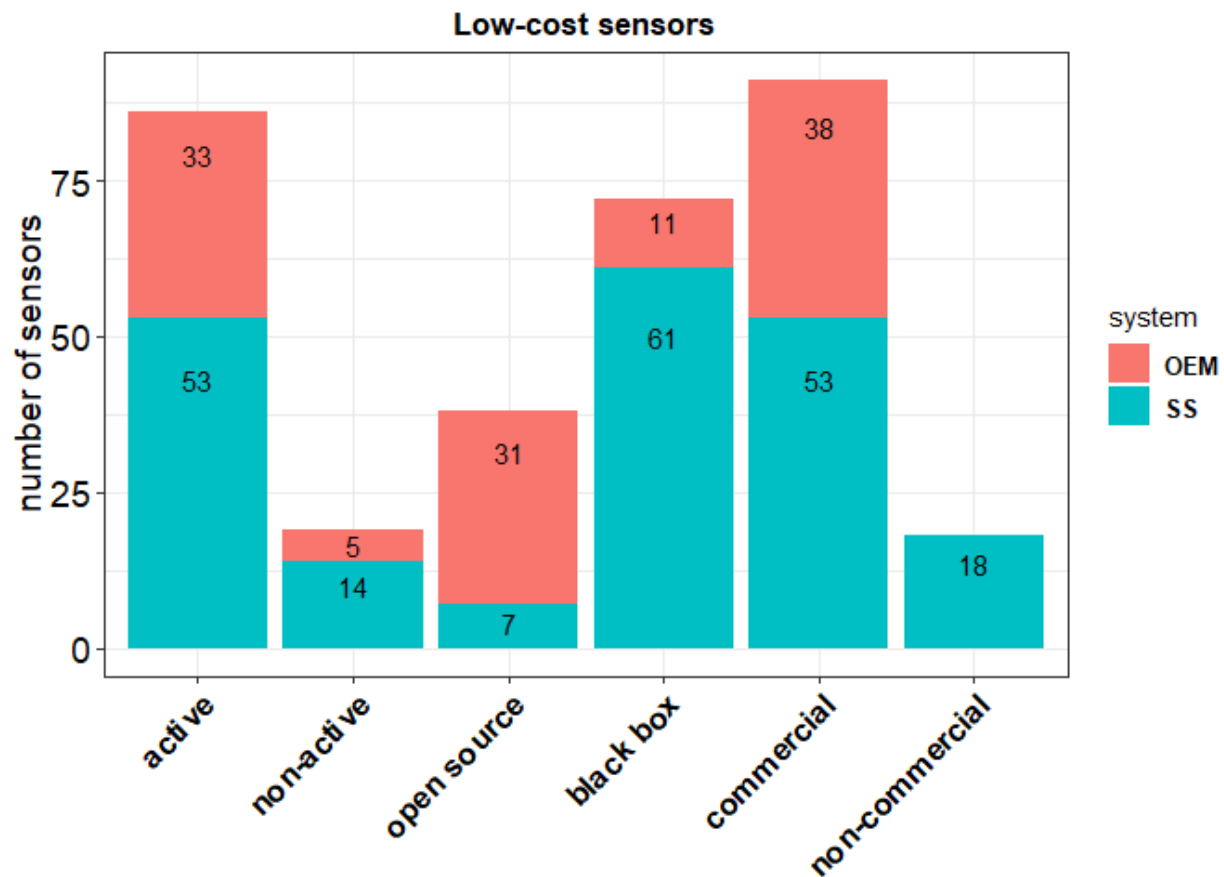


Figure 2. Number of sensor models gathered from the literature review. Sensors has ben classified by their type of technology, availability, openness and commerciality.

3.2. Sensors for air quality

For the detection of Particulate Matter, the largest number of sensor tests, carried out with OEM and SS, was found for Optical Particle Counters (OPC) with 602 records followed by Nephelometers with 248 records (**Table 1**). Both systems detect particulate matter by measuring the light scattered by particles, with the OPC being able to directly count particles according to their size. On the other hand, nephelometers estimate particle density that is subsequently converted into particle mass. For the detection of gaseous pollutant such as, NO_2 , CO and O_3 , the largest number of tests was found for electrochemical sensors with 306 records, followed by metal oxides sensors (MOs) with 112 records (**Table 2**). Electrochemical sensors are based on a chemical reactions between gases in the air and the working electrode of an electrochemical cells. The current of electrons being created is measured between the working and counter electrode that are dipped into an electrolyte in a metal oxide sensor (also named resistive sensor, semiconductor). Therefore, gases in the air react on the surface of a semi-conductor and exchange electrons modifying its conductance.

Table S3 reports the models of OEM sensors currently used to monitor particulate matter according to principle of operation and the cut-off of particulate size. For the sake of clarity, we aggregated records from $PM_{2.5}$ together with $PM_{0.5-2.5}$, PM_2 and PM_3 . The same was done for PM_{10} records that were aggregated with coarse $PM_{2.5-10}$. On the other hand, models of sensor systems measuring concentration of particulate matter were reported in **Table S4**^{1-4,8-10,12,18,20,22,24,25,27-34,37,38,43,48-50,52,54,63,69,70,72-75}. Several sensor systems can use the same OEM. In very few cases, the same model of sensor system was tested using different types of OEM sensors when performing validation tests. **Table S5** and **Table S6** report the models of OEM and sensor systems, respectively, currently used to measure concentration of gaseous air pollutants NO_2 , O_3 , NO and, CO according their their type of technology.^{2,6,7,9,11,12,19,21,23,24,26,28,31,37,44-47,51,56,58,59,61,62,64,65,67,68,71,73,76}

4. Calibration of Sensors

Calibration of the sensor is somewhat considered a sensitive information from most of sensor manufacturers. Several studies performed calibration of sensors during laboratory or field tests. The calibration consisted in the application of a regression model in order to adjust the response of the sensor to a reference system. We found calibration records for both OEMs and sensor systems. Overall, we gathered over 322 records about calibration of sensors using different types of mathematical models (**Table 3**) and at different time resolutions. The *linear* model and the multi linear regression model (*MLR*) were largely used to calibrate the sensor response against a reference measurement. Other calibration approaches used the *exponential*, *logarithmic*, *quadratic*, *Random Forest* and, few types of *neural network* models. We could observe that most of MLR models, covariates such as meteorological parameters *Temperature* and *Relative Humidity*, and gaseous pollutant such as, Nitric Dioxide (NO_2), Nitric Monoxide (NO) and Ozone (O_3), were used to optimize the calibration. Some types of model also took into consideration the *time – drift* of the sensor as covariate. The calibration of OEMs was performed using the raw signal of the

sensor that most of the time was expressed as a voltage or as a current. On the other hand, for sensor systems, the calibration was carried out using the units of the reference system.

Table 3. Types of calibration models used for the calibration of sensors at different time resolutions (ANN: artificial neural network, exp: exponential; log: logarithmic; MLR: multilinear regression; quad: quadratic; RF: random forest; SVM: support vector machine; SVR: support vector regression)

calibration model	n. records	references
ANN	8	Cordero[19], Gerboles[27]
exp	9	Dacunto[22], AQ-SPEC[2], Kelly[34], Austin[3]
linear	97	Mukherjee[48], Sun[65], Spinelle[58], Wang[71], Alvarado[1], Cavaliere[12], Castell[11], Cross[21], Gerboles[26], Sousan[54], Northcross[49], Steinle[64], Han[29], Jovasevic[32], Olivares[50], Spinelle[59], Spinelle[60], Kelly[34], Zheng[75], Holstius[30], Zimmerman[77], Lin[41], AQ-SPEC[2]
log	20	AQ-SPEC[2], Laquai[38]
MLR	125	Jiao[31], Sun[65], Mijling[46], Spinelle[58], Mueller[47], Bigi[7], Cordero[19], Gerboles[27], Wei[72], Spinelle[57], Piedrahita[51], Spinelle[59], Spinelle[60], Sun[66], Zheng[75], Holstius[30], Zimmerman[77], Liu[42]
quad	42	Chakrabarti[18], AQ-SPEC[2], Manikonda[43], Alvarado[1], Zheng[75], Gao[25]
RF	13	Bigi[7], Cordero[19], Zimmerman[77], Liu[42]
SVM	4	Cordero[19]
SVR	4	Bigi[7]

As explained above, from the analyzed records, we found several type of regression model that were used to calibrate sensors from OEM and sensor systems against reference systems. In order the estimate quality of the used calibration model, we reported the coefficient of determination R^2 as indication of the amount of total variability explained by the model. On a first instance, The coefficient of determination can be used as indication of performance of the calibration model chosen to validate the sensor with a reference system. In addition to simple linear models, raw sensor data were validated using multilinear and quadratic models which included the use of covariates to improve the quality of the calibration (**Table 3**).

Figure 3 shows a summary of all mean R^2 obtained from the calibration of sensor systems against reference measurements. Results were grouped by model of sensor system and averaged per reference work. For the same sensor systems we can observe R^2 ranging from low to high values up to the unit. This show the variability of the performance of sensor systems depending from the type of calibration. In the following we are going to report a detailed discussion about performance of several OEM and sensor systmens during their calibration at different averaging-times.

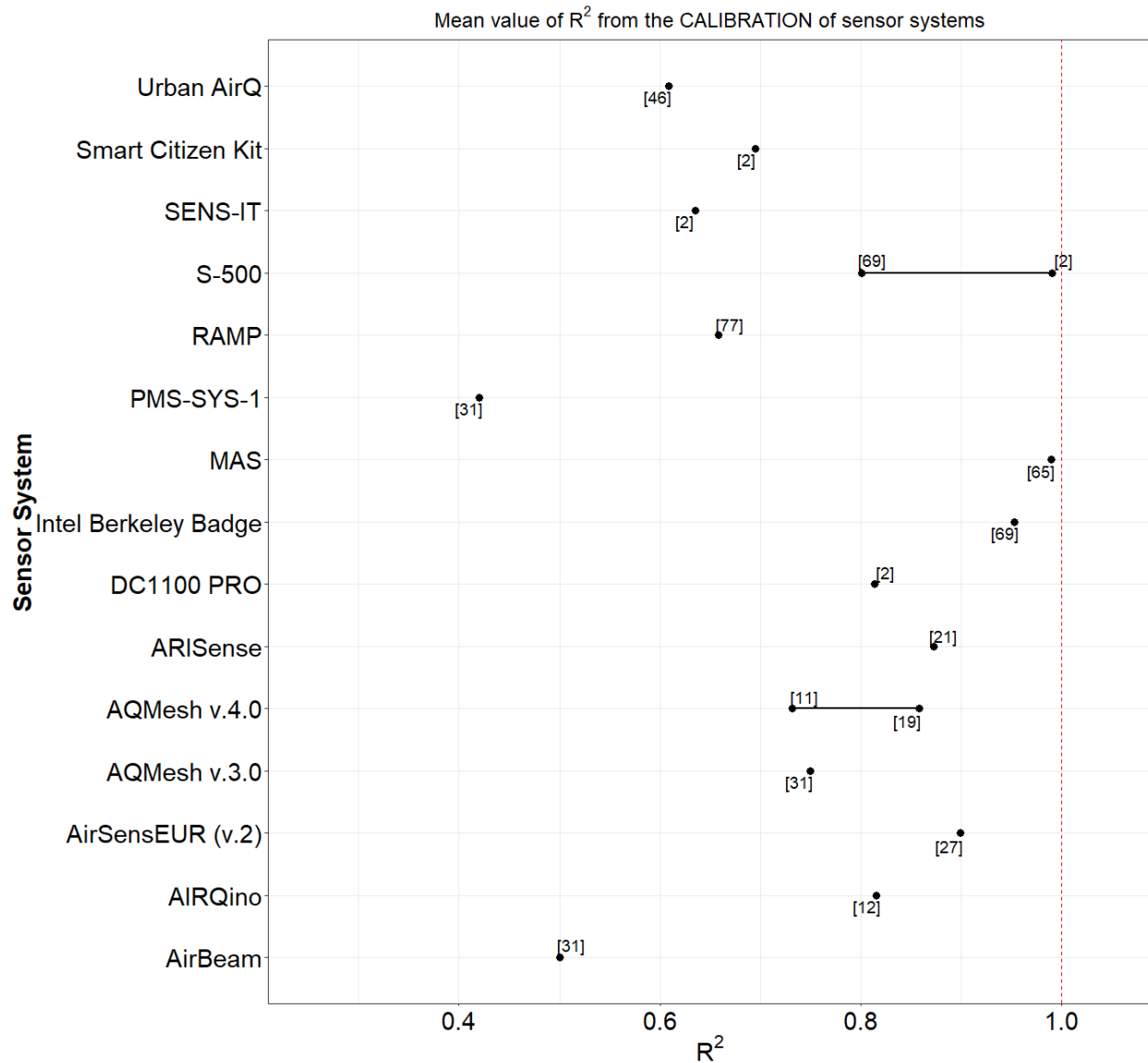


Figure 3. Mean R^2 for obtained from the calibration of sensor systems against reference measurements.

Calibration of sensor data against a reference system was found to be carried out using input data at different time resolution. Therefore, in order to make a comparison of R^2 obtained at the same time resolution data, we chose records averaged over different time-scale of 1 hour (**Figure S1**) and 1 minute (**Figure S2**). Most of these records were from OEMs (109) whereas only a limited number were from sensor systems (109). For the measurement of $PM_{2.5}$, values of $R^2 \sim 1$ were found for the sensors **PMS1003** by **Plantower**³⁴ at 1-hour resolution and for the the **PMS3003** , **Dylos DC1100 PRO** and **DC1700** by **Dylos** at a resolution of 1 minute.^{2,63,74} The Plantower and Dylos sensors

showed higher R^2 when calibrated with 1 minute resolution reference data. Other sensors such as, the **OPC-N2** by **AlphaSense**² reported values of R^2 falling within the range of 0.7 - 1.0 at a resolution of 1 hour. The same OEM sensor OPC-N2, reported values of R^2 just above 0.7 when measuring PM_1 while it did not show a good performance when measuring PM_{10} ². We need to stress out that optical sensors, such as OPCs and nephelometers, are somewhat limited when detecting coarse particulate pattern PM_{10} because of the low-efficiency of the sampling system when sampling large particles in ambient air.

