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Review

Review of the Performance of Low-Cost Sensors for Air Quality Monitoring

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Abstract: A growing number of companies have started commercializing low-cost sensors (LCS) that are said to be able to monitor air pollution in outdoor air. The benefit of the use of LCS is the increased spatial coverage when monitoring air quality in cities and remote locations. Today, there are hundreds of LCS commercially available on the market with costs ranging from several hundred to several thousand euro. At the same time, the scientific literature currently reports independent evaluation of the performance of LCS against reference measurements for about 110 LCS. These studies report that LCS are unstable and often affected by atmospheric conditions—cross-sensitivities from interfering compounds that may change LCS performance depending on site location. In this work, quantitative data regarding the performance of LCS against reference measurement are presented. This information was gathered from published reports and relevant testing laboratories. Other information was drawn from peer-reviewed journals that tested different types of LCS in research studies. Relevant metrics about the comparison of LCS systems against reference systems highlighted the most cost-effective LCS that could be used to monitor air quality pollutants with a good level of agreement represented by a coefficient of determination $R^2 > 0.75$ and slope close to 1.0. This review highlights the possibility to have versatile LCS able to operate with multiple pollutants and preferably with transparent LCS data treatment.

Keywords: electrochemical sensors; metal oxide sensors; optical particle counters; nephelometers; citizen science; performance evaluation; sensor validation; air quality monitoring

1. Introduction

The increase of the commercial availability of micro-sensor technology is contributing to the rapid adoption of low-cost sensors for air quality monitoring by both citizen science initiatives and public authorities [1]. In general, public authorities want to increase the density of monitoring and measurements and often want to rely on low-cost sensors because they cannot afford sufficient reference air quality monitoring stations (AQMS) [2]. Low-cost sensors can provide real time measurements at lower cost, allowing higher spatial coverage than the current reference methods for air pollutant measurements. Additionally, the monitoring of air pollution with reference measurement methods requires skilled operators for the maintenance and calibration of measuring devices, which are described in detailed standard operational procedures [3–7]. Conversely, it is expected that low-cost sensors can be operated without human intervention, making it possible for unskilled users to monitor air pollution without the need for additional technical knowledge.

Plenty of institutes in charge of air quality monitoring for regulatory purposes, as well as local authorities, are considering including low-cost sensors among their routine methods of measurements to supplement monitoring with reference measurements. However, the lack of exhaustive and accessible information in order to compare the performance of low-cost sensors and the wide commercial offerings make it difficult to select the most appropriate low-cost sensors for monitoring purposes.

For classification and understanding of sensor deployment, one should distinguish between the sole sensor detectors produced by original equipment manufacturers (hereafter such sensors are called OEM, or OEM sensors) and sensor systems (SSys), which include OEM sensors together with a protective box, sampling system, power system, electronic hardware, and software for data acquisition, analogue to digital conversion, data treatment, and data transfer [8]. Hereafter, OEMs and SSys are referred to as low-cost sensors (LCS). From a user point of view, SSys are ready-to-use out of the box systems, while OEM users need to add hardware and software components for protection from meteorological conditions, data storage, data pushing, interoperability of data, and generally the calibration of LCS. The use of LCS is of major interest for citizen science initiatives. Therefore, small and medium enterprises have made SSys available that can be deployed by citizens who want to monitor the air quality in a chosen environment.

Although a number of reviews of the suitability of LCS for ambient air quality have been published [1,9–15], quantitative data for comparing and evaluating the agreement between LCS and reference data are mostly missing from the existing reviews. Several protocols have been developed by research institutes worldwide (for example: [16,17] and http://www.aqmd.gov/docs/default-source/aq-spec/protocols/sensors-field-testing-protocol.pdf?sfvrsn=0) or are currently being standardized (CEN/TC 264 Air quality—Performance evaluation of air quality sensors—Part 1: Gaseous pollutants in ambient air and Part 2: Performance evaluation of sensors for the determination of concentrations of particulate matter (PM_{10}; $PM_{2.5}$) in ambient air; WI 00264179ASTM Work Item Number WK64899 Standard Test Method for the Performance Evaluation of Ambient Air Quality Sensors and other Sensor-based Instruments; US-EPA: Draft Performance Parameters and Test Protocols for Ozone Air Sensors and Draft Performance Parameters and Test Protocols for Fine Particulate Matter Air Sensors) by national standardization institutes, or have been published very recently (http://ecolibrary.me.go.kr/nier/search/DetailView.ax?cid=5668661). These protocols set different requirements, including sensor data treatment, levels and duration of tests, seasonality of tests, sensor averaging time, and type of reference measurements to which sensor data are compared to. In the absence of an internationally accepted standardized protocol for testing LCS [18], there is a lack of harmonization of the tests being carried out. Consequently, the conditions of tests and the metrics reported are generally diverse, making it difficult to compare the performance of LCS in different evaluation studies.

Among the available tests for LCS, there are clear indications that the accuracy of LCS measurements can be questionable [19,20] when comparing LCS values and reference measurements. Even though the sources of these inaccuracies are known, accurate models able to correct for these effects are currently unavailable. The main sources of these inaccuracies are related to the selectivity of gas sensors being generally poor because the principles of measurement of sensors are not specific to the gas compound of interest. Some factors related to this process are as follows:

(1) For gas sensors, electrochemical gas sensors measure currents of electrons of several possible redox reactions, and hence several possible species. Metal-oxide sensors measure the conductance of charges on semiconductor material of species undergoing either reduction or oxidation with reactive oxygen.
(2) The calibration function is generally set at one reference station and it is likely to introduce biases when used at other locations due to different air composition and meteorological conditions.

(3) For PM, optical sensors measure light scattering converted by computation to mass concentration. Light scattering is strongly affected by parameters such as particle density, particle hygroscopicity, refraction index, and particle composition. All of these factors vary from site to site and with seasonality.

At the present time there is no common protocol to test LCS against a reference measurement. As a consequence, sensor data can be of variable quality. Therefore, it is of fundamental importance to evaluate LCS in order to choose the most appropriate ones for routine measurements or other case studies [21]. However, only a few independent tests are reported in academic publications.

Hereafter, the results of the exhaustive review of existing literature on LCS evaluation are presented, which are not available elsewhere. The main purpose of this review was to estimate the agreement between LCS data against reference measurements, both with field tests and controlled conditions tests, carried out by laboratories and research institutes independent from sensor manufacturers and commercial interests. This can provide all stakeholders with exhaustive information for selection of the most appropriate LCS. Quantitative information was gathered from the existing literature about the performance of LCS according to the following criteria:

(1) Agreement between LCS and reference measurements.
(2) Availability of raw data and transparency of data treatment, making a posteriori calibration possible.
(3) Capability to measure multiple pollutants.
(4) Affordability of LCS considering the number of provided OEMs.

2. Sources of Available Information, Method of Classification and Evaluation

2.1. Origin of Data

The research was focused on LCS for measurement of particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2), and carbon monoxide (CO), the pollutants that are included into the European Union Air Quality Directive [2]. References were also included for nitrogen monoxide LCS (NO).

Approximately 1423 independent laboratory or field tests of LCS versus reference measurements (called "records" in the rest of the manuscript) were gathered from peer-reviewed studies of LCS available in the Scopus database, the World-Wide Web, the AirMontech website (http://db-airmontech.jrc.ec.europa.eu/search.aspx), ResearchGate, Google search, and reports from research laboratories. Sensor validation studies provided by LCS manufacturers or other sources with concern of a possible conflict of interest were not considered. In total, 64 independent studies were found from different sources, including reports and peer-reviewed papers.

Additionally, a significant number of test results came from reports published by research institutes. In fact, the rapid technological progress of LCS, the difficulty to publish LCS data that do not agree with reference measurements, and the time needed to publish studies in academic journals means the publication of articles is not the preferred route. Instead, a great part of the available information is found in "grey" literature, mainly in the form of reports. A substantial quantity of presented results come from research institutes having a LCS testing program in place, e.g., the Air Quality Sensor Performance Evaluation Center (AQ-SPEC) [19], the European Union Joint Research Centre (EU JRC) [9,20,22–28], and the United States Environmental Protection Agency (US EPA) [14,29–32].

A significant portion of the data comes from the first French field inter-comparison exercise [33] for gas and particle LCS carried out in January–February of 2018. This exercise was carried out by two members of the French Reference Laboratory for Air Quality Monitoring (LCSQA). The objective of the study was to test LCS under field conditions at urban air quality monitoring stations of situated at the IMT Lille Douai research facilities in Dorignies. A large number of different SSys and OEMs were installed in order to evaluate their ability to monitor the main pollutants of interest in the ambient air: NO_2, O_3, and $PM_{2.5}$/PM_{10}. This exercise involved nearly five French laboratories in charge of air pollution monitoring, 10 companies (manufacturers or distributors/sellers), and 23 SSys and OEMs of different design and origin (France, Netherlands, United Kingdom, Spain, Italy, Poland, United States), for a total of more than sixty devices when considering replicates.

Within another project, called AirLab (http://www.airlab.solutions/), many LCS were tested through field and indoor tests. Results are reported based on the integrated performance index (IPI) developed by Fishbain et al. [34], which is an integrated indicator of correlation, bias, failure, source apportionment with LCS, accuracy, and time series variability of LCS and reference measurements. Since the IPI is not available in other studies and cannot be compared with the metrics used in the current review, it was decided not to include the AirLab results in the current work.