Most of regression models used for the calibration of sensors detecting gaseous pollutants used a time-resolution of 1 hour. For the calibration of sensors measuring O_3 , the largest values of R^2 was reported for the OEM sensors **FIS SP-61** by **FIS** and **O3-3E1F** by **CityTechnology**, when using a time-resolution of 1 hour (**Figure S1**)⁵⁶. On the other hand, when using a time-resolution of 1 minute, values of $R^2 \sim 1$ were found for the sensor system **AirSenseEUR (v.2)** by **LiberalIntentio**²⁷ as well as for the OEM **S-500** by **Aeroqual**² (**Figure S2**). The AirSenseEUR uses a built-in OEM **OX-A431**. We want to point out that, most of the MLR models used for calibration ozone sensors foresees the use of reference NO_2 because of the strong oxidizing effect of O_3 on gas sensors with consequent formation of NO_2 . For the calibration of sensors measuring NO_2 we found values of R^2 within the range 0.7 - 1.0 for the OEM sensor **NO2-B42F** (by Alphasense⁷¹), at a time resolution of 1 hour, and the sensor systems **AirSenseEUR (v.2)** (by LiberalIntentio)²⁷ and **MAS**⁶⁴ at a time resolution of 1 minute (**Figure 3**). We need to point out that for the measurement of NO_2 , the AirSenseEUR (v.2) uses the OEM sensor NO2-B43F by AlphaSense.

Most of the records about the calibration of sensor measuring CO showed high values of R^2 . As shown in **Figure S1**, the OEMs **CO 3E300** by **City Technology**²⁶ and **CO-B4** by **Alphasense**⁷¹ reported $R^2 \sim 1$ for time-resolution of 1 hour. High values of R^2 were also reported for the sensor system **AirSenseEUR (v.2)** when calibrating for CO at a time-resolution of 1 minute (**Figure S2**)²⁷. Other sensors reporting values of R^2 within the range 0.7 - 1.0 where the **MICS-4515** by and **SGX Sensortech**⁵¹, the **Smart Citizen Kit** by **Acrobotic**² and the **RAMP**⁷⁶. All these sensors used 1 hour time-resolution data.

5. Comparison with reference systems

We found about 1103 records about the comparison of calibrated sensors against a reference instrument. All comparisons were carried out by using a *linear regression* model between calibrated and reference data. The performance of the regression was evaluated with the coefficient of determination R^2 and the *slope* of the regression. As explained above, we need to stress out that not all the analyzed records reported the *Root Mean Square Error (RMSE)* of the regression therefore, we decided to omit it in the present review.

In this work, records gathered from the comparison of sensors with reference systems came from OEMs and sensor systems using a custom calibration or a built-in calibration directly setup by the manufacturer. As for the records collected from the calibration of sensor, comparison with reference system was carried out at different time-resolutions.

Here we only report comparisons performed at a time-resolution of 1 hour with 416 and 169 records from sensor systems and OEMs, respectively. In **Figure 3a** we have reported the averaged R^2 for all reviewed sensor systems found from each reference workd. As for the evaluation of the calibration of sensors, we have averaged R^2 valuse obtained from the same raference and for the same sensor systems. It was observed that, for the same sensor system, we could find different R^2 value for the comparison with reference measurements. In the following we give a more detalied breakdown about the performances of each OEM / SS upon their comparison with reference mesurements at different averaging-times.

Figure S3 shows the distribution of R^2 for sensors systems measuring $PM_{2.5}$, PM_{10} , PM_1 , O_3 , NO_2 and CO against reference at 1-hour time-resolution. For the measurements of particulate matter, most of the comparisons were performed during field tests with the highest R^2 obtained from the sensor **PA-II** by **PurpleAir**² and **PATS+** by **Belkley Air**⁵². These sensors reported values of R^2 between 0.8 and 1.0. Other sensors with R^2 values falling in the range 0.7-1.0 were identified in the **PMS-SYS-1** by **Shinyei**, the **Dylos 1100 PRO** by **Dylos**, the **MicroPEM** by **RTI**, the **AirNUT** by **Moji China** the **Egg (2018)** by **Air Quality Egg**, the **AQT410 v.1.15** by **Vaisala**, the **AirVeraCity** by **AirVeraCity** and, the **Air Quality Station** by **AS LUNG**². Records from other sensors showed different values of R^2 depending of the type of field test and for the averaging time chosen to process the time-series of data. We need to point out that the performance of sensor systems measuring PM_{10} , on average, was very poor.

For gaseous pollutants, high R^2 values were found for the sensor systems **2B Tech. (POM)** by **2B Technologies** (O_3)², the **AirSenseEUR (v.2)** by **LiberaIntentio**²⁷ the **Bettair** by **Bettair Cities**⁶ the **AirCasting** by **HabitatMap**⁷² the **KUNAKAIR A10 V2** by **kunak**³⁷ (O_3 , NO_2 , CO and NO), the **Spec**, the **AQMesh**. These sensors reported values of R^2 between 0.8 and 1.0. As shown in **Figure S3**, we found a non-negligible number of records for sensor systems whose R^2 resulting from the comparison with reference systems was within the range 0.7 - 1.0 using 1-hour averaged data. We want to point out that, among all tested sensor systems, only the **AirSenseEUR (v.2)** was the only one measuring multiple pollutants.

The comparison of OEMs against reference systems, showed only few sensors for the measurement of PM had R^2 within the range 0.7 - 1.0 when average over a time-scale of 1 hour. Among them we could identify the **Dylos DC 1700**^{30,32,43,54} and the **OPC-N2 (Figure S4)**^{2,4,20,24,48} when measuring $PM_{2.5}$. On the other hand, when the comparison was performed over a time-scale of 24 hour we found R^2 within the range 0.7 - 1.0 for several OEMs which included the **PMS7003** by **Plantower**⁴, the **SDS011** by **Nova Fitness**⁴, the **OPC-NO2**², and the **Egg v.2 (PM)** by **Air Quality Egg**² when measuring $PM_{2.5}$ (**Figure S5**). The same behavior was observed from the comparison of sensor systems against a reference system when measuring 24-hour averaged data of $PM_{2.5}$. As we can see from **Figure S6**, several sensor systems such as, **Dylos DC 1700**⁴⁹, **PA-II**,² **AirQUINO** by **CNR**¹² reported values of $R^2 \sim 1$.

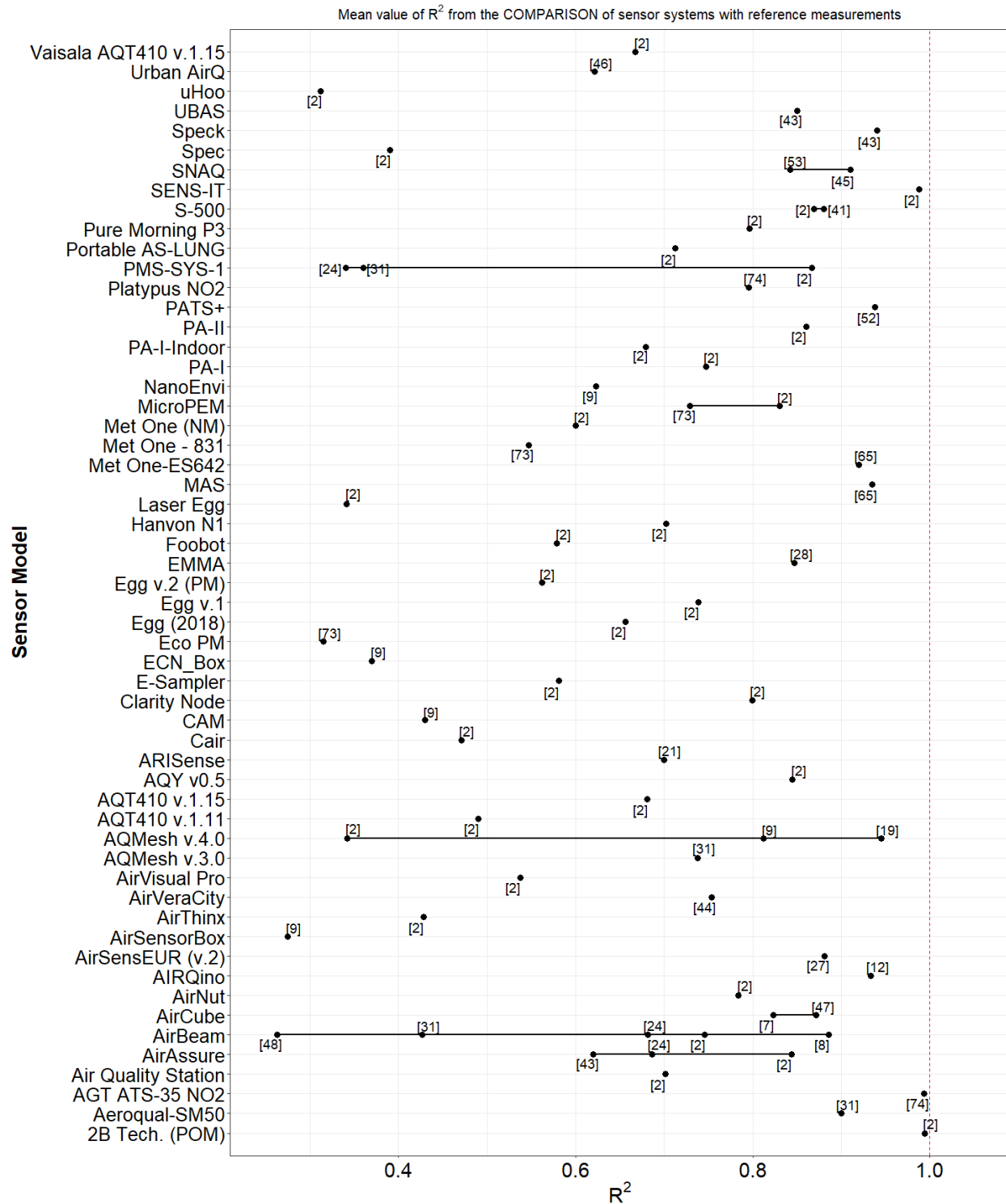


Figure 3a. Mean R^2 for obtained from the comparison of sensor systems against reference measurements.

For the evaluation of gaseous pollutants, we found very few OEMs with R^2 within 0.7 - 1.0 when using data at a time-resolution of 1 hour. These sensors included the **CairClip O3/NO2** by CairPol^{23,24,58,73}, the **Aeroqual Series 500 (and SM50)**²⁴, the **O3-3E1F** by CityTechnology^{24,26,58,60} and the **NO2-B43F** by Alphasense^{65,76} (Figure S4). On the other hand, we found very few records for sensor systems using 24 hour data. As a general remark, we can see that the performance of OEMs sensors is enhanced when they are integrated inside a sensor systems. It is also evident that most of the gathered records from $PM_{2.5}$ and gaseous pollutants O_3 , NO_2 , CO and NO , used 24 hours and 1 hour time-resolution data as required by the European Air Quality Directive.

To check the accuracy of a sensor, when compared to a reference system, we looked at the value of the slope obtained from the linear regression of the sensor measurements against a reference measurement. Most of comparisons were carried out during field tests, while only a limited number laboratory tests were available. Ideally, only an $R^2 \sim 1.0$ and a **slope** ~ 1.0 should be a good indicator of performance for a sensor. Therefore, we only selected records with $R^2 > 0.7$ and **slope** within the range 0.5-1.5.

Figure S7 shows sensor systems such as, the **AQM 60**, the **KUNAKAIR A10 V2**, the **AirSenseEUR (v2)** has *slopes* ~ 1 for most of measured gaseous pollutants when using 1 hour time-resolution data. On the other hand, only few records from $PM_{2.5}$ sensor systems showed *slopes* ~ 1 for 1-hour (**PATS+** and **AirNut**) and 24-hour (**AIRQuino**) time-averaged sensor systems. Only few $PM_{2.5}$ sensors performed well at ideal conditions. Sensor systems such as, **AIRQuino**, **SidePak AM510**, **Air Quality Egg (v.2) (PM)**, **Dylos DC1100 PRO**, **AirNut** and the OEM **OPC-N2** were in good agreement with a reference system (Figure S7, Figure S8).

Among OEMs showing *slopes* ~ 1 when using 1-hour time-averaged data, we found the **SM50**, the **CairClip O3/NO2**, the **S-500**, (NO_2 , O_3) and, the **NO2-B4F** (NO_2) and the **Egg v.2 (PM)** ($PM_{2.5}$) (Figure S9). On the other hand, when using 24-hour time-averaged data, the OEM **OPC-N2** by Alphasense and the **Egg v.2 (PM)** by Air Quality Egg, showed *slopes* ~ 1 when measuring PM_{10} (Figure S10).

As general remark, from the above analysis we could observe that for some OEMs and sensor systems, the width of the interquartile range IQR (H-spread) was very narrow. This is an indication of the *reproducibility* of the regression parameters used in their calibration. This becomes relevant when it comes to the development of a reliable sensor system that uses the same OEM sensor and the same calibration algorithms. From the present analysis,

6. Price of sensors

As preliminary outcome of the present analysis, we have started identifying sensors systems that are in good agreement with reference instruments commonly used to monitor pollutant concentrations. Although the sensor market constantly develops, we decided to

identify a sensor system that is commercially available or that can be assembled with commercially available OEM sensors.

Usually, the price of OEM sensors only represents a small fraction of the selling value of the entire sensor system. In the common understanding, a sensor for air quality is classified as low-cost when its price is less than 10000 EUR. In addition, if a low-cost sensor can measure multiple pollutants, potentially it could be used by local authorities as complementary source of air quality data as substitute of reference instruments whose cost might rise up to one order of magnitude.