A shared database of laboratory and field test results and the associated scripts for summary statistics were created using the collected information. It will be possible to update the database with future results of LCS tests. The purpose of this development was to setup a structured repository to be used to compare the performances of LCS.

Each database "record" describing laboratory or field LCS test results was included in the database only if comparison against a reference measurement (hereinafter defined as "comparison") was provided. The comparison data allowed evaluation of the correlation between LCS data and reference measurements. Most of the reviewed studies only reported regression parameters obtained from the comparison between LCS and reference measurements, generally without more sophisticated metrics such as root mean square error and measurement uncertainty (see Section 3).

2.2. Classification of Low-Cost Sensors

For each model of SSys, the OEM manufacturer was identified along with the manufacturer of the SSys. Overall, we found 112 models of LCS, including both OEMs (31) and SSys (81), manufactured by 77 manufacturers (16 OEMs and 61 SSys).

In addition, 19 projects evaluating OEMs, SSys, or both, and reporting quantitative comparisons of LCS data and reference measurements were identified. They include the Air Quality Egg, Air Quality Station, AirCasting [19,35–37], Carnegie Mellon [36,38], CitiSense [30], Cairsense [39], Developer Kit [19], HKEPD/14-02771 [40], making-sense.eu [41], communitysensing.org [32], MacPoll.eu [20], OpenSense II [42,43], Proof of Concept AirSensEUR [22], and SNAQ Heathrow [44,45]. Out of the 1423 records collected from literature, we identified 1188 records (197 OEMs and 991 SSys) from 89 alive LCS (24 OEMs and 65 SSys) and 235 records (123 OEMs and 112 SSys) from 23 "non active" (or discontinued) LCS (7 OEMs and 16 SSys).

"Low-cost" refers to the purchase price of LCS [9] compared to the purchase and operating cost of reference analyzers [46] for the monitoring of regulated inorganic pollutants and PM, which can easily be an order of magnitude more costly. More recently, ultra-affordable OEMs have started to appear on the market for PM monitoring [47–49]. Many of them are designed to be integrated into Internet of Things (IoT) networks of interconnected devices. Currently, for PM detection it is possible to purchase optical sensors that cost between several tens and several hundreds of euro. Those devices are manufactured in emerging economies, such as the Republic of China and the Republic of Korea [50]. Some of these LCS can achieve similar performance to more expensive OEMs [18,19,29–31,37,48,49,51–56].

The data treatment of LCS can be classified into two distinct categories:

(1) Processing of LCS data performed by "open source" software tuned according to several calibration parameters and environmental conditions. All data treatments from data acquisition until the conversion to pollutant concentration levels is known to the user. There were 234 records identified, comprising 108 OEMs and 126 SSys using open source software for data management. These 401 records came from 34 unique LCS. Usually, outputs from these LCS are already in the same measurement units as the reference measurements. In this category, LCS devices are generally connected to a custom-made data acquisition system to acquire LCS raw data. Generally, users are expected to set a calibration function in order to convert LCS raw data to validated

pollutant concentrations. The calibration equations are set by fitting a model (see Section 4.1) during a calibration time interval (typically 1 or 2 weeks) when sensor and reference data are co-located. Subsequently, the calibration is applied to compute pollutant levels outside the calibration time interval. Two-thirds of calibration functions are established by fitting LCS raw data versus reference measurements, and vice versa.

(2) LCS with calibration algorithms whose data treatment is unknown and without the possibility to change any parameter have been identified as "black boxes". This is due to the impossibility for the user to know the complete chain of data treatment. 1189 records were identified, made up of 212 OEMs and 977 SSys that did not use an open source software for data treatment. These 1189 records came from 83 unique LCS. In most cases, these SSys are pre-calibrated against a reference system, or the calibration parameters can be remotely adjusted by the manufacturer. Finally, we should point out that some LCS used for the detection of PM (such as the Alphasense (Great Notley, UK) OPC-N2 and OPC-N3, and the PMS series from Plantower (Beijing, CN) could be used as open source devices if users compute PM mass concentration using the available counts per bins. However, these PM sensors are mostly used as a "black box", with mass concentration computed by unknown algorithms developed by manufacturers.

Clear definitions and examples of the principles of operations used by the different types of sensors (electrochemical, metal oxides, optical particulate counter, optical sensors) are reported in a recent work by World Meteorological Organization [8]. This work also describes observed limitations of each type of sensor, such as interference by meteorological parameters, cross-sensitivities to other pollutants, drift, and aging effect. To date, there is a larger number of active and commercially available LCS (Figure 1). However, while most of the OEMs are open source, allowing end-users to integrate them into SSys, most of the SSys themselves were found to be "black-box" devices. This is a limitation, as the SSys might need a posteriori calibration in addition to the one provided by the manufacturer, but raw data are unavailable.

LCS are also classified according to their commercial availability. LCS were assigned to the "commercial" category if they could be purchased and operated by any user. LCS fell under the "non-commercial" category when it was not possible to find a commercial supplier selling them. Typically, this type of LCS are used for research and publication, while it is difficult for any user to repeat the same sensor setup.

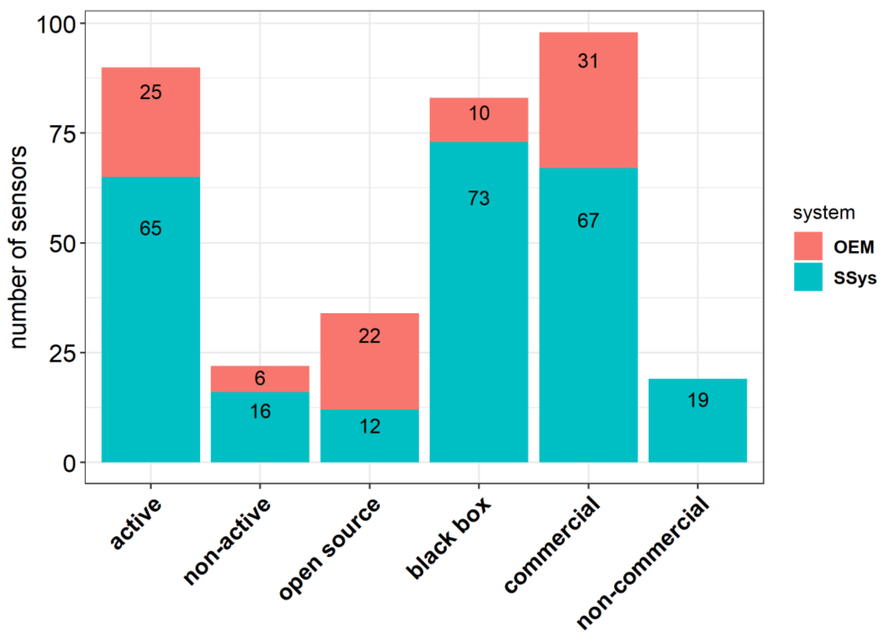

Figure 1. Number of LCS models gathered from the literature review highlighting their open data treatment (open source vs. black box) and commercial availability.

Figure 1 shows the number of LCS, either OEMs or SSys, still active or discontinued, with open or "black box" type of data treatment, and that are commercially available.

2.3. Recent Tests Per Pollutant and Per Sensor Type

Table 1 reports the number of "records", by pollutant and sensor technology, gathered in literature regarding validation and testing of LCS against a reference system. Records were collected from laboratory (133) and field tests (1290). The majority of records refer to commercially available OEMs and SSys, even though a few references regarding non-commercial LCS were also picked up.

Table 1. Number of analyzed "records" for LCS by pollutant and by type of technology.

Pollutant	Type	n. Records Field	n. Records Laboratory	References
CO	electrochemical	51	9	AQ-SPEC [19], Jiao [39], Sun [40], Marjovi [57], Karagulian [22], Mead [44], Popoola [45], Borrego [53], Castell [10], Cross [58], Gerboles [23], Wei [59], Gillooly [60], Zimmerman [61], Spinelle [24,27]
CO	MOs	27	2	AQ-SPEC [19], Piedrahita [62], Spinelle [24]
NO	electrochemical	44	6	Jiao [39], Bigi [42], Karagulian [22], Mead [44], Popoola [45], AQ-SPEC [19], Castell [10], Borrego [53], Cross [58], Gillooly [60], Spinelle [24], Gerboles [23], Wei [59], Crunaire [33]
NO	MOs	1	-	Crunaire [33]
NO_2	electrochemical	137	21	AQ-SPEC [19], Jiao [39], Williams [30], Sun [40], Mijling [41], Vaughn [32], Spinelle [20], Mueller [43], Bigi [42], Marjovi [57], Cordero [63], Karagulian [22], Mead [44], Popoola [45], Borrego [53], Castell [10], Cross [58], Spinelle [26], Duvall [64], Gillooly [60], Gerboles [23], Wei [59], Sun [65], Zimmerman [61], Lin [66], Crunaire [33]
NO_2	MOs	28	10	AQ-SPEC [19], Vaughn [32], Williams [30], US-EPA [67], Borrego [53], Piedrahita [62], Spinelle [20], Crunaire [33]
O_3	electrochemical	65	10	AQ-SPEC [19], Jiao [39], Spinelle [20], Mueller [43], Marjovi [57], Karagulian [22], Borrego [53], Castell [10], Cross [58], Duvall [64], Feinberg [36], Gerboles [23], Wei [59], Crunaire [33]
O_3	MOs	54	3	AQ-SPEC [19],Jiao [39], Spinelle [20], Borrego [53], Feinberg [36]
O_3	UV	9	1	Sun [40], AQ-SPEC [19]
$PM_{2.5}$	Electrical	6	-	AQ-SPEC [19]
$PM_{2.5}$	nephelometer	129	24	AQ-SPEC [19]], Borghi [37], Jiao [39], Feinberg [36], US-EPA [67], Williams [31], Manikonda [54], Zikova [55], Wang [68], Alvarado [69], Chakrabarti [70], Sousan [56],Borrego [53], Olivares [71],Sun [40], Pillarisetti [72], Holstius [51], Austin [73], Gao [74], Kelly [75], Karagulian [28], Badura [49], Crunaire [33]
$PM_{2.5}$	OPC	428	27	AQ-SPEC [19], Mukherjee [35], Feinberg [36], Jiao [39], Cavaliere [76], Borrego [53], Viana [77], Williams [31], Manikonda [54], Northcross [78], Holstius [51], Steinle [79], Han [80], Jovasevic [81], Dacunto [82], Gillooly [60], Sousan [83], Crilley [84], Badura [49], Kelly [75], Zheng [85], Laquai [48], Budde [47], Liu [52], Crunaire [33]
PM_1	Electrical	6	-	AQ-SPEC [19]
PM_1	nephelometer	1	-	Crunaire [33]
PM_1	OPC	102	8	AQ-SPEC [19], Williams [31], Sousan [83], Crilley [84], Crunaire [33]
PM_{10}	nephelometer	26	1	AQ-SPEC [19], Borrego [53], Alvarado [69], Crunaire [33]
PM_{10}	OPC	176	11	AQ-SPEC [19], Cavaliere [76], Borrego [53], Feinberg [36], Manikonda [54], Sousan [56], Han [80], Jovasevic [81], Williams [31], Sousan [83], Crilley [84], Budde [47], Crunaire [33]

For the detection of PM, the largest number of LCS tests were carried out for optical particle counters (OPC) with 752 records, followed by nephelometers with 181 records (see Table 1). Both systems detect PM 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 pollutants, such as CO, NO, NO_2, and O_3, the largest number of tests were performed using electrochemical sensors with 343 records, followed by metal oxides sensors (MOs) with 125 records (see Table 1). Electrochemical sensors are based on a chemical reaction between gases in the air and the working electrode of an electrochemical cell that is dipped into an electrolyte. In a MOs, also named a resistive sensor or semiconductor, gases in the air react on the surface of a semiconductor and exchange electrons, modifying its conductance.

Table A2 reports the OEM models currently used to monitor PM and gaseous pollutants (NO_2, O_3, NO, and CO) according to their type of technology. SSys models measuring concentration of PM and gaseous pollutants are reported in Table A3. We want to point out that several SSys can use the same set of OEMs. In a few cases, the same model of SSys was tested using different types of OEMs when performing validation tests [22,23].

"Living" LCS are devices currently available for commercial or research purposes. Considering only the "living" LCS from Tables A2 and A3, one may observe that there are fewer OEMs (24) than SSys (65), and therefore different SSys are using the same sets of OEMs. Additionally, there is a lack of laboratory tests for the OEMs compared to SSys. Among the reviewed records only ~11% were attributed to laboratory tests. Most LCS (~90%) were calibrated at a few field sites where it is not possible to isolate the effect of single pollutants or meteorological parameters, since in ambient air many of these parameters are correlated with each other. Establishing calibration models relying only on field results obtained at few sites might lead to the situation where parameters that have no effect on the sensor data but that are correlated with other variables that do have an effect are taken into account in the calibration. Consequently, the performance of such calibration models can be poor when LCS are used at sites other than the ones used for calibration where the relationship between the parameter used for calibration and the ones having an effect on the response of LCS may change [43,86,87]. If the performance of sensors at sites other than the calibration sites worsen, it is likely that the calibration model should be improved because of its lack of fit.

The research covered the period between 2010 and 2019 (year of publication). As shown in Figure 2, only a few preliminary studies on the evaluation of performance of LCS were published between 2010 and 2014. In 2015, we recorded the largest number of references with 27 different works publishing results on performances of LCS for air quality monitoring. For the test studies carried out by AQ-SPEC [19], records were evaluated per model of LCS.

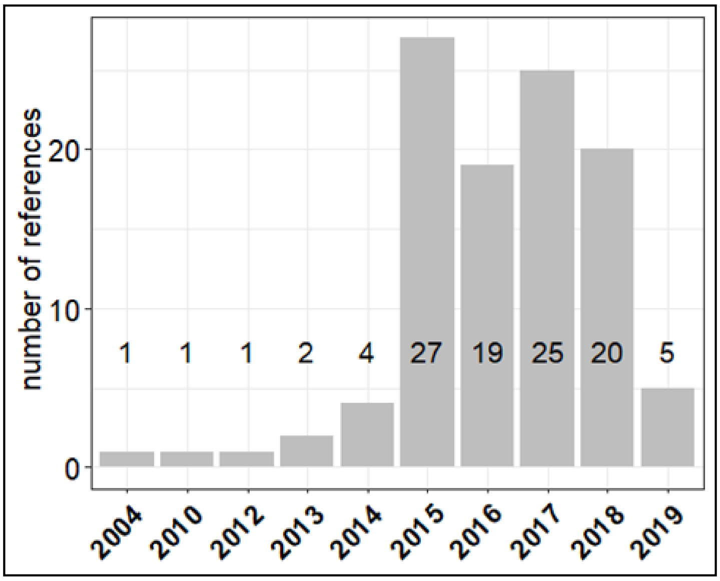

Figure 2. Number of references per year of publication that includes quantitative comparison of sensor data with reference measurements. For 2019, the number of publications covers the publications from the period between January and April.

Overall, 34 references reporting field tests with LCS co-located at urban sites were found, as well as 8 references for rural sites, and 10 references for traffic sites. Most of the laboratory and field tests reported hourly data (610 records for 86 models of LCS). We also found 253 records for 40 LCS using daily data and 248 records for 42 LCS using 5-minute averages (Table A1). Therefore, records from hourly data were considered statistically more significant.

3. Method of Evaluation

The European Union Air Quality Directive indicates that measurement uncertainty [88] shall be the main indicator used for the evaluation of the data quality objective of air pollution measurement methods [2]. However, the evaluation of this metric is cumbersome [89,90] and it is not included in the majority of sensor studies (see Table 2). For the performance criteria used to evaluate air quality modeling applications [91], the set of statistical indicators includes the root mean square error (RMSE), the bias, the standard deviation (SD), and the correlation coefficient (R), of which RMSE is thought to be the most explicative one. The statistical indicators can be better visualized in a target diagram [20]. Unfortunately, Table 2 also shows that RMSE is mainly unreportable in the literature. As already mentioned above, integrated indicators, such as the IPI [34], would breach our objective to use solely quantitative and comparable indicators. Additionally, it is impossible to compute IPIs a posteriori, since time series are mainly not available in literature.

Table 2. Number of records gathered by metrics available in literature.

Metrics	n. Field Tests	n. Laboratory Tests
Total tests	1290	133
R^2, calibrations	218	60
R^2, comparisons	1160	72
slope of regression line	1063	55
intercept	1027	54
RMSE	285	5
Measurement uncertainty (U)	153	29
MAE	40	0
Bias	19	3

Therefore, we had to rely on the most common metrics, i.e., the coefficient of determination R^2 and the slope and intercept of the linear regression line between LCS data and the reference measurement. 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 the level of accuracy. R^2 measures the strength of the association between two variables but it is insensitive to bias between LCS and reference data—either relative bias (slope different from 1) or absolute bias (intercept different from 0). R^2 is a partial measure of how much LCS data agree with reference measurements according to a regression model [92]. A larger R^2 reflects an increase in the predictive precision of the regression model. The majority of the reviewed works reported R^2 value as a main metric when comparing LCS with reference measurements. Table 2 clearly shows that only a few records were found for the measurements reporting mean absolute error (MAE), bias, and RMSE [42,49,52–54,56]. However, we would like to stress that other statistical parameters, such as the mean normalized bias (MNB), mean normalized error (MNE), and the root mean square error (RMSE), are also very important in evaluating the relationship between LCS and reference instruments.

An increase of R^2 may not be the result of an improvement of LCS data quality, since R^2 may increase when the range of reference measurements increases [93] or according to the seasonality of sampling reported in different studies. Because of the different time ranges and seasonality reported in the reviewed records, it was not possible to have a homogeneous dataset with the same meteorological trends and conditions. This might represent a limitation of the present work and could be an element to improve future LCS comparison for the characterization of their calibration performances. Moreover, since LCS are affected by long time drift and ageing, longer field studies are more likely to report lower R^2 than shorter ones.

Nearly all published studies report the coefficient of determination (R^2) between reference and LCS data (see Table 2). Fortunately, the majority of these studies also report the slope and intercept of the regression line between LCS data and reference measurements that describe the possible bias of LCS data. A few studies also report the RMSE [10,20,22,36,41–43,51,52,58,60,62,63,85] which clearly indicates that the magnitude of the error in LCS data is also sensitive to extreme values and outliers. Only a few studies report the measurement uncertainty [10,22,25,30,48,52,59,61]. Therefore, for the purpose of this work, we only focused on the analysis of the comparison of laboratory and field tests of LCS.

Table 2 also gives the R^2 of calibration that was found in the literature. Generally, these studies also present the model equations used for calibration. The number of studies reporting the R^2 of calibration represents about 10% of the studies reporting R^2 of comparison of calibrated LCS and reference data using linear regressions.