For the evaluation of the price of sensors, we considered all sensor systems manufactured by commercial companies as well as sensor systems built for laboratory testing by research groups. The latter ones are custom-built devices assembled around an OEM sensor. We must stress out that, while for the detection of different size of particulate matter it is possible to use the same optical sensor, for the detection of gaseous pollutant it is necessary to have a dedicated sensor for each pollutant. Therefore, among all the analyzed records, we tried identifying sensor systems that can measure concentration of particulate matter together with gaseous pollutants.

Figure S12 and **Figure 4** show the commercial price of OEMs and sensor systems by model and number of pollutant measured by each sensor. There is a large number of sensor systems measuring single pollutants but few ones measuring multiple pollutants. This is an indication about the complexity to have a sensor system measuring multiple pollutants. Most of OEMs are open source devices (**Figure S12**). This means that OEMs can be used to build sensor systems for data acquisition and therefore to calibrate the sensor. On the other hand, most of the sensor systems are black box (**Figure 4**). This means that most of the manufacturers of sensor systems does not commercialize sensors that can be re-calibrated according to the requirements of the user. Sensor systems are intended to be ready-to-use air quality monitors. When purchased by the end-user, a sensor system should estimate the concentration of pollutants with a close agreement to the traditional reference systems used to monitor air quality.

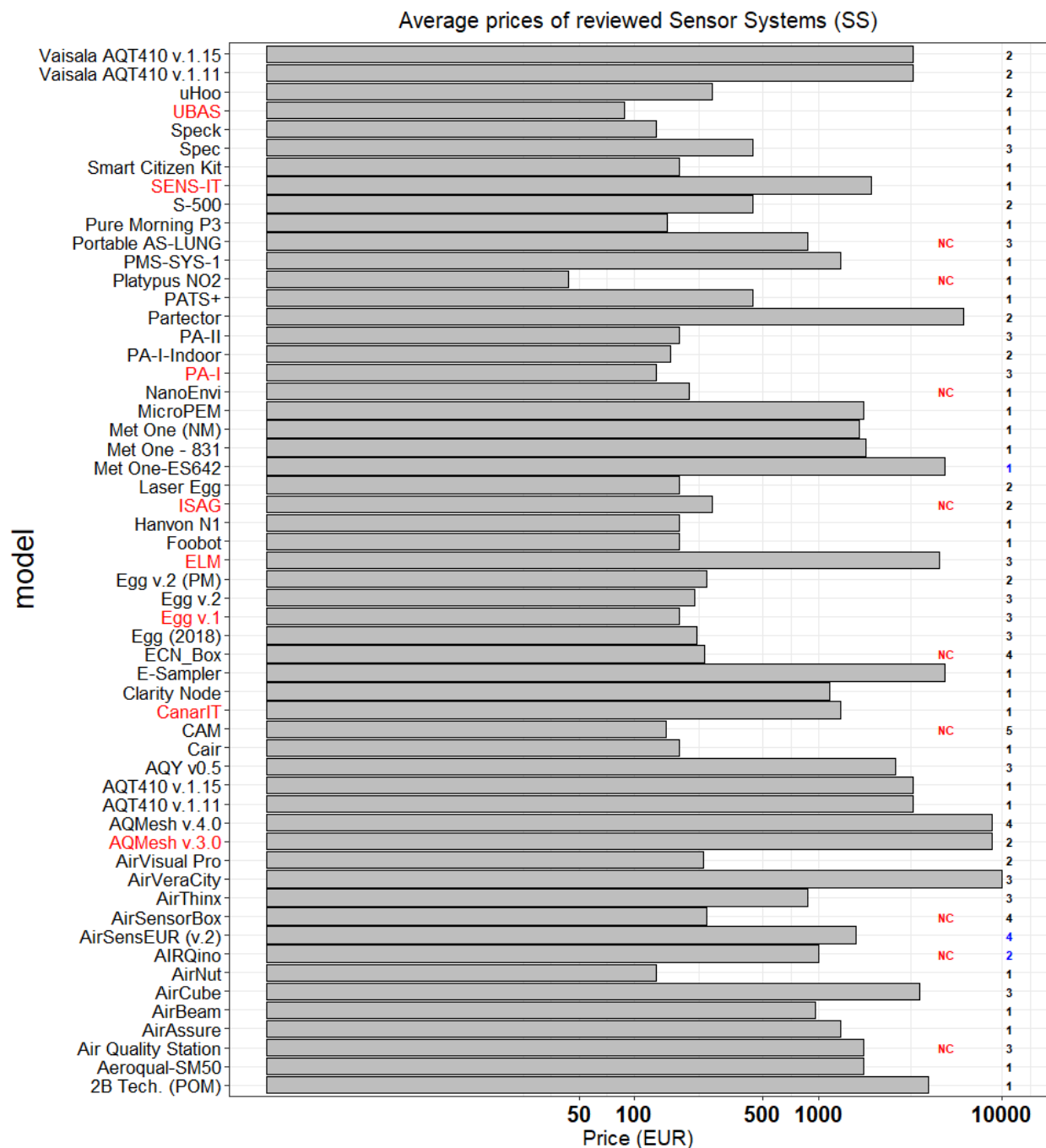


Figure 4. Prices of SS grouped by model. (Numbers in bold indicates the number of pollutant measured by each sensor. x-axis uses logarithmic scale). Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' & 'updated' and 'non-living' sensors are indicated in black and red color, respectively. NC indicates non commercially available sensor.

In **Figure 5** We have shortlisted sensor systems according to their level of agreement to reference systems. For this purpose, we considered metrics obtained from 1 hour and 24 hour averaged data of sensor systems with $R^2 > 0.85$ and $0.8 < slope < 1.2$.

Among open source sensor systems we could identify the **AirSenseEUR (v.2)** by **LiberaIntentio** and the **AIRQuino** by the **CNR** for the detection of NO_2 , CO , O_3 , NO and PM , respectively. The remaining shortlisted sensor systems were identified as black box. **Table 4** and **Table S7** report the mean value of R^2 and of the *slope* for the sensors systems shortlisted in Figure 15 for 1 hour and 24 hour averaged data. As we can see, the **AirSenseEUR (v.2)** resulted in a mean R^2 value of ~ 0.90 and a *slope* of ~ 0.94 while the **AIRQuino** resulted in a mean R^2 value of ~ 0.91 and a *slope* of ~ 0.97 . We need to point out that, at the date, the **AIRQuino** can measures up to five pollutants ($PM_{2.5}$, PM_{10} , NO_2 , O_3 , CO and NO , CO_2 and $VOCs$), however, only data from PM were available at the time of this review. On the other hand, the **AirSenseEUR (v2)** is a complete sensor system that can also measure particulate matter beside gaseous pollutants including " CO_2 and Rn (radon)". This sensor system is already operative and has undergone multiple calibrations and field tests where measurements of gaseous pollutants showing good agreement with reference measurements.

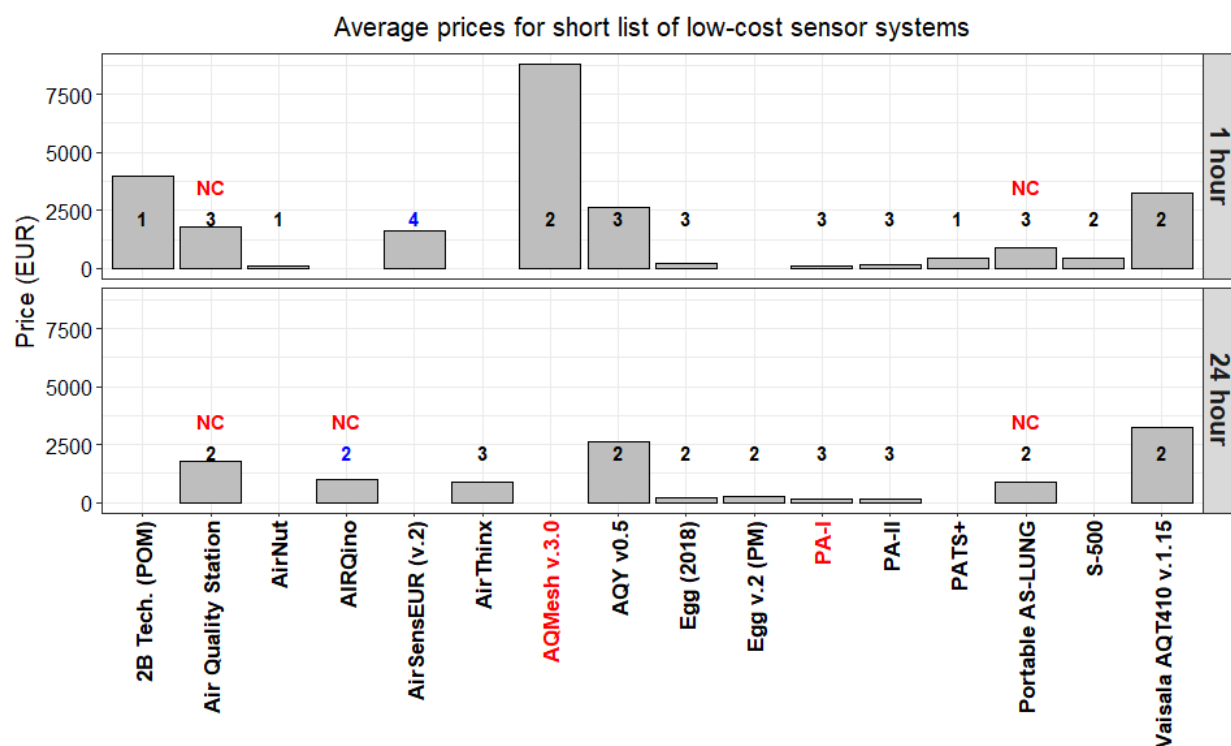


Figure 5. Price of low-cost sensor systems. Numbers in bold indicate the number of pollutant measured by open source (blue) and black box (black) sensors. Only records with $R^2 > 0.85$ and $0.8 < slope < 1.2$ are shown. Names of 'living' & 'updated' and 'non-living' sensors are indicated in black and red color, respectively. NC indicates non commercially available sensor.

As shown in **Table 4**, the price of sensor systems ranged from few hundreds of euros to about 9000 euros. We have investigated the possibility of having a relationship between the performance of the sensor (here expressed as R^2) and the selling price of the sensor. For this purpose we have compared the mean R^2 of all sensor models against their price.

Table 4. Shortlist of sensor systems showing good agreement with reference systems ($R^2 > 0.85$; $0.8 < \text{slope} < 1.2$) for 1 hour time averaged data.

model	pollutant	mean R^2	mean slope	open/close	living	commercial	price (EUR)
AirNut	$PM_{2.5}$	0.8618	0.8838	black box	Y	commercial	132
PA-I	PM_1	0.9464	0.9234	black box	N	commercial	132
PA-II	PM_1	0.9874	0.823	black box	Y	commercial	176
Egg (2018)	PM_1	0.8736	0.8484	black box	Y	commercial	219
PATS+	$PM_{2.5}$	0.96	0.92	black box	Y	commercial	440
S-500	NO_2, O_3	0.88	1.03	black box	Y	commercial	440
Portable AS-LUNG	PM_1	0.8858	0.8678	black box	Y	non commercial	880
AirSenseEUR (v.2)	NO_2, O_3, CO, NO	0.8938	0.9425	open source	Y	commercial	1600
Air Quality Station	PM_1	0.88	0.896	black box	Y	non commercial	1760
AQY v0.5	$PM_{2.5}$	0.8654	0.9673	black box	updated	commercial	2640
Vaisala AQT410 v.1.15	CO	0.8734	0.97	black box	Y	commercial	3256
2B Tech. (POM)	O_3	0.9972	1.007	black box	Y	commercial	3960
AQMesh v.3.0	NO	0.87	0.883	black box	N	commercial	8800

In **Figure 6** we reported the relation between the mean R^2 and the selling price of OEM/SS for field tests comparisons of sensors against reference systems using 1 hour averaged data. As shown in **Figure 6**, we did not find a significative relation between the commercial price of OEM sensors and the value of R^2 . On the other hand, we could observe a slight increase of the price of sensor systems together with R^2 . The regression equations indicated in **Figure 6** have been calculated only considering “living” (or active) OEM/sensor when compared to reference measurements during field tests. For 24 hour averaged data from both OEMs and SS we did not show any relationship between mean R^2 and selling price.

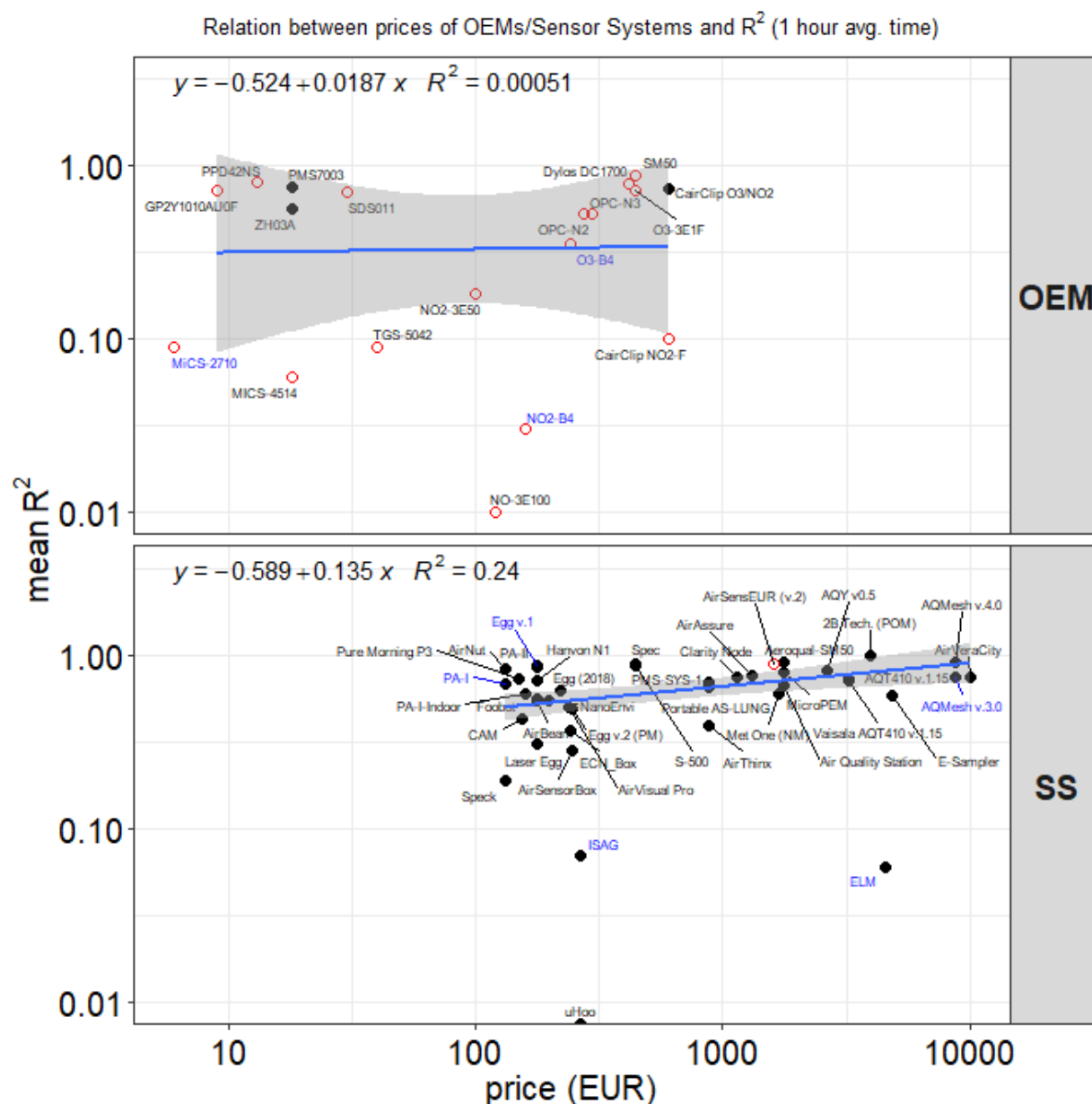


Figure 6. Relation between prices of OEMs/Sensor Systems (SS) and R^2 for field test only. Logarithmic scale has been set for both axis. Open source and black box models are indicated with open and full circles, respectively. Names of 'living' and 'non-living' sensors are indicated in black and blue color, respectively. R^2 refers to data averaged over 1 hour. Grey shade in the fit plots indicate a pointwise 95% confidence interval on the fitted values.

As shown in **Figure 6**, most of the reviewed sensor systems are “black box” systems. This means that the end-user cannot perform any further correction or re-calibration on the sensor system itself. The relationship observed between the coefficient of determination R^2 and the price of the sensor system, it is an evidence that complexity of building a detector

for air quality is somewhat linked to the choice of materials, multi-functionality and time-spent to develop a reliable sensor system.

In order to target sensor systems in closer agreement and accuracy with reference systems, we displayed the distribution of SS models with $mean R^2 > 0.75$ and $0.5 < mean slope < 1.2$. **Figure 7** indicates the **2B Tech. (POM)** by **2B Technologies**, the **AirSensEUR (v.2)** by **Liberantentio**, the **S-500** by **Aeroqual**, the **Egg (v.2)** by **Air Quality Egg**, the **AQT410 v.1.15** by **Vaisala** and the **AirVeraCity** as the one having $mean R^2 \rightarrow 1$ and $mean slope = 1$. These sensor systems give indicative measurements of air pollutants when compared with the traditional reference monitoring systems over 1 hour averaging time. On the other hand, other sensors such as the **PA-II** by **Purple Air**, the **AirNut**, the **AQMesh v.3.0** by **AQMesh** and, the **AQY v0.5** by **Aeroqual** showed good agreement with reference systems but lower accuracy.

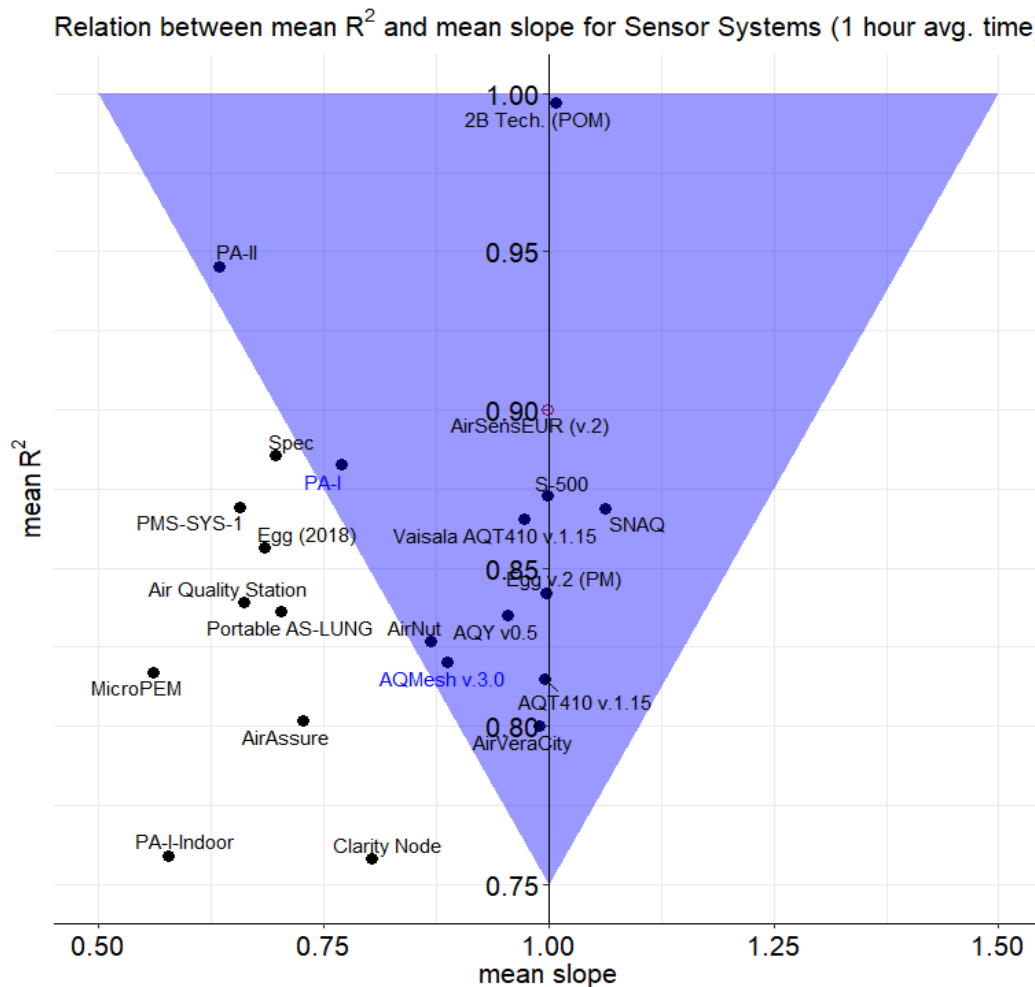


Figure 7. Correspondence between R^2 and slope for sensor systems (SS). Only sensor models with $mean R^2 > 0.75$ and $0.5 < mean slope < 1.2$ are shown. Names of 'living' and 'non-living' sensors are indicated in black and blue color, respectively.

7. Conclusions

According to the European Air Quality Directive², a sensor system can be considered “Equivalent” when it meets the Data Quality Objectives (DQOs) set for data capture and uncertainty^{3,4}. In order for sensor system measurement to be incorporated into the legal framework set by the Air Quality Directive in Europe, they shall satisfy one of the data quality objectives (DQOs) of the Directive. DQOs, defined as the maximum allowed relative uncertainty, are defined either for reference and indicative measurements or for objective estimations. For inorganic gaseous pollutants, they correspond to 15, 25 to 30 and 75 %, respectively. Although, the objective of sensor systems is to provide the most accurate air pollution measurements, it is most likely that the DQO for reference measurements is out reach while it is believed that by improving the sensor calibration procedures the DQO of “Indicative Measurements” could be met at fixed monitoring sites³⁵.

Supplementary material

Table S1. Number of analyzed records and sensor models by averaging time.

Averaging time	n. records	n. OEMs & SS
1 hour	591	85
5 min	253	42
24 hour	249	42
1 min	102	23

Table S2. Metrics used for comparing sensor data, M_i , and reference measurements, RM_i .

Comparison metrics	Short name	Mathematical formulas	Characteristics
Coefficient of determination	R^2	$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}}$, where SS_RES is the sum of squares of residuals and SS_TOT is the total sum of squares	R^2 measures the strength of relationship between M_i and RM_i , of the percentage of total variance that is explained by a linear relationship
Slope of linear relationship	<i>slope</i>		
Intercept of the linear relationship $M_i = \text{Slope } RM_i + \text{Offset}$	<i>Offset</i>		
Root Mean Square Error	<i>RMSE</i>	$\sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - RM_i)^2}$	indicates the magnitude of the error and retains the variable's unit; is sensitive to extreme values and to outliers; tends to vary as a function of

Measurement uncertainty U

$$U = kU_c$$

the standard deviation of the RM

Correlation Coefficient r

$$r = \frac{\frac{1}{n} \sum_{i=1}^n (M_i - M)(M_i - RM)}{\sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - M)^2 \frac{1}{n} \sum_{i=1}^n (RM_i - RM)^2}}$$

measures the strength and the direction of a linear relationship between two variables, and receives a value between -1 and 1; is independent of the difference in the variance (var) of M and RM, thus if $r=1$ and $\text{var}(M) < \text{var}(RM)$, then variance correction may be required

Table S3. Model of OEMs for the detection of Particulate Matter.

	model	type	pollutant		references
1	CairClip PM2.5	nephelometer	$PM_{2.5}$		Williams[73]
2	DataRAM pDR-1200	nephelometer	$PM_{2.5}$		Chakrabarti[18]
3	DN7C3CA006	nephelometer	$PM_{2.5}$		Sousan[54]
4	DSM501A	nephelometer	$PM_{2.5}$		Wang[71], Alvarado[1]
5	Dylos DC1100	OPC	$PM_{2.5}$		Jiao[31], Williams[73], Feinberg[24]
6	Dylos DC1100 PRO	OPC	$PM_{2.5}$		Jiao[31], AQ-SPEC[2], Manikonda[43]
19	Dylos DC1100 PRO	OPC		PM_{10}	Feinberg[24], Manikonda[43]
7	Dylos DC1700	OPC	$PM_{2.5}$		Manikonda[43], Northcross[49], Holstius[30], Steinle[64], Han[29], Jovasevic[32], Dacunto[22]
20	Dylos DC1700	OPC		PM_{10}	Manikonda[43], Sousan[54], Han[29], Jovasevic[32]
8	GP2Y1010AU0F	nephelometer	$PM_{2.5}$		Olivares[50], Manikonda[43], Sousan[54], Alvarado[1], Wang[71]
21	GP2Y1010AU0F	nephelometer		PM_{10}	Alvarado[1]
9	OPC-N2	OPC	$PM_{2.5}$		AQ-SPEC[2], Mukherjee[48], Sousan[55], Feinberg[24], Crilley[20], Badura[4]
22	OPC-N2	OPC		PM_{10}	AQ-SPEC[2], Sousan[55], Feinberg[24], Crilley[20]
24	OPC-N2	OPC		PM_1	AQ-SPEC[2], Sousan[55], Crilley[20]
10	OPC-N3	OPC	$PM_{2.5}$	PM_{10} PM_1	AQ-SPEC[2]
11	PMS1003	OPC	$PM_{2.5}$		Kelly[34]
12	PMS3003	OPC	$PM_{2.5}$		Zheng[75], Kelly[34]
13	PMS5003	OPC	$PM_{2.5}$		Laquai[38]
14	PMS7003	OPC	$PM_{2.5}$		Badura[4]
15	PPD42NS	nephelometer	$PM_{2.5}$		Wang[71], Holstius[30], Austin[3], Gao[25], Kelly[34]
16	SDS011	OPC	$PM_{2.5}$		Budde[10], Laquai[38], Badura[4], Liu[42]

23	SDS011	OPC		PM_{10}	Budde[10]
17	SidePak AM510	nephelometer	$PM_{2.5}$		Karagulian[33]
18	ZH03A	nephelometer	$PM_{2.5}$		Badura[4]

Table S4. Models of Sensor Systems for the detection of Particulate Matter.