Although the data set of R^2 for calibration is limited in size, we have investigated if the type of calibration has an influence on the agreement between calibrated LCS data and reference measurements.

In order to estimate the efficiency of calibration models, the reported coefficient of determination R^2 was used as an indicator of the amount of total variability explained by the model (see calibration of LCS). This can be used as an indication of performance of the calibration model chosen to validate the LCS against a reference system.

Using the highest R^2 of comparison together with the slope of the comparison line near to 1.0, a shorter set of best performing LCS will be drawn together with their sensor technology. It was decided to drop the analysis of intercepts differing from 0, accepting that LCS may produce unscaled data with bias provided that LCS data would vary in the same range as reference measurements due to the slope being close to 1. In any case, the extent of deviation from 0 of the intercepts did not contribute significantly to the bias of LCS data for the best performing LCS as shown in Section 5 and in Appendix A.

4. Evaluation of Sensor Data Quality

4.1. Calibration of Sensors

The method used for the calibration of LCS is generally considered confidential information by the majority of LCS manufacturers and little information can be found about the calibration of LCS that fall under the category "black box" compared to the ones that fall under the category "open source". In fact, several studies can be found on the calibration of "open source" LCS, both with laboratory and field tests. Calibration consists of setting a mathematical model describing the relationship between LCS data and reference measurements. However, most of the calibrations were carried out during field tests, while only a limited number of laboratory based calibration experiments were found.

Out of a total of 1423 records in the database, 352 records (25%) included information about LCS calibration giving details of used statistical or deterministic models (see Table 3). However, among these 352 records with details of the calibration method, about 20% do not report R^2, that is, the principal metrics used for LCS performance evaluation. This is typically the case for artificial neural networks, random forest, and support vector regression calibration methods (see below), and it explains why the number of R^2 found for calibration in Table 2 is lower than 352.

Table 3. Types of calibration models used for the calibration of LCS.

Pollutant	Calibration Model	n. Records	References	Median R^2 Calibration	Median R^2 Comparison
CO	ANN	2	Wastine [94], Spinelle [24]	-	0.58
CO	linear	12	Sun [40], Wastine [94], Castell [10], Cross [58], Gerboles [23], Spinelle [24], Zimmerman [61]	0.85	0.15
CO	MLR	21	Jiao [39], Karagulian [22], Wastine [94], Wei [59], Piedrahita [62], Spinelle [24], Zimmerman [61]	0.89	0.83
CO	quad	12	AQ-SPEC [19]	0.63	-
CO	RF	1	Zimmerman [61]	0.91	-
NO	ANN	2	Wastine [94], Spinelle [24]	-	0.57
NO	linear	8	Wastine [94], Castell [10], Cross [58], Spinelle [24], Karagulian [22], Crunaire [33]	0.96	0.032
NO	MLR	20	Jiao [39], Bigi [42], Karagulian [22], Wastine [94], Spinelle [24], Wei [59]	0.92	0.91
NO	RF	2	Bigi [42]	-	0.9
NO	SVR	2	Bigi [42]	-	0.90
NO_2	ANN	7	Cordero [63], Spinelle [20], Wastine [94], Wastine [95]	0.87	0.94
NO_2	linear	25	Sun [40], Spinelle [20], Wastine [94], Wastine [95], Castell [10], Cross [58], Karagulian [22], Zimmerman [61], Lin [66], Crunaire [33]	0.25	0.17
NO_2	log	1	Vaughn [32]	0.89	-
NO_2	MLR	48	Jiao [39], Sun [65], Mijling [41], Spinelle [20], Mueller [43], Bigi [42], Cordero [63], Karagulian [22], Wastine [94], Wastine [95], Piedrahita [62], Wei [59], Zimmerman [61]	0.81	0.81
NO_2	quad	6	AQ-SPEC [19]	0.61	-
NO_2	RF	7	Bigi [42], Cordero [63], Zimmerman [61]	0.86	0.91
NO_2	SVM	4	Cordero [63]	0.85	0.94
NO_2	SVR	2	Bigi [42]	-	0.78
O_3	ANN	2	Spinelle [20], Wastine [94]	-	0.89
O_3	linear	13	Sun [40], Spinelle [20], Wastine [94], Castell [10], Cross [58], Karagulian [22], AQ-SPEC [19], Crunaire [33]	0.84	0.53
O_3	log	1	Vaughn [32]	0.88	-
O_3	MLR	20	Jiao [39], Spinelle [20], Karagulian [22], Wastine [94], Spinelle [25], Wei [59]	0.91	0.88
O_3	quad	9	AQ-SPEC [19]	0.72	-
PM_1	Kholer	2	Di Antonio [96]	-	0.74
PM_1	log	6	AQ-SPEC [19]	0.76	-
PM_{10}	exp	6	AQ-SPEC [19]	0.59	-
PM_{10}	linear	3	Cavaliere [76], Jovanovic [81], AQ-SPEC [19]	0.77	0.73
PM_{10}	log	7	AQ-SPEC [19]	0.58	-
PM_{10}	quad	1	Alvarado [69]	0.65	-
$PM_{10\text{-}2.5}$	linear	4	Sousan [56], Han [80], Jovasevic [81]	0.63	0.98
$PM_{2.5}$	exp	3	Dacunto [82], Kelly [75], Austin [73]	0.91	0.97
$PM_{2.5}$	Kholer	2	Crilley [84], Di Antonio [96]	-	0.78

Table 3. *Cont.*

Pollutant	Calibration Model	n. Records	References	Median R^2 Calibration	Median R^2 Comparison
$PM_{2.5}$	linear	37	Mukherjee [35], Wang [68], Alvarado [69], Cavaliere [76], Jovasevic [81], Olivares [71], Kelly [75], Zheng [85], Holstius [51]	0.84	0.64
$PM_{2.5}$	log	7	AQ-SPEC [19], Laquai [48]	0.73	-
$PM_{2.5}$	MLR	17	Jiao [39], Sun [65], Zheng [85], Holstius [51], Liu [52]	0.81	0.65
$PM_{2.5}$	quad	8	Chakrabarti [70], Alvarado [69], Zheng [85] Gao [74]	0.87	0.88
$PM_{2.5}$	RF	3	Liu [52]	-	0.79
$PM_{2.5–0.5}$	linear	9	Northcross [78], Steinle [79], Han [80], Jovasevic [81]	0.84	0.98
$PM_{2.5–0.5}$	MLR	1	Jiao [39]	0.6	0.45
$PM_{2.5–0.5}$	quad	6	AQ-SPEC [19], Manikonda [54]	0.82	-

The linear model and the multi-linear regression model (MLR), which includes the use of covariates to improve the quality of the calibration, are the most widely used techniques to calibrate the LCS data against a reference measurement. Other calibration approaches use the exponential, logarithmic, and quadratic methods, the Kohler theory of particle growing factor, and several types of supervised learning techniques, including artificial neural networks (ANN), random forest (RF), support vector machine (SVM), and support vector regression (SVR). Most of the MLR models use covariates such as meteorological parameters (temperature and relative humidity) and cross-sensitivities from gaseous interferents, such as NO_2, NO, and O_3, in order to improve LCS calibration. LCS data time-drift was rarely included in the list of calibration covariates [39,62]. Several works have demonstrated how electrochemical and metal-oxides LCS are dependent on temperature, humidity, and other gaseous interferent compounds. This dependency is related to the physico-chemical properties of the sensors according to the type of electrolyte, electrode, or semiconductor material used in the sensor; it is not repeated here since it can be found in the literature [97–99]. LCS used for the detection of PM are sensitive to the effect of relative humidity. As explained below, relative humidity larger than 70–80% contributes to particle growth with consequent erroneous reading of the particulate number counts. One of the solutions for this shortcoming consists of implementing a theory for the growth of particulates due to humidity when converting particulate numbers into mass concentrations [48,84,96].

When R^2 is both available for calibration and comparison, the median of R^2 is higher for calibration (mean of R^2 = 0.70) than for comparison (median of R^2 = 0.58). This is to be expected, as it is easier to fit a model on a short calibration dataset than correctly forecast LCS data using the calibration model at later dates. For gaseous LCS, calibration using a linear model was shown to be the worst R^2 for field comparison (see Table 3). Therefore, linear calibration should be avoided for gas LCS.

For CO and NO, we observed that the calibration method giving the highest R^2 (about 0.90) is the MLR method using temperature or relative humidity as covariates. The use of supervised learning techniques (ANN, RF, or SVR) either did not improve performance for CO or gave similar results as MLR for NO. This is in slight contradiction with other studies on the performance of supervised techniques [100,101]. In the majority of cases, these tested LCS consisted of electrochemical sensors. Only for NO_2 did we observe that supervised learning techniques (ANN, RF, SVM) performed slightly better than MLRs when looking at the R^2 of comparison tests in the field, except for SVR, which is in slight contradiction with other studies [101]. However, the number of records is much higher for MLR than for supervised learning techniques. MLR was applied to both MOs and electrochemical sensors, which resulted in scattered R^2 when looking at individual studies. Additionally, supervised learning techniques may be more sensitive to re-location than MLR [86,87].

For O_3, ANN and MLR calibration gave similar R^2 of comparison (median value about 0.90). As for NO_2, the higher number of studies makes the R^2 of the MLR method more significant than the one for ANN.

In general, all machine-learning techniques are able to account for multiple and unknown effects resulting in a more accurate prediction of the outputs based on training data and depending on the correctness of the list of input parameters. For CO, the lower R^2 values of the ANN calibration method were likely caused by an incorrect choice of input parameters. For O_3 and NO, the R^2 values were already high (about 0.9, as indicated in the manuscript) for both MLR and supervised learning techniques, leaving little room for improvement using supervised learning techniques. For NO_2, the higher R^2 values when calibrating with supervised learning techniques likely came from using O_3 as input parameters, a quantitative interferent for electrochemical NO_2 sensors. The ratio of O_3/NO_2 distinguishing the type of field site often has a direct influence on the performance of electrochemical NO_2 sensors.

For PM, the R^2 for comparison tests are very scattered over the calibration methods. Some high values (R^2 higher than 0.95) were reported for studies using a linear calibration, while MLR did not perform well ($R^2 < 0.5$). These results are misleading, since the good results with linear calibration are generally obtained by discarding LSC data obtained with relative humidity exceeding a threshold between 70 and 80%, above which humidity is responsible for particle growth [84,96]. This effect is more important for PM_{10} than for PM_1 and $PM_{2.5}$. Other studies did not discard high relative humidity, they took into consideration the particle growth factor, either on mass concentration with an exponential calibration model ([73,75,82]) with a median R^2 of 98 or using the Kölher theory on PM mass concentration [80], or directly for the particle beans of each OPC bin [96], leading to R^2 of about 0.80.

Figure 3 shows a summary of all mean R^2 obtained from the calibration of SSys against reference measurements. Results were grouped by model of SSys and averaged per reference work. For the same SSys we can observe R^2 ranging between 0.40 and 1.00. This shows the variability of the performance of SSys depending on the type of calibration, type of testing sites, and seasonality, making it difficult to compare the results of the different studies.

Calibration of LSC against a reference analyzer was found to be carried out using different averaging times. Test results with hourly data are presented in Figure A1 and test results with minute data time are given in Figure A2.

The best performance, according to the time average availability in the literature and tests in the laboratory or in the field, were as follows:

- For the measurement of $PM_{2.5}$, values of R^2 close to 1 were found for hourly data of PMS1003 and PMS3003 by Plantower [75] DC1100 PRO and DC1700 by Dylos (Riverside, USA) for minute data [14,19,79]. Strangely, higher R^2 were reported for the Plantower and Dylos when calibrated with minute data than for hourly data. The OPC-N2 by AlphaSense [19] reported values of R^2 falling within the range of 0.7–1.0. The same 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} [19] (R^2 less than 0.5). We need to stress that optical sensors, such as OPCs and nephelometers, are somewhat limited in coping with gravity effects when detecting coarse PM because of the low-efficiency of the sampling system. Most of the regression models used for the calibration of LCS used hourly data.
- For the calibration of O_3 LCS, the highest values of R^2 for hourly data was reported for FIS SP-61 by FIS (Osaka, Japan) and O3-3E1F [20] by CityTechnology (Figure A1) (Portsmouth., UK). On the other hand, for minute data, values of R^2 close to 1 were found for AirSensEUR (V.2) [22] by LiberaIntentio (Malnate, IT), as well as for the S-500 [19] by Aeroqual (Figure A2) (Auckland, NZ). AirSensEUR used a built-in AlphaSense OX-A431 OEM. We want to point out that most of the MLR models used to calibrate O_3 LCS need NO_2 to correct for the strong NO_2 cross-sensitivity.

- For the calibration of NO_2 LCS, we found values of R^2 for hourly data within the range of 0.7–1.0 for the NO_2-B42F [59] (by Alphasense), for the AirSensEUR (v.2) [22] by LiberaIntentio, and for the minute values of MAS [40] (see Figure 3). The NO_2 measurement by AirSensEUR (v.2) is carried out using the NO_2-B43F OEM by AlphaSense.
- Most of the records of the calibration of CO LCS showed high values of R^2. As shown in Figure A1, the OEMs CO 3E300 [23] by City Technology and CO-B4 [59] by Alphasense reported R^2~1 for hourly data. High values of R^2 were also reported for the SSys AirSensEUR (v.2) when calibrating CO minute data [22] (Figure A2). Other LCS reporting values of R^2 within the range of 0.7–1.0 for hourly data consisted of the MICS-4515 [62] by SGX Sensortech (Corcelles-Cormondreche, CH), the Smart Citizen Kit [19] by Acrobotic (https://acrobatic.com), and RAMP [61].

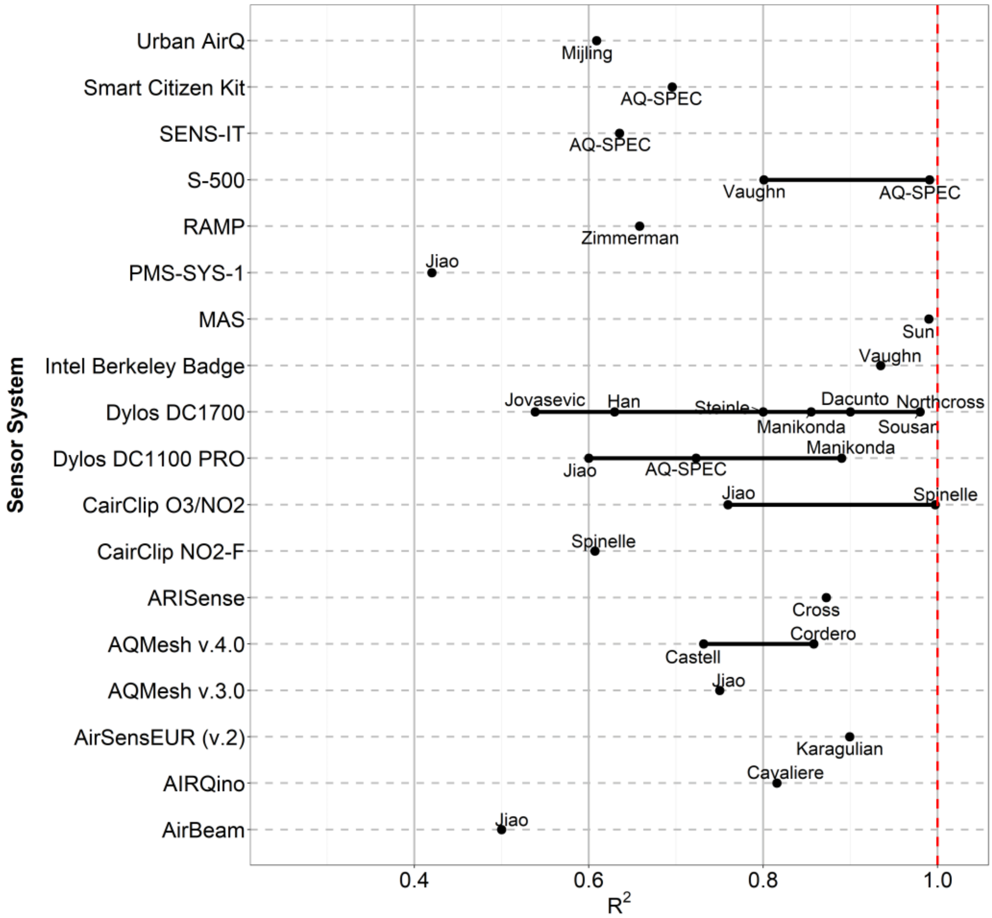

Figure 3. Mean R^2 found for LCS reporting calibration against reference measurements for all used calibration methods. The author name below each bullet gives the first author of the publication from which results were drawn.

4.2. Comparison of Calibrated Low-Cost Sensors with Reference Measurements

In this review, records describing the comparison of LCS data with reference measurements came from "open source" and "black box" LCS. As for the records collected from the calibration of LCS, comparison with reference systems was carried out at different time-resolutions. Here, we only report comparisons of hourly data with 565 and 151 records from SSys and OEMs, respectively. In Figure 4, we show the R^2 values for SSys per reference averaged for all pollutants measured by each SSys. One can observe scattered R^2 for a few SSys that are tested in several references in different locations, seasons, and durations.