	model	type	pollutant			references
1	Air Quality Station	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
2	AirAssure	nephelometer	$PM_{2.5}$			AQ-SPEC[2], Feinberg[24], Manikonda[43]
3	AirBeam	nephelometer	$PM_{2.5}$			Borghi[8], Jiao[31]
4	AirBeam	OPC	$PM_{2.5}$			AQ-SPEC[2], Mukherjee[48], Feinberg[24]
5	AirNut	nephelometer	$PM_{2.5}$			AQ-SPEC[2]
6	AIRQino	OPC	$PM_{2.5}$	PM_{10}		Cavaliere[12]
36	AirSensorBox	OPC		PM_{10}		Borrego[9]
7	AirThinX	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
8	AirVisual Pro	nephelometer	$PM_{2.5}$	PM_{10}		AQ-SPEC[2]
9	AQY v0.5	OPC	$PM_{2.5}$			AQ-SPEC[2]
10	Cair	OPC	$PM_{2.5}$	PM_{10}		AQ-SPEC[2]
11	CAM	OPC	$PM_{2.5}$	PM_{10}		Borrego[9]
37	CAM	nephelometer		PM_{10}		Borrego[9]
12	Clarity Node	nephelometer	$PM_{2.5}$			AQ-SPEC[2]
13	DC1100 PRO	OPC	$PM_{2.5}$			AQ-SPEC[2]
14	E-Sampler	OPC	$PM_{2.5}$			AQ-SPEC[2]
15	ECN_Box	nephelometer	$PM_{2.5}$	PM_{10}		Borrego[9]
40	Eco PM	OPC			PM_1	Williams[73]
16	Egg (2018)	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
17	Egg v.2 (PM)	nephelometer	$PM_{2.5}$	PM_{10}		AQ-SPEC[2]
38	ELM	nephelometer		PM_{10}		AQ-SPEC[2]
18	EMMA	OPC	$PM_{2.5}$			Gillooly[28]
19	Foobot	OPC	$PM_{2.5}$			AQ-SPEC[2]
20	Hanvon N1	nephelometer	$PM_{2.5}$			AQ-SPEC[2]
21	Laser Egg	nephelometer	$PM_{2.5}$	PM_{10}		AQ-SPEC[2]
22	Met One-ES642	nephelometer	$PM_{2.5}$			Sun[65]
39	Met One - 831	OPC		PM_{10}		Williams[73]
23	Met One (NM)	OPC	$PM_{2.5}$			AQ-SPEC[2]
24	MicroPEM	nephelometer	$PM_{2.5}$			AQ-SPEC[2], Williams[73]
25	PA-I	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
26	PA-I-Indoor	OPC	$PM_{2.5}$	PM_{10}		AQ-SPEC[2]
27	PA-II	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
28	Partector	Electrical	$PM_{2.5}$		PM_1	AQ-SPEC[2]
29	PATS+	nephelometer	$PM_{2.5}$			Pillarisetti[52]
30	PMS-SYS-1	nephelometer	$PM_{2.5}$			Jiao[31], AQ-SPEC[2], Williams[73],

						Feinberg[24]
31	Portable AS-LUNG	OPC	$PM_{2.5}$	PM_{10}	PM_1	AQ-SPEC[2]
32	Pure Morning P3	OPC	$PM_{2.5}$			AQ-SPEC[2]
33	Speck	nephelometer	$PM_{2.5}$			Feinberg[24], US-EPA[68], Williams[73], AQ-SPEC[2], Manikonda[43], Zikova[76]
34	UBAS	nephelometer	$PM_{2.5}$			Manikonda[43]
35	uHoo	nephelometer	$PM_{2.5}$			AQ-SPEC[2]

Table S5. Model of OEMs for the detection of NO_2 , CO , NO and O_3 .

	model	type	pollutant		references
1	CairClip NO2-F	electrochemical	NO_2		Spinelle[56], Spinelle[58], Duvall[23]
2	CairClip O3/NO2	electrochemical	NO_2		Jiao[31], Williams[74]
16	CairClip O3/NO2	electrochemical		O_3	Jiao[31], Spinelle[56], Duvall[23], Feinberg[24]
10	CO-B4	electrochemical	CO		Wei[72]
11	CO 3E300	electrochemical	CO		Gerboles[26]
17	FIS SP-61	MOs		O_3	Spinelle[57]
3	MiCS-2710	MOs	NO_2		Spinelle[58], Williams[74]
4	MICS-4514	MOs	NO_2		Spinelle[58]
12	MICS-4514	MOs	CO		Spinelle[59]
14	NO-3E100	electrochemical		NO	Spinelle[60], Gerboles[26]
15	NO-B4	electrochemical		NO	Wei[72]
5	NO2-3E50	electrochemical	NO_2		Spinelle[58], Spinelle[56], Gerboles[26]
6	NO2-A1	electrochemical	NO_2		Williams[74]
7	NO2-B4	electrochemical	NO_2		Spinelle[56], Spinelle[58]
8	NO2-B42F	electrochemical	NO_2		Wei[72]
9	NO2-B43F	electrochemical	NO_2		Sun[66]
18	O3-3E1F	electrochemical		O_3	Spinelle[56], Spinelle[58], Gerboles[26]
19	O3-B4	electrochemical		O_3	Spinelle[56], Spinelle[58], Wei[72]
20	SM50	MOs		O_3	Feinberg[24]
13	TGS-5042	electrochemical	CO		Spinelle[59]

Table S6. Model of Sensor Systems for the detection of NO_2 , CO , NO and O_3 .

	model	type	pollutant	pollutant.y	references
35	2B Tech. (POM)	UV			O_3 AQ-SPEC[2]
36	Aeroqual-SM50	MOs			O_3 Jiao[31]
1	AGT ATS-35 NO2	MOs	NO_2		Williams[74]
2	AirCube	electrochemical	NO_2		Mueller[47], Bigi[7]
34	AirCube	electrochemical		NO	Bigi[7]

37	AirCube	electrochemical				O_3	Mueller[47]
3	AirSensEUR (v.2)	electrochemical	NO_2	CO	NO	O_3	Gerboles[27]
4	AirSensorBox	electrochemical	NO_2	CO		O_3	Borrego[9]
5	AirVeraCity	electrochemical	NO_2	CO		O_3	Marjovi[44]
31	AQMesh v.3.0	electrochemical		CO	NO		Jiao[31]
6	AQMesh v.4.0	electrochemical	NO_2				Cordero[19], AQ-SPEC[2], Castell[11], Borrego[9]
32	AQMesh v.4.0	electrochemical		CO	NO		AQ-SPEC[2], Castell[11], Borrego[9]
38	AQMesh v.4.0	electrochemical				O_3	Castell[11], Borrego[9]
39	AQT410 v.1.11	electrochemical				O_3	AQ-SPEC[2]
40	AQT410 v.1.15	electrochemical				O_3	AQ-SPEC[2]
7	AQY v0.5	electrochemical	NO_2				AQ-SPEC[2]
41	AQY v0.5	MOs				O_3	AQ-SPEC[2]
8	ARISense	electrochemical	NO_2	CO	NO	O_3	Cross[21]
9	CAM	electrochemical	NO_2	CO	NO		Borrego[9]
10	ECN_Box	electrochemical	NO_2			O_3	Borrego[9]
11	Egg v.1	MOs	NO_2	CO		O_3	AQ-SPEC[2]
12	Egg v.2	electrochemical	NO_2	CO		O_3	AQ-SPEC[2]
13	ELM	MOs	NO_2				AQ-SPEC[2], US-EPA[68]
42	ELM	MOs				O_3	AQ-SPEC[2]
14	EMMA	electrochemical	NO_2	CO	NO		Gillooly[28]
15	Intel Berkeley Badge	electrochemical	NO_2				Vaughn[69]
16	Intel Berkeley Badge	MOs	NO_2				Vaughn[69]
17	ISAG	MOs	NO_2			O_3	Borrego[9]
18	M-POD	MOs	NO_2	CO			Piedrahita[51]
19	MAS	electrochemical	NO_2	CO			Sun[65]
43	MAS	UV				O_3	Sun[65]
20	NanoEnvi	electrochemical	NO_2	CO			Borrego[9]
44	NanoEnvi	MOs				O_3	Borrego[9]
21	Platypus NO2	MOs	NO_2				Williams[74]
22	RAMP	electrochemical	NO_2	CO			Zimmerman[77]
23	S-500	electrochemical	NO_2				Lin[41]
24	S-500	MOs	NO_2				Vaughn[69]
45	S-500	MOs				O_3	AQ-SPEC[2]
25	SENS-IT	MOs	NO_2	CO		O_3	AQ-SPEC[2]
33	Smart Citizen Kit	MOs		CO			AQ-SPEC[2]
26	SNAQ	electrochemical	NO_2	CO	NO		Mead[45], Popoola[53]
27	Spec	electrochemical	NO_2	CO		O_3	AQ-SPEC[2]
46	uHoo	MOs				O_3	AQ-SPEC[2]
28	Urban AirQ	electrochemical	NO_2				Mijling[46]
29	Vaisala AQT410 v.1.11	electrochemical	NO_2	CO			AQ-SPEC[2]

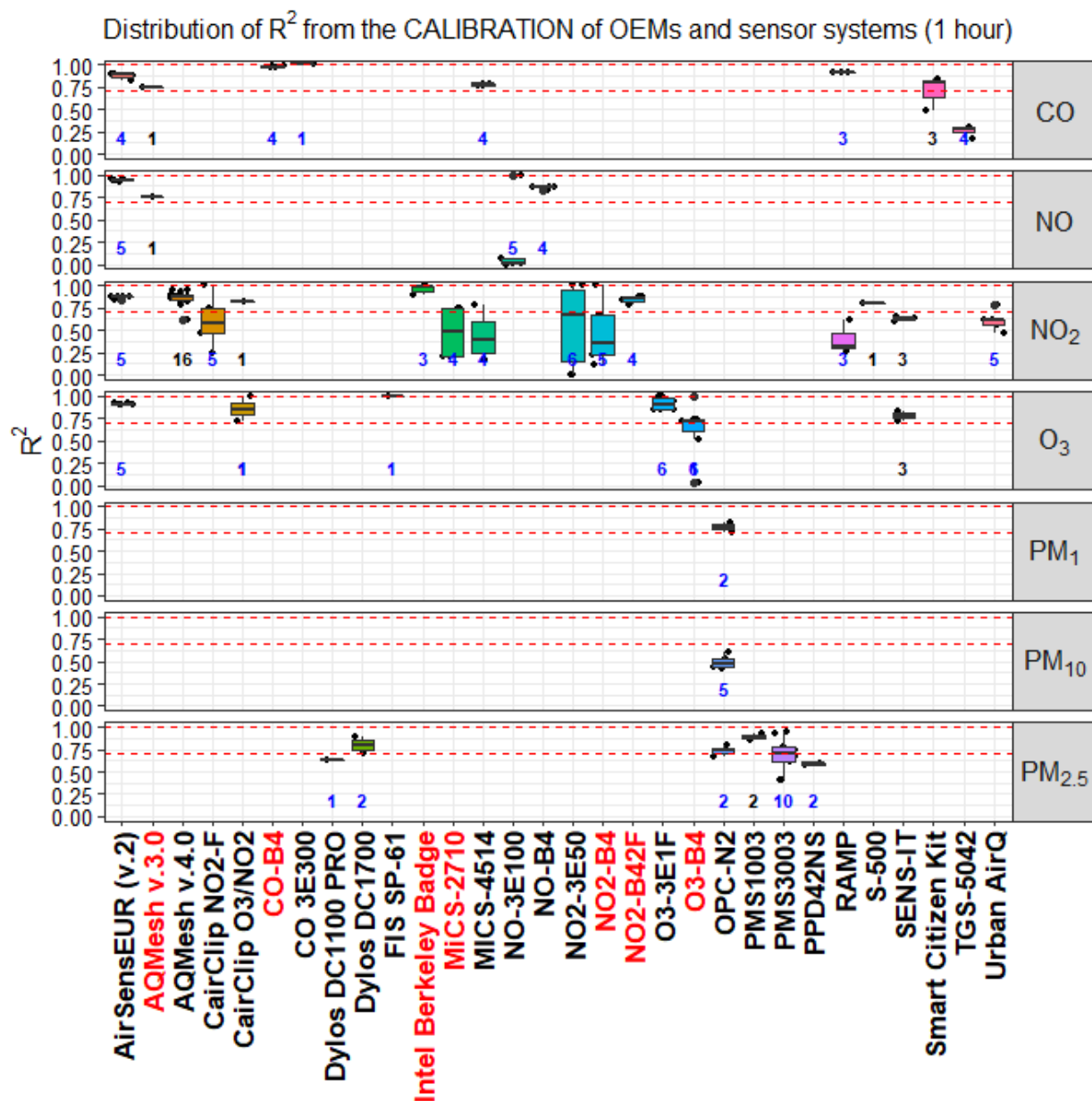


Figure S1. Distribution of R^2 for OEMs and sensor systems against the reference for different pollutants. Records were averaged over a time-scale of 1 hour. Dashed lines indicate the value of 0.7 and 1.0. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

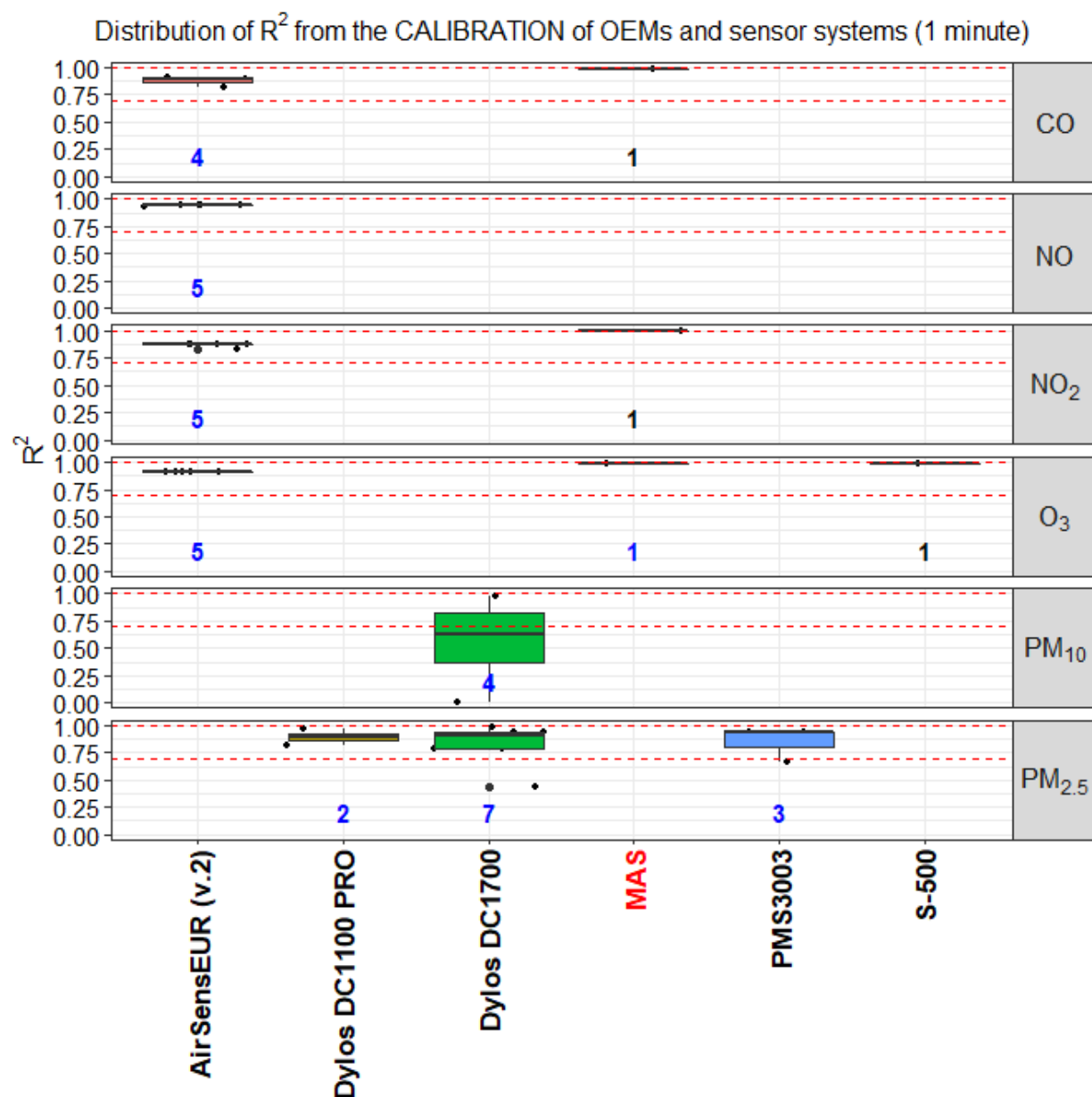


Figure S2. Distribution of R^2 for OEMs and sensor systems against the reference for different pollutants. Records were averaged over a time-scale of 1 minute. Dashed lines indicate the value of 0.7 and 1.0. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

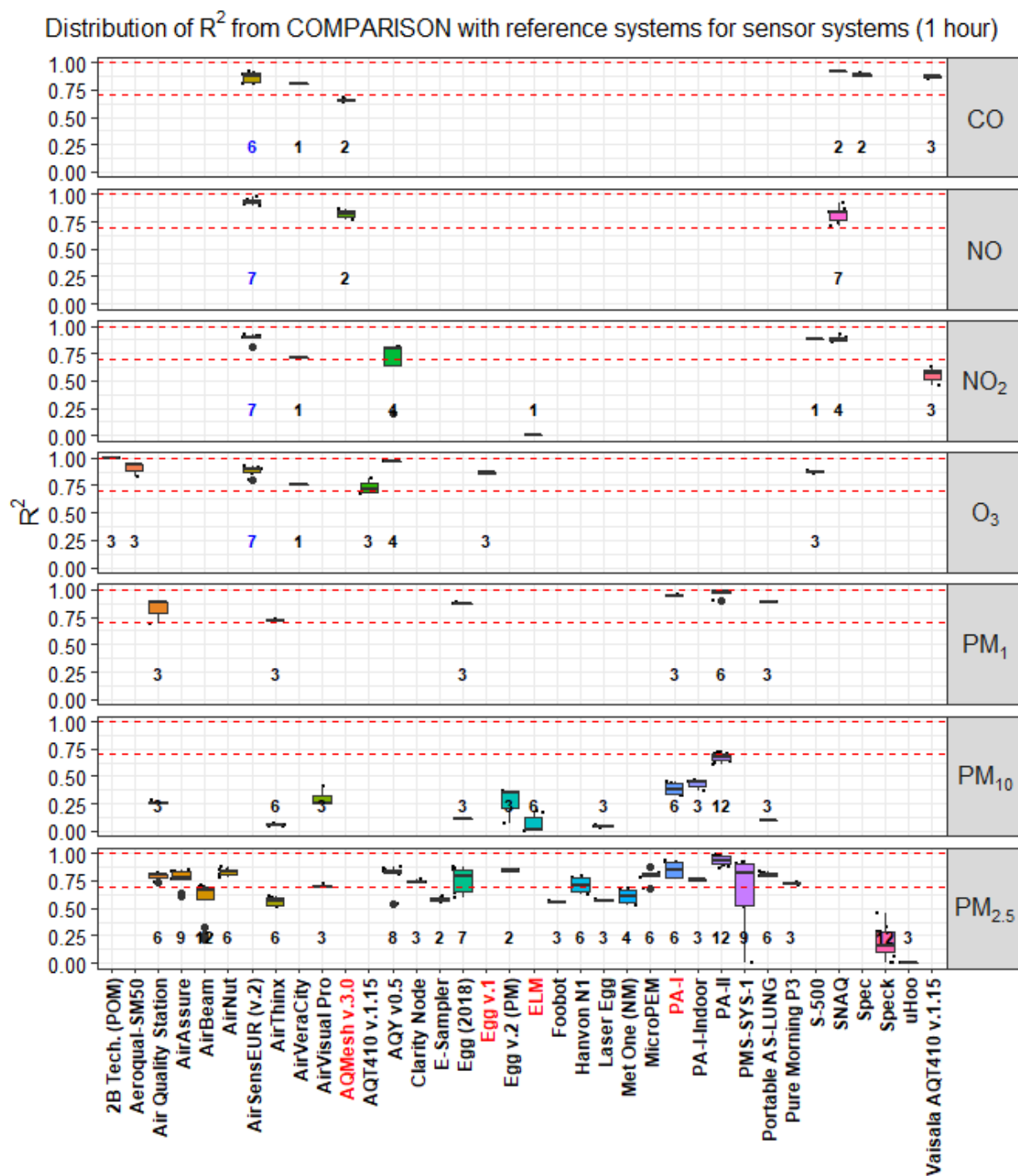


Figure S3. Distribution of R^2 from the comparison of all sensor systems against reference systems. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

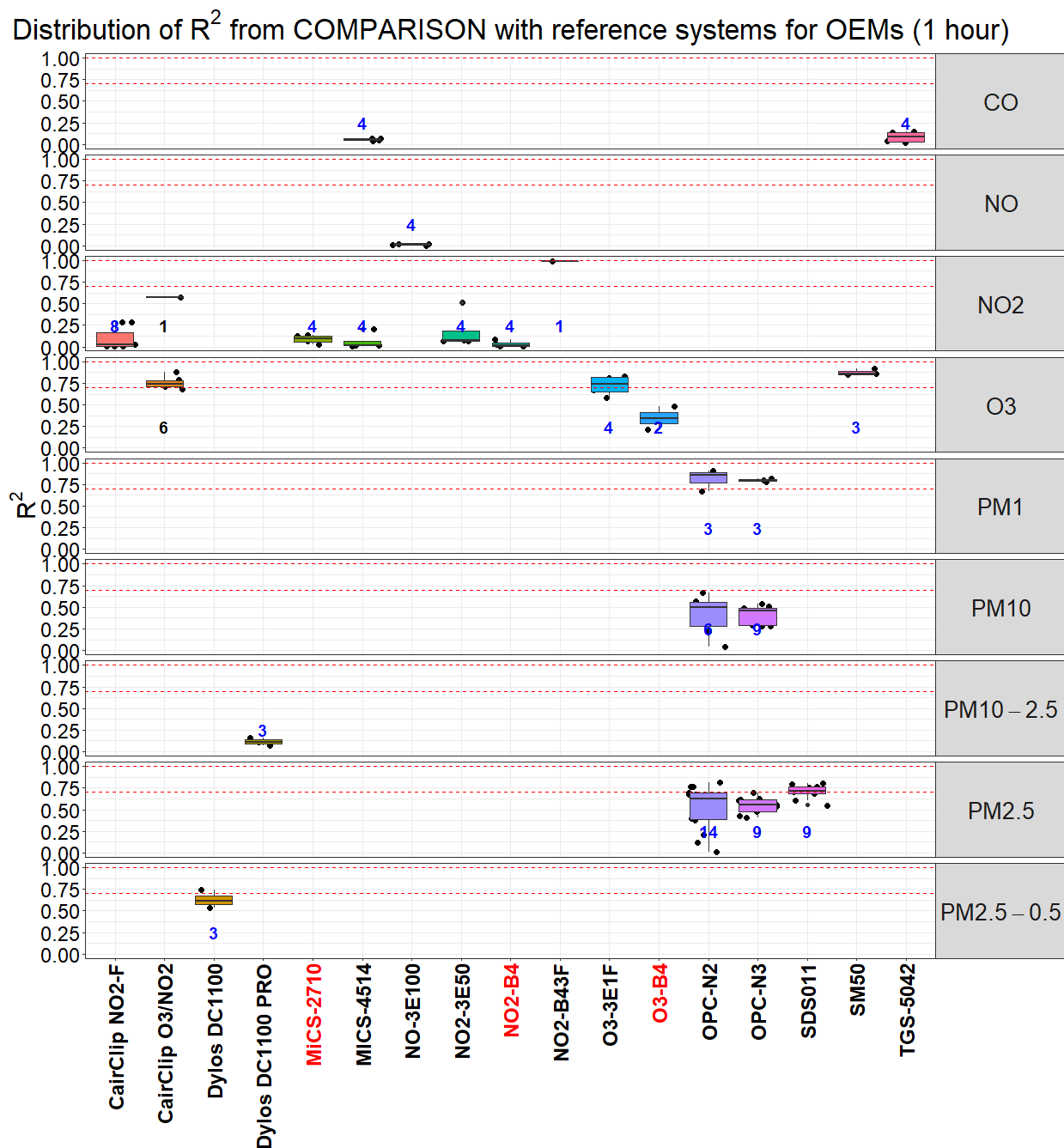


Figure S4. Distribution of R^2 from the comparison of all OEMs against reference systems. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of ‘living’ and ‘non-living’ sensors are indicated in black and red color, respectively.

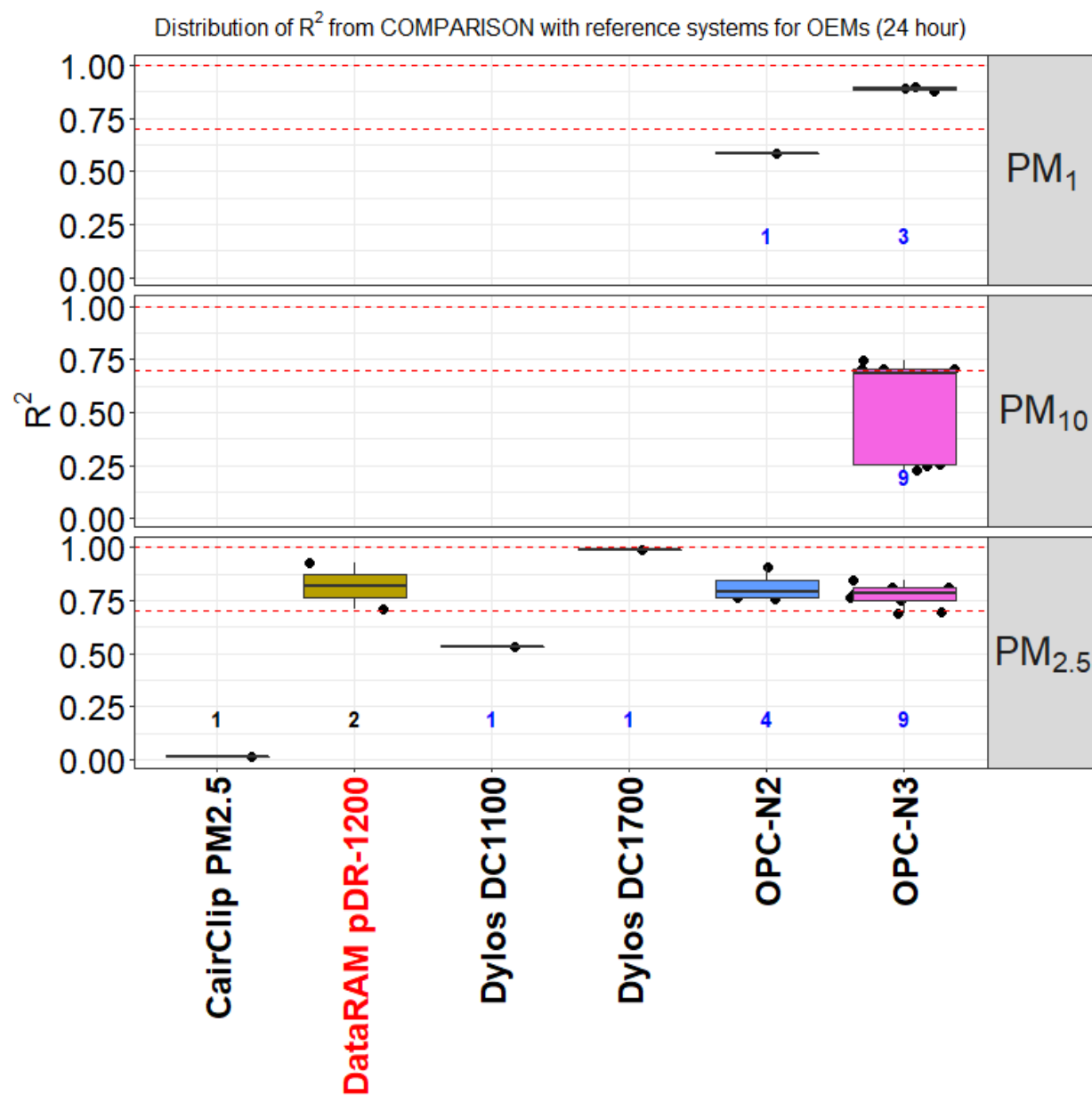


Figure S5. Distribution of R^2 from the comparison of all OEMs against reference systems. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