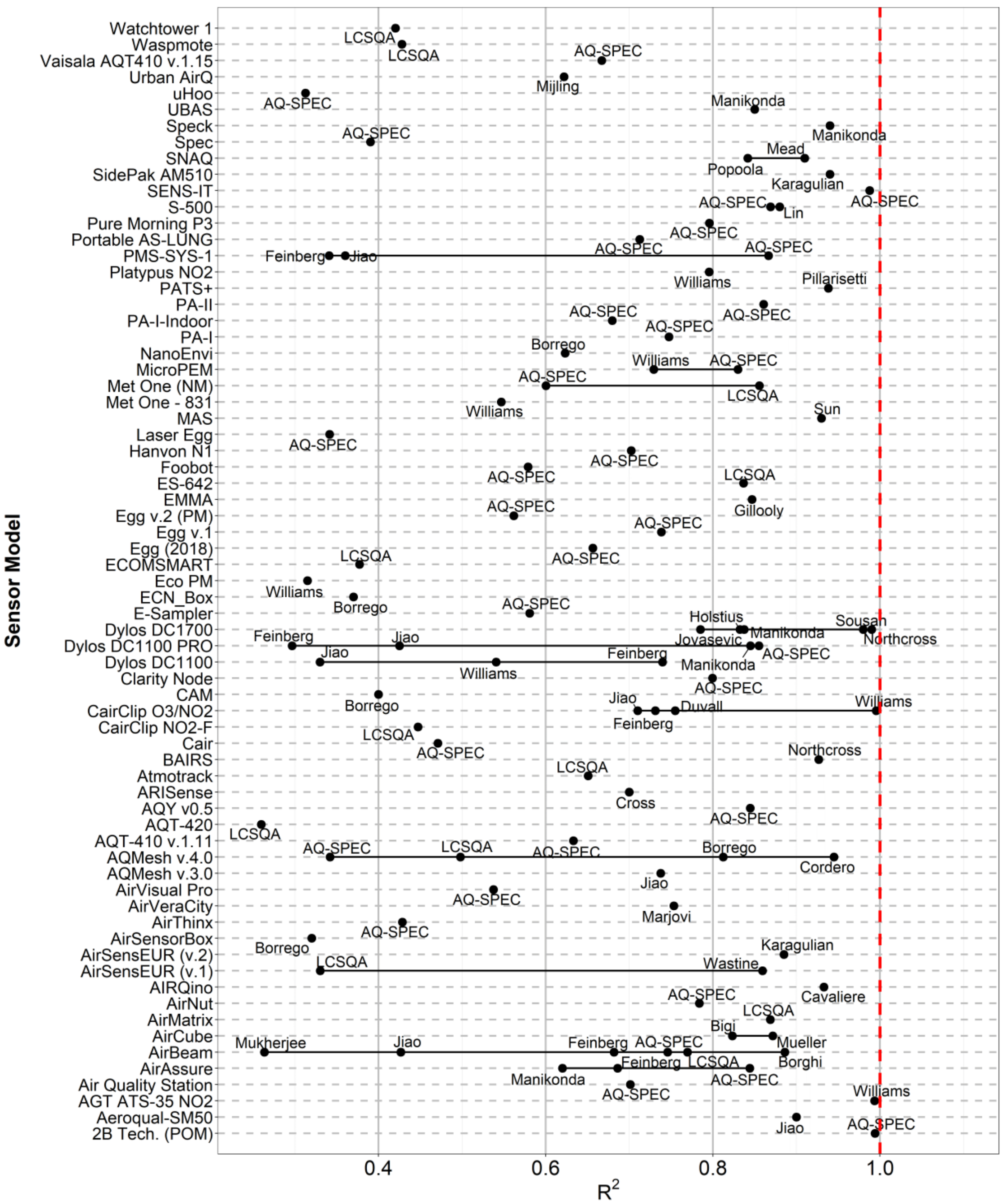

Figure 4. Mean R^2 obtained from the comparison of SSys against reference measurements at all averaging times (1 min, 5 min, 1 h, and 24 h). The author name below each bullet gives the first author of the publication from which results were drawn.

Figures A3 and A4 show the distribution of R^2 of LCS hourly and minute values measuring PM_{10}, $PM_{2.5}$, PM_1, O_3, NO, NO_2, and CO against reference measurements:

- For the SSys, PA-II by PurpleAir [19] and PATS + by Berkley Air [72] showed the highest R^2 with values between 0.8 and 1.0. Other LCS with R^2 values ranging between 0.7 and 1.0 included PMS-SYS-1 by Shinyei (Kobe, JPN) , Dylos 1100 PRO by Dylos, MicroPEM by RTI (Research Triangle Park, USA), AirNUT by Moji (Beijing, CN), the Egg (2018) by Air Quality Egg (https://airqualityegg.com/home), AQT410 v.1.15 by Vaisala (Helsinki, Finland), AirVeraCity by AirVeraCity (Lausane, CH), NPM2 [33] by MetOne (Grants Pass, OR, USA), and the Air

Quality Station [19] by AS LUNG. Nevertheless, we need to point out that the performance of LCS measuring PM_{10}, on average, was very poor.

- For the hourly PM measurements of OEMs (Figure A5), the OPC-N2, OPC-N3 [19,35,36,49,84] and the SDS011 [49] by Nova Fitness (Jinan, CN) showed R^2 values in the range of 0.7–1.0. For the 24-hour PM measurements of OEMs (Figure A6), we found R^2 within the range of 0.7–1.0 for the OPC-N2 and the OPC-N3 [19].
- For the 24-hour PM measurements of SSys (Figure A7), PA-II [19] and AirQUINO [76] by CNR (Firenze, IT) showed R^2 values close to 1 for $PM_{2.5}$
- For gaseous pollutants, high R^2 values ranging between 0.7 and 1.0 were found for the following multipollutant LCS: AirSensEUR [22] by LiberaIntentio, AirVeraCity, AQY and S-500 by Aeroqual, and SNAQ by the University of Cambridge (Cambridge, UK) (Figure A3).
- For the hourly gaseous measurements (Figure A5), we found very few OEMs with R^2 in the range of 0.7–1.0. These included CairClip O3/NO2 [20,30,36,64] by CairPol (Poissy, France), Aeroqual Series 500 (and SM50) [33] and O3-3E1F [20,23,36] by CityTechnology, and NO2-B43F [61,65] by Alphasense. On the other hand, we found very few records for SSys using daily data. Additionally, one can notice when comparing Figures A4 and A5 that the performance of OEMs is generally enhanced when they are integrated inside SSys, except for PM_{10}.

Figures A8 and A10 show selected SSys that gave the slope of the linear regression line of hourly LCS data versus reference measurements from 0.5 to 1.5 and R^2 higher than 0.7. This selection includes AirSensEUR, AirVeracity, and S-500 for gaseous pollutants and AirNut, AQY v0.5, Egg v.2 (PM), NPM2 for hourly data and AIRQuino, AQY v0.5, Egg v.2 (PM), and PA-I for daily data.

Figures A9 and A11 show the same selection as Figure A8, but for OEMs. This list includes the SM50, CairClip O3/NO2, S-500 (NO_2, O_3), and NO2-B4F (NO_2) for gaseous measurements, Nova Fitness SDS011 for $PM_{2.5}$ measurements for hourly data, and the OPC-N2 by Alphasense and DataRAM for daily data.

The influence of the type of reference methods was evaluated by plotting the R^2 of sensor data versus reference measurements. In total, 657 of the studies used GRIMM Environmental Dust Monitor (Airing, GE) (58%), Beta Attenuation Monitor (BAM) (36%), DustTrack (<1%), and Aerodynamic Particle Sizer (<1%), all based on light scattering, the same principle as PM sensors. Other studies used the Tapered Element Oscillating Microbalance method (TEOM) (5%) and Gravimetry (<1%). The 25%, 50%, and 75% percentiles of R^2 were 0.56, 0.78, and 0.91 for GRIMM and 0.41, 0.66, and 0.81 for BAM, respectively. Consequently, it was not possible to identify any significant difference for the two mainly used analyzers (GRIMM, BAM) because of the overlap of the distributions of R^2. In fact, the effect of the type of reference method must be considered together with the background conditions at which the comparison is carried out. These conditions might have a non-negligible effect on the PM concentration measured by the sensor, and therefore may influence the value of R^2 more than the type of reference measurement. Additionally, the relationship between R^2 (obtained from the comparison of LCS with reference instruments) and the maximum reference concentration of each study did not show any trend.

5. Cost of Purchase

For the evaluation of the price of LCS, we considered all SSys manufactured by commercial companies. Operating costs, such as calibration, maintenance, deployment, and data treatment, were not included in the estimated price of SSys.

Figure 5 shows the commercial price of LCS by model and number of measured pollutants and Figure A13 shows the prices for OEMs. There are a large number of SSys measuring one pollutant and only a few measuring multiple pollutants. Most OEMs are open source devices (Figure A13). On the other hand, most of the SSys are "black box" devices (Figure 5). Therefore, most of the SSys cannot be easily re-calibrated by users. In fact, most SSys are intended to be ready-to-use air quality monitors.