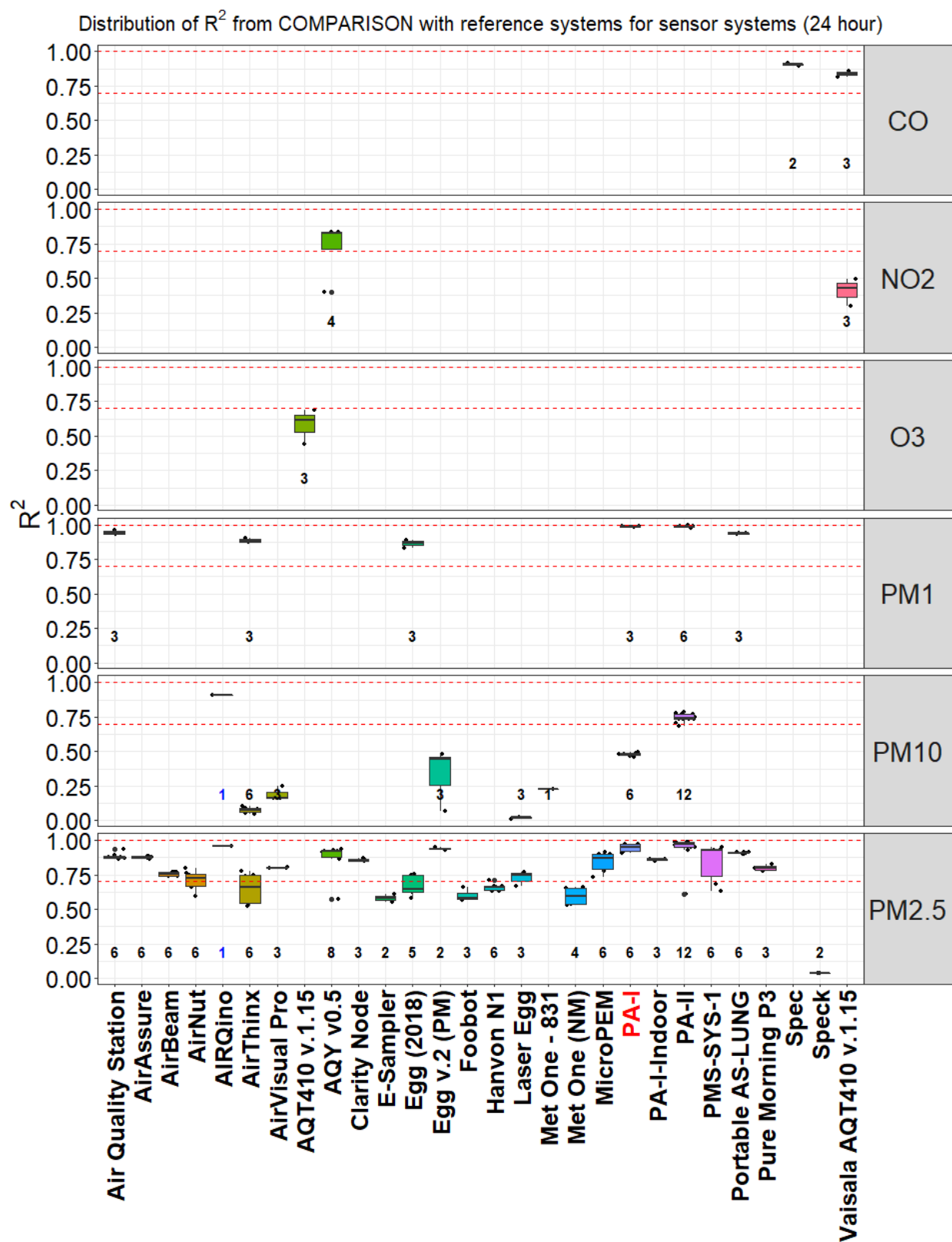


Figure S6. Distribution of R^2 from the comparison of all sensor systems against reference systems. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the

number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

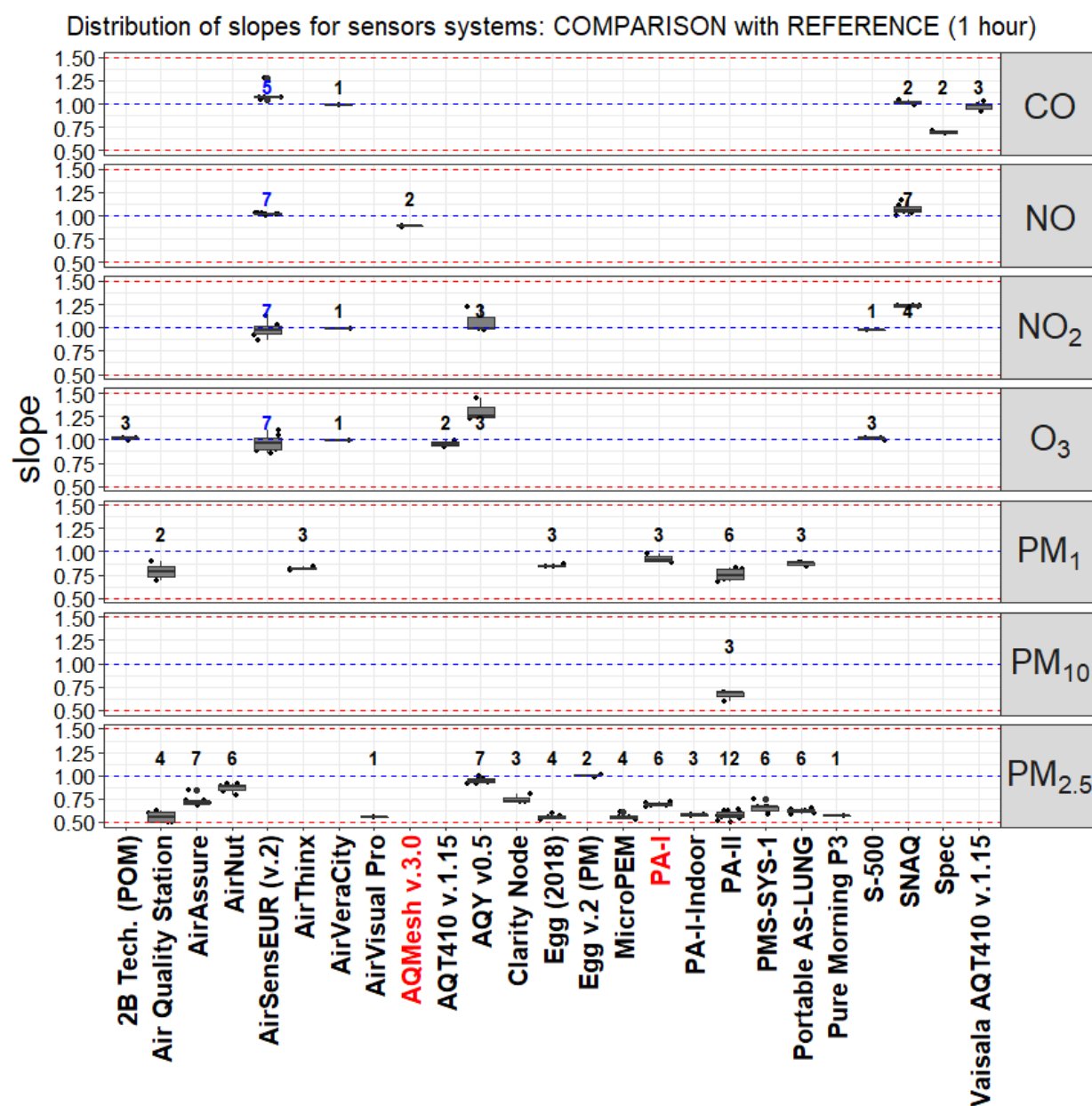


Figure S7. Distribution of slopes from the comparison of sensors systems against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

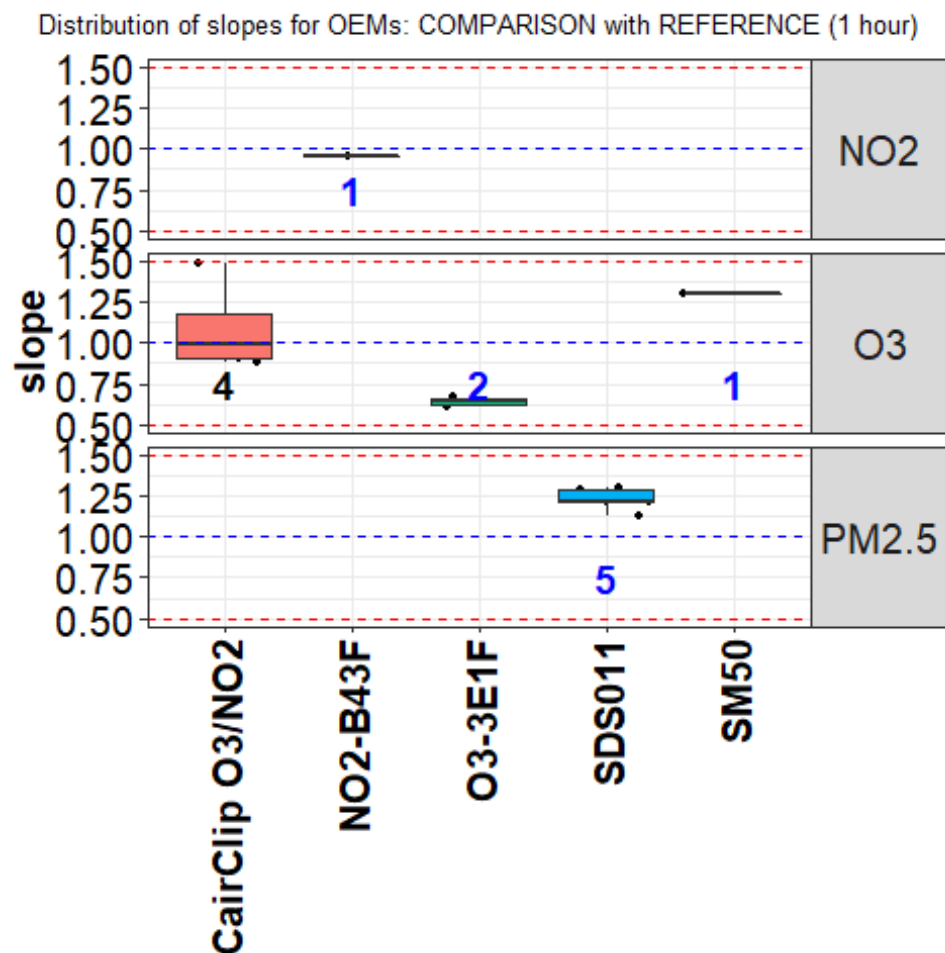


Figure S8. Distribution of slopes from the comparison of OEMs against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of 1 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

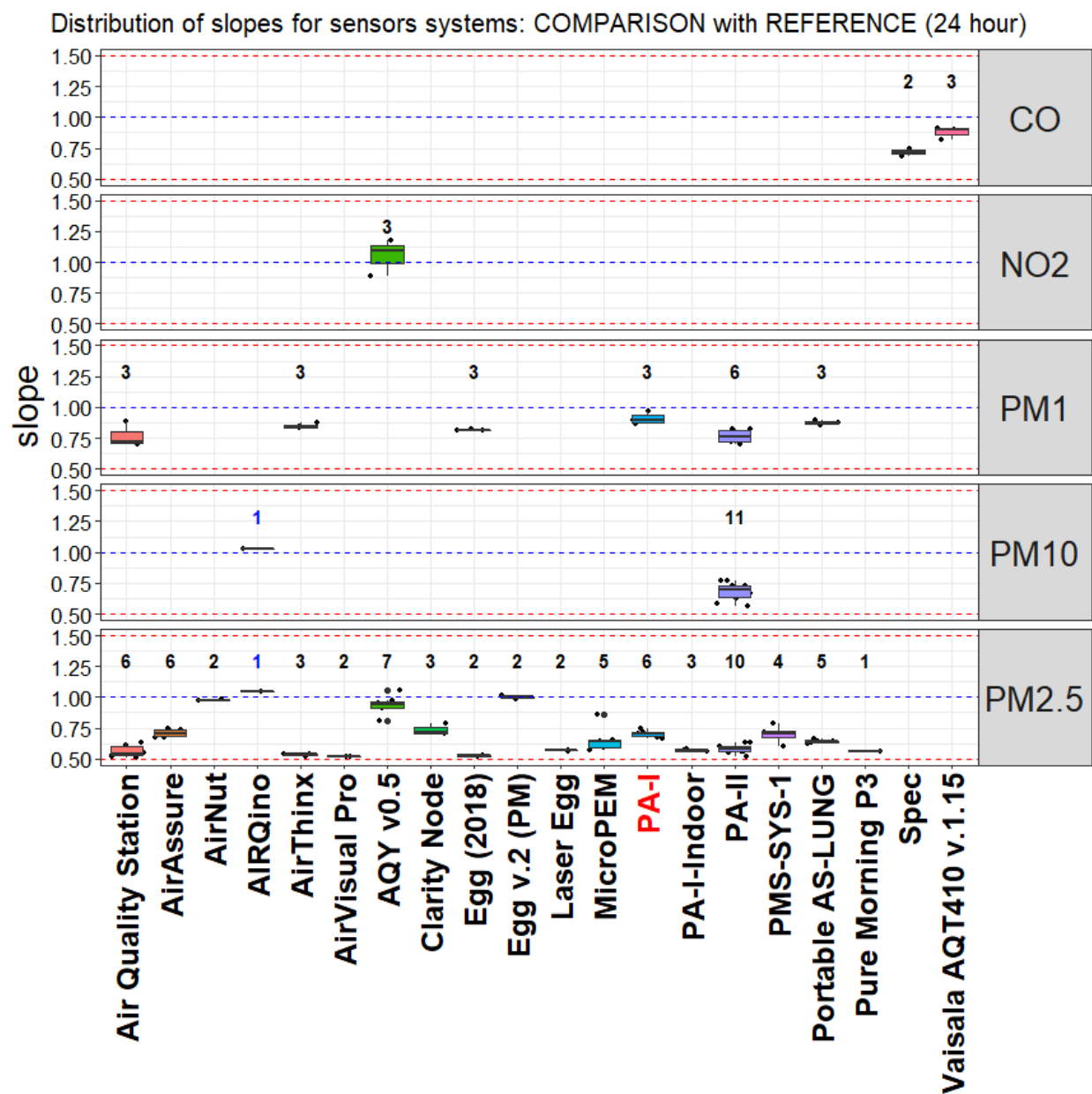


Figure S9. Distribution of slopes from the comparison of sensors systems against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