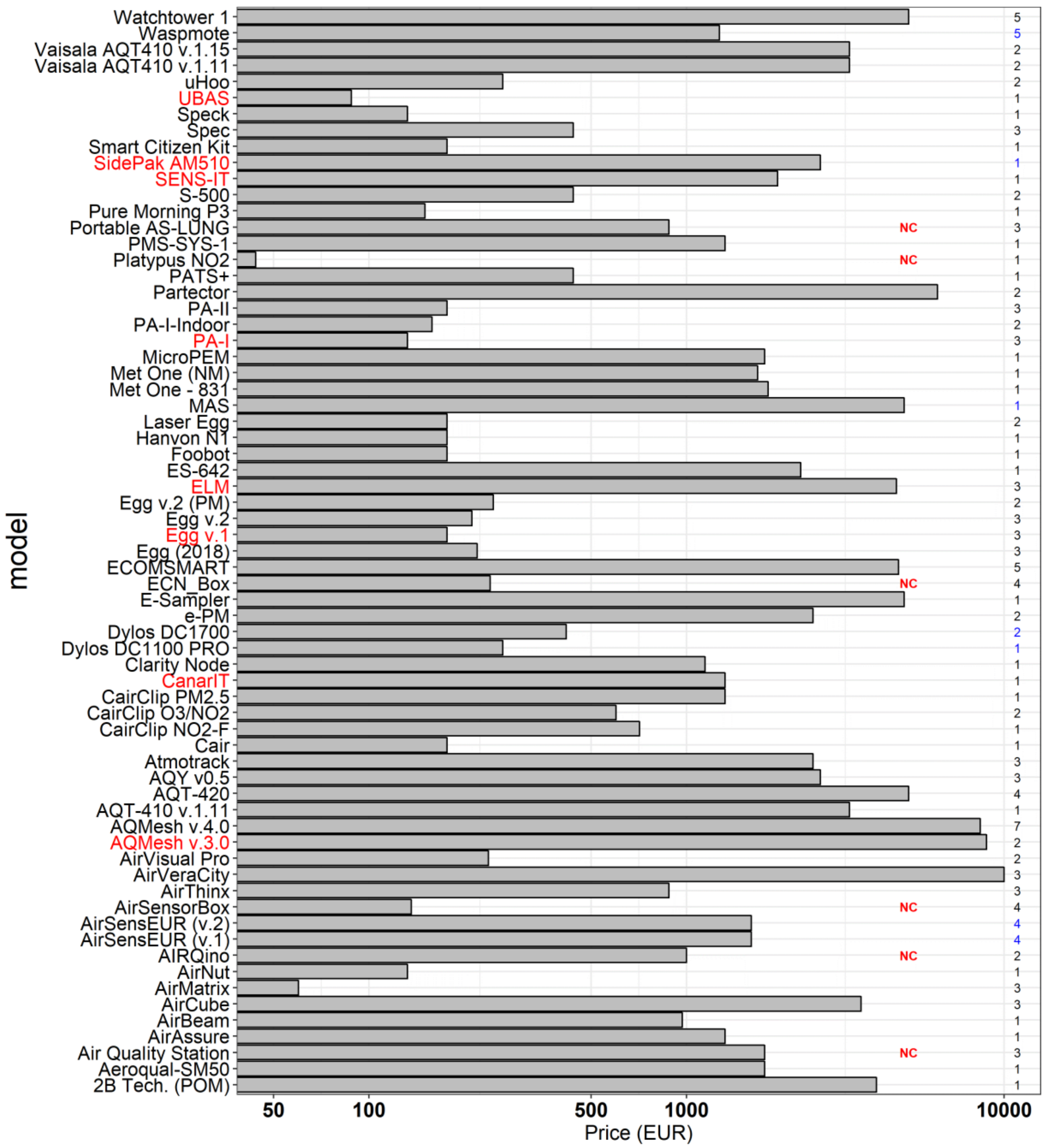

Figure 5. Prices of SSys grouped by model. Numbers on the right indicate the number of pollutants measured by each SSys, with open source in blue and black box in black. The x-axis uses a logarithmic scale. Names of "living" and "non-living" SSys are indicated in black and red colors on the labels of the y-axis, respectively. NC indicates commercially unavailable sensors.

In Figure 6 we have shortlisted the best SSys according to their level of agreement with reference systems. Figure 6 includes SSys with hourly and daily data showing R^2 higher than 0.85 and slopes ranging between 0.8 and 1.2. The figure shows the price, the number of pollutants being measured, the averaging time, and the data openness of the selected SSys. Table 4 reports the SSys shortlisted in Figure 6 with the R^2 and slope mean values, the list of pollutants being measured, the openness of data, their commercial availability, and price.

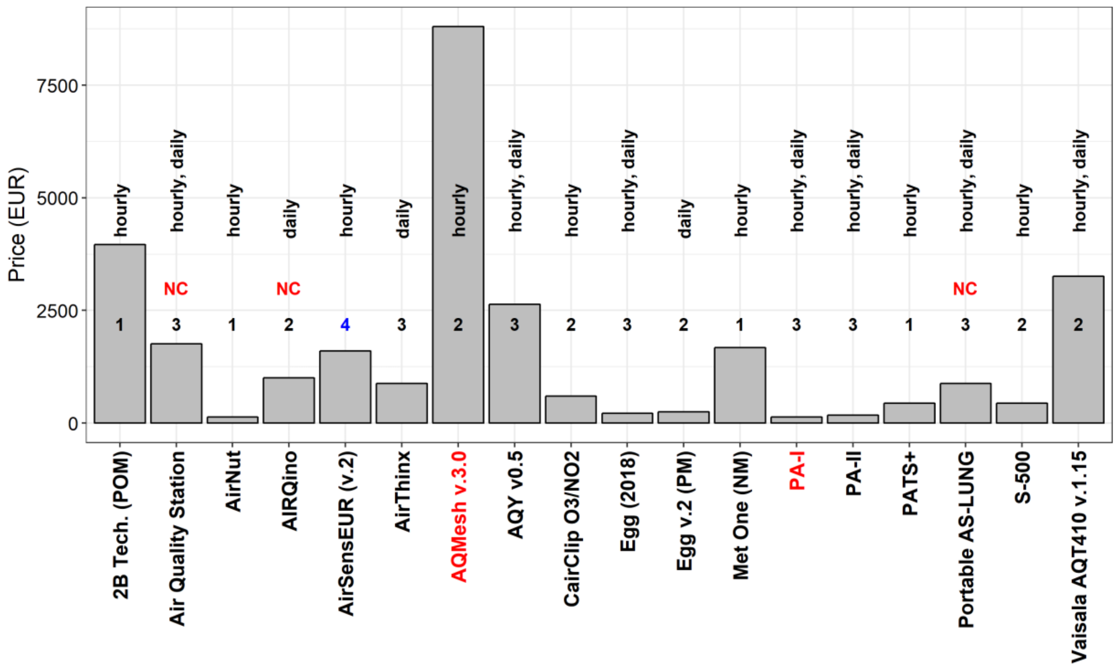

Figure 6. Price of low-cost SSys. Numbers in bold indicate the number of pollutants measured by open source (blue) and black box (black) sensors. Only records with $R^2 > 0.85$ and $0.8 < \text{slope} < 1.2$ are shown. Names of "living" and "updated" and "non-living" sensors are indicated in black and red on the labels of the x-axis, respectively. NC indicates commercially unavailable sensor. Labels reporting hourly/daily indicate the averaging time of reviewed records.

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

Model	Pollutant	Mean R^2	Mean Slope	Mean Absolute Intercept	Open/Close	Living	Commercial	Price (EUR)
AirNut	$PM_{2.5}$	0.86	0.88	8.6	black box	Y	commercial	132
PA-I	PM_1	0.95	0.92	0.52	black box	N	commercial	132
PA-II	PM_1	0.99	0.82	1.8	black box	Y	commercial	176
Egg (2018)	PM_1	0.87	0.85	0.095	black box	Y	commercial	219
PATS+	$PM_{2.5}$	0.96	0.92	0.05	black box	Y	commercial	440
S-500	NO_2, O_3	0.88	0.97	0.27	black box	Y	commercial	440
CairClip O3/NO2	O_3	0.88	0.88	12	black box	Y	commercial	600
Portable AS-LUNG	PM_1	0.89	0.87	1.0	Black Box	Y	non-commercial	880
AirSensEUR (v.1)	NO_2, O_3, CO, NO	0.95	0.98	-	open source	Y	commercial	1600
AirSensEUR (v.2)	NO_2, O_3, CO, NO	0.89	1.1	5.7	open source	Y	commercial	1600
Met One (NM)	$PM_{2.5}$	0.86	1.1	2.8	black box	Y	commercial	1672
Air Quality Station	PM_1	0.88	0.90	0.85	black box	Y	non-commercial	1760
AQY v0.5	$PM_{2.5}$	0.87	0.97	4.0	black box	updated	commercial	2640
Vaisala AQT410 v.1.15	CO	0.87	0.97	0.23	black box	Y	commercial	3256
2B Tech. (POM) *	O_3	1.00	1.00	0.74	black box	Y	commercial	3960
AQMesh v.3.0	NO	0.87	0.88	0.76	black box	N	commercial	8800

Note: * The 2B Tech. (POM) is a miniaturized reference method, UV photometry, which explains the perfect R^2 And slope of 1.

Among "open source" SSys, we identified the AirSensEUR by LiberaIntentio and the AIRQuino by CNR. The remaining shortlisted SSys were identified as "black box". AirSensEUR (v.2) resulted in a mean R^2 value of 0.90 and a slope of 0.94, while AIRQuino resulted in a mean R^2 value of 0.91 and a slope of 0.97. We need to point out that, to date, AIRQuino can be used for the detection of up to five pollutants (NO_2, CO, O_3, NO, and PM). However, only data for PM were available at the time of this review.

Figure 7 shows the relationship between the mean R^2 of SSys and the decimal logarithm of the price of LCS. In Figure 7, only the "living" LCS are compared. This shows that for OEMs there is not a significant linear relationship between the price of OEMs and the value of R^2. Conversely, there is a significant increase in R^2 with the logarithm of the price of SSys. The regression equations indicated in Figure 7 shows that R^2 can increase 14 ± 6% for a 10-fold increase of the prices of SSys, which is a limited increase at high cost. Figure 7 also shows a higher scattering of R^2 at the low end of the price scale at SSys price lower than 500 euro, with more fluctuation of the SSys performance.

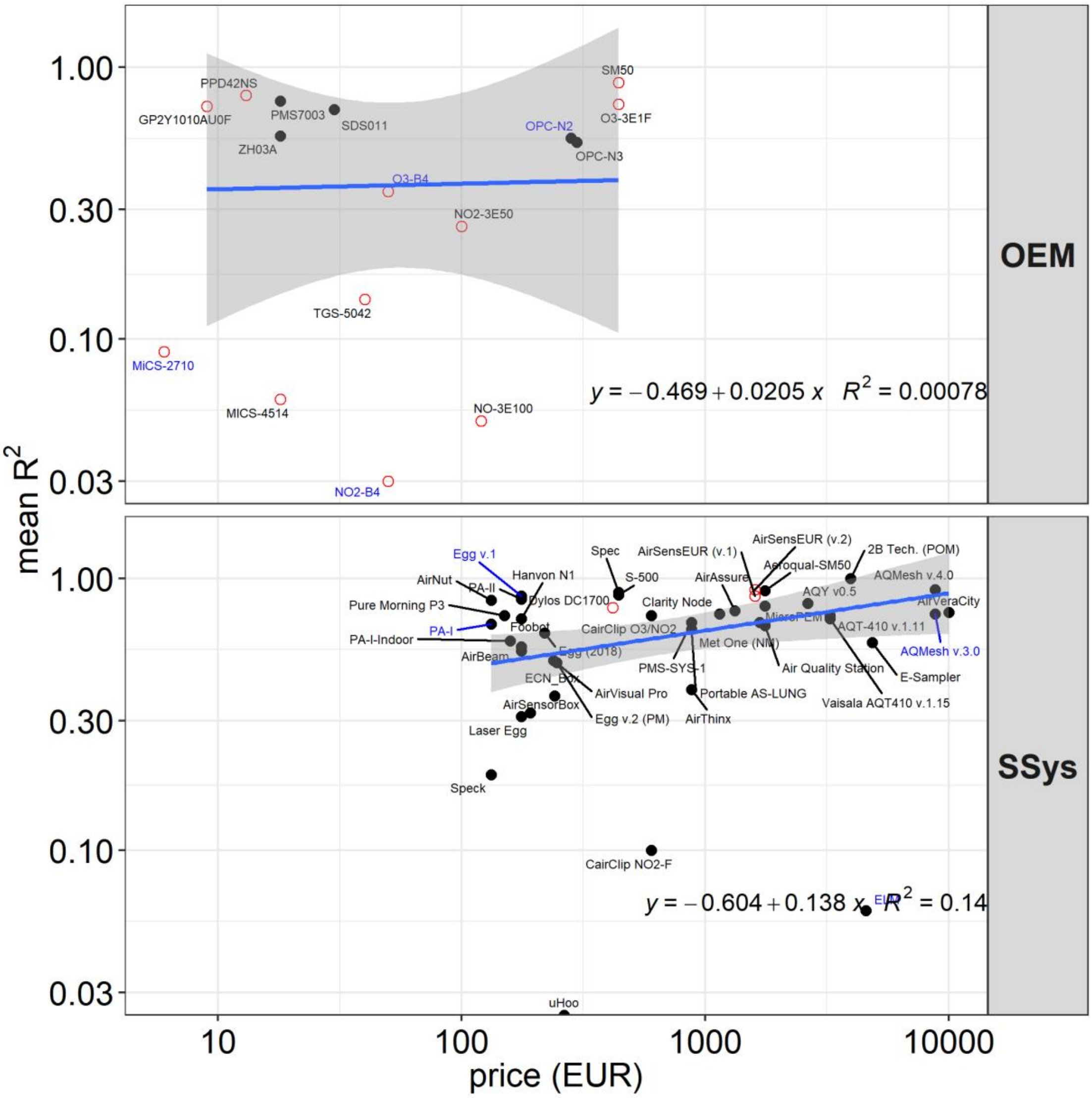

Figure 7. Relationship between prices of LCS and R^2 for field test only. A logarithmic scale has been set for both axes. Open source and black box models are indicated with red open dots and black solid dots, respectively. Names of "living" and "non-living" sensors are indicated by black and blue colors, respectively. R^2 refers to data averaged over 1 h. Grey shade in the fit plots indicate a pointwise 95% confidence interval on the fitted values.

6. Conclusions

There is little information available in the literature regarding calibration of LCS. Nevertheless, it was possible to list the calibration methods giving the highest R^2 when applied to the results of field tests. For CO and NO, our review showed that the MLR models were the most suitable for calibration. ANN gave the same level of performance as MLR only for NO. For NO_2 and O_3, supervised learning models, such as, SVR, SVM (though not for O_3), ANN, and RF, followed by MLR models, proved to be the most suitable method of calibration. Regarding $PM_{2.5}$, the best results were obtained with linear models. However, these models were applied only to $PM_{2.5}$ with relative humidity data < 75–80%. For higher relative humidity, models accounting for the growth of the particulates must be further developed. So far, the calibration using the Khöler theory seems to be the most promising method.

A list of SSys with R^2 and slope close to 1.0 were drawn from the whole database of records of comparison tests of LCS data versus reference measurements, which indicates the best performance of SSys, as shown in Figure 8. In fact, in Figure 8 the blue background represents the best selection region for SSys. The best SSys would be the one that reaches the point with coordinates $R^2 = 1$ and slope = 1. Within the blue background region, the following SSys can be found: 2B Tech. (POM), PA-II, AirSensEUR (v.1), PA-I, S-500, AirSensEUR (v.1), SNAQ, Vaisala AQT410 v.15, MetOne (NM), the Egg (v.2), AQY v0.5, CairClip O3/NO2, AQMesh v3.0, AQT410 v.11, and AirVeraCity. Additionally, Figure 8 shows that there are more SSys underestimating reference measurements with slopes lower than 1 than SSys overestimating reference measurements.

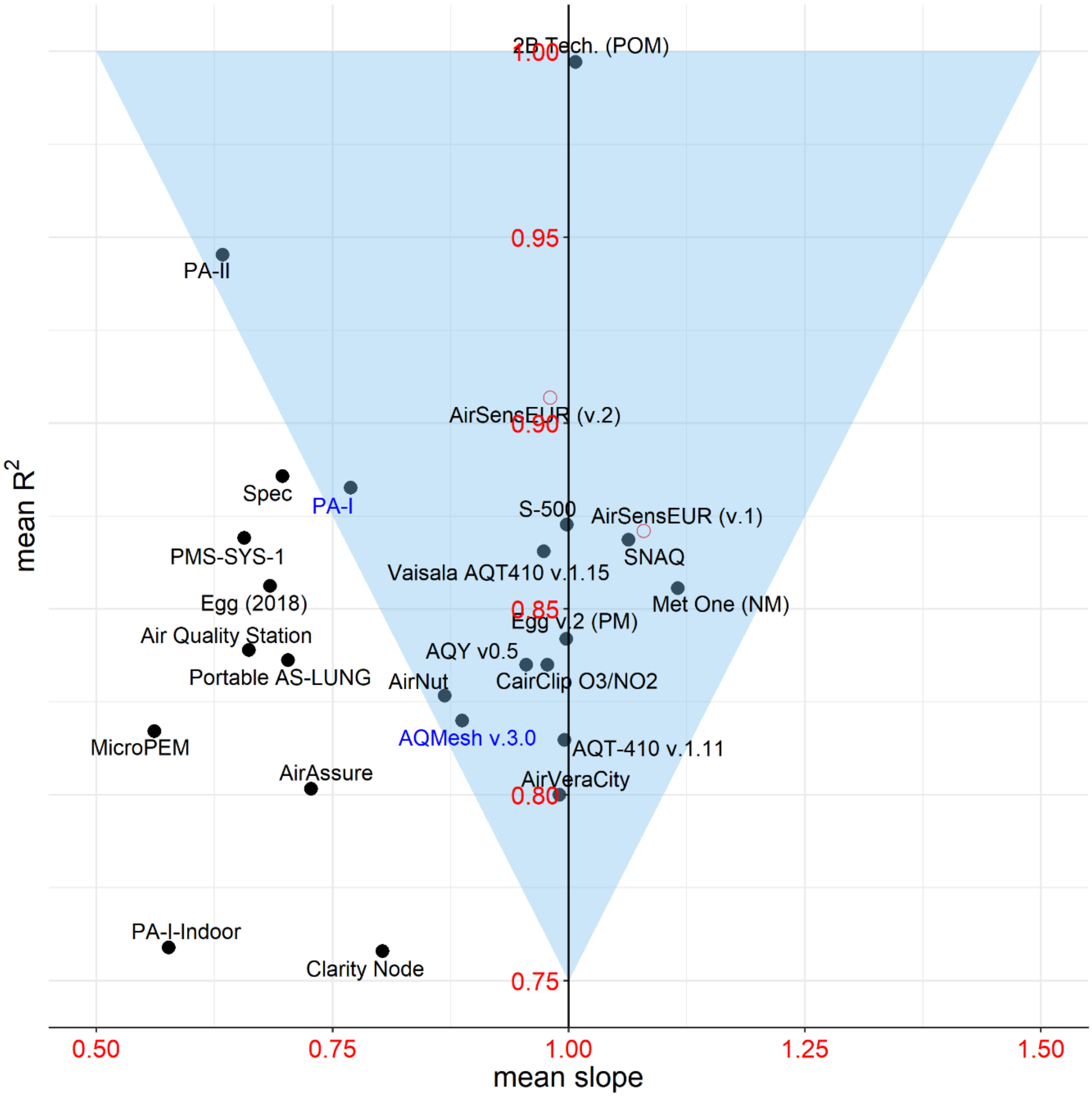

Figure 8. Correspondence between R^2 and *slope* for SSys. Only SSys models with $R^2 > 0.75$ and 0.5 < slope < 1.2 are shown. Names of "living" and "non-living" sensors are indicated in black and blue colors, respectively.

Analyzing the SSys and their price, it was found that R^2 increases of 14% results in a 10-fold increase of the price of SSys—a limited improvement for a large price increase.

This review work clearly shows that there is a considerable number of field-work carried out with LCS. Therefore, field-calibrations were performed to correct outputs from LCS. However, as shown in recent work [27], during filed-calibrations it is not always possible to distinguish the single effect of each covariate that might affect the correct operation of the LCS. While this is only possible at controlled laboratory conditions, this could be overcome by co-locating clusters of sensors at reference sites to provide calibration outside of laboratory