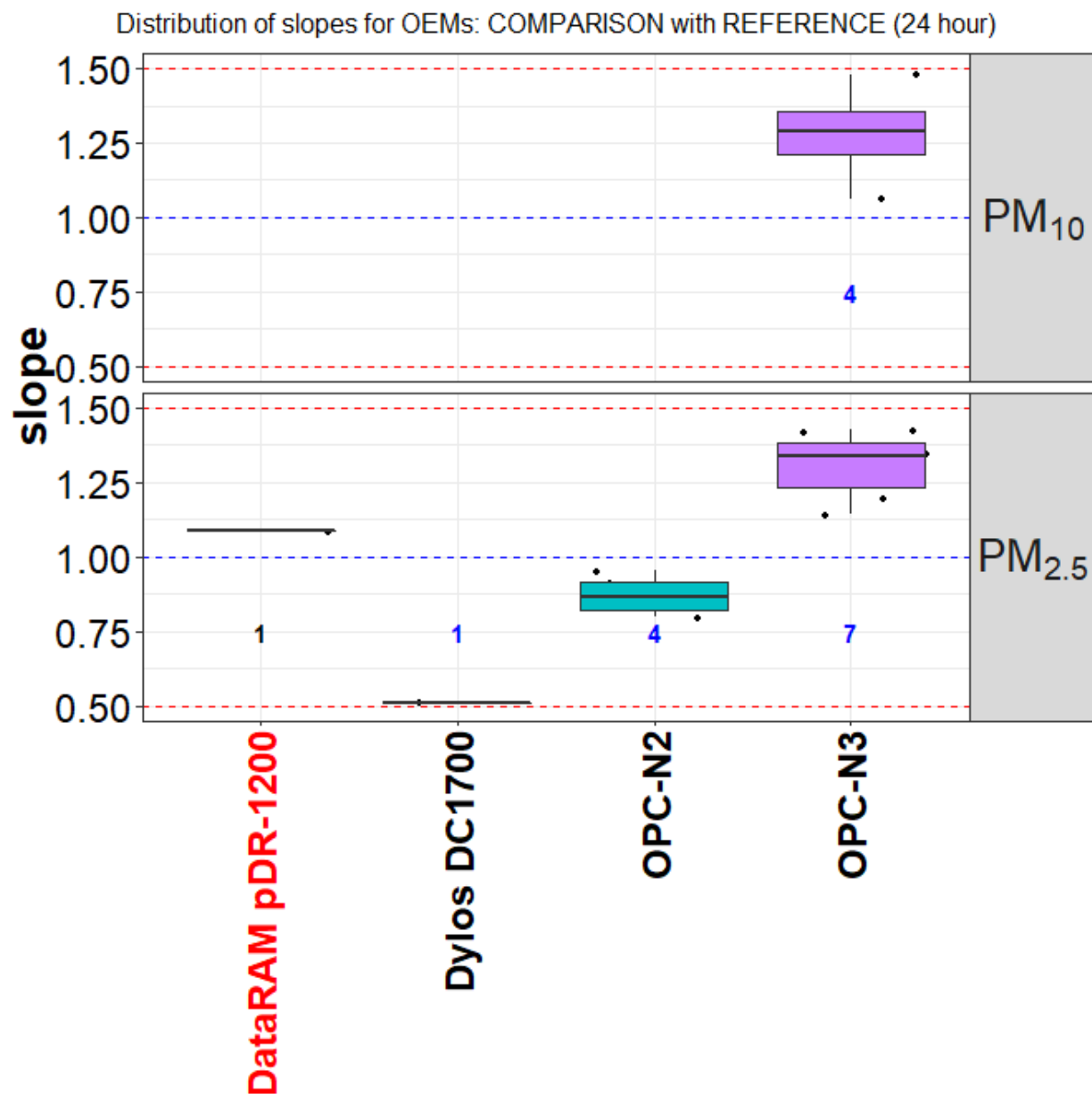


Figure S10. Distribution of slopes from the comparison of OEMs against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of 24 hour. Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

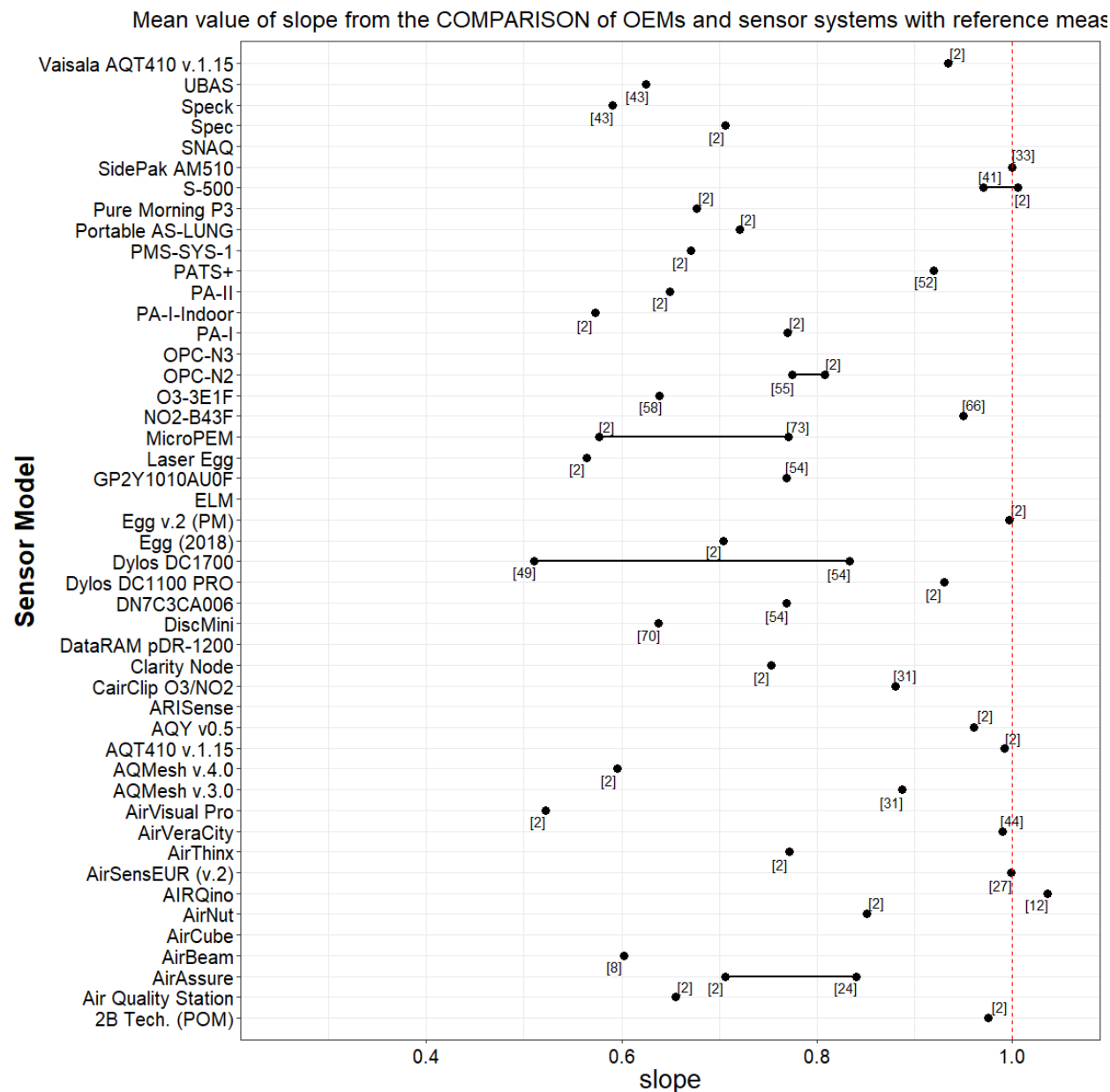


Figure S11. Mean slope for obtained from the comparison of OEMs and sensor systems against reference measurements.

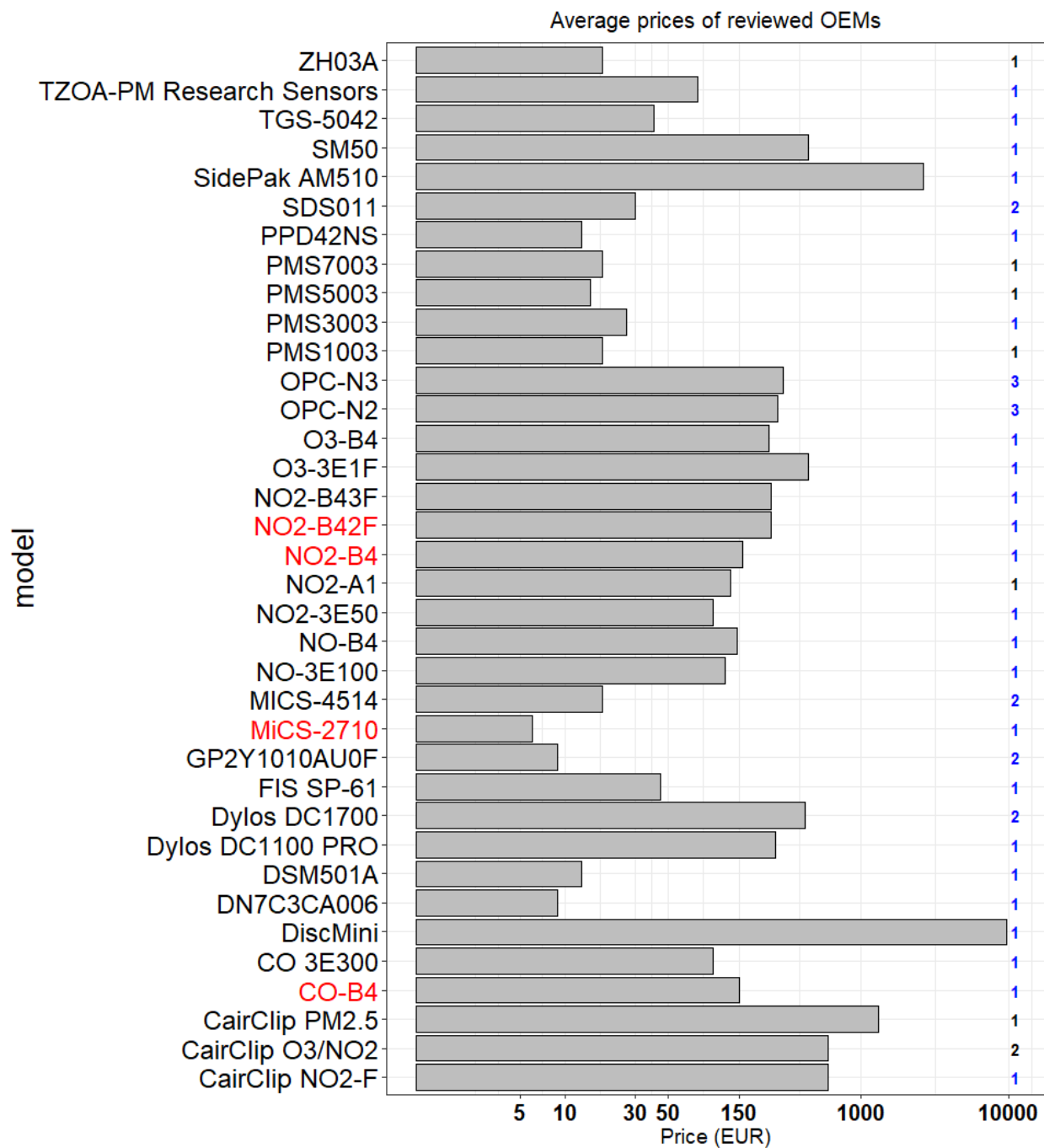


Figure S12. Prices of OEMs available on the market (Numbers in bold indicates the number of pollutant measured by each sensor. x-axis uses logarithmic scale). Numbers in bold indicate the number of open source (blue) and black box (black) records. Names of 'living' and 'non-living' sensors are indicated in black and red color, respectively.

Table S7. Shortlist of sensor systems showing good agreement with reference systems ($R^2 > 0.85$; $0.8 < \text{slope} < 1.2$) for 24 hour time averaged data.

model	pollutant	mean R^2	mean slope	open/close	living	commercial	price (EUR)
PA-I	PM_1	0.9867	0.9086	black box	N	commercial	132
PA-II	PM_1	0.9937	0.8252	black box	Y	commercial	176
Egg (2018)	PM_1	0.8776	0.8145	black box	Y	commercial	219
Egg v.2 (PM)	$PM_{2.5}$	0.9375	1.001	black box	Y	commercial	246
AirThinx	PM_1	0.8858	0.8483	black box	Y	commercial	880
Portable AS-LUNG	PM_1	0.9347	0.876	black box	Y	non commercial	880
AIRQino	$PM_{2.5}$, PM_{10}	0.909	0.972	open source	Y	non commercial	1000
Air Quality Station	PM_1	0.94	0.89	black box	Y	non commercial	1760
AQY v0.5	$PM_{2.5}$	0.9092	0.9393	black box	updated	commercial	2640
Vaisala AQT410 v.1.15	CO	0.8612	0.9105	black box	Y	commercial	3256

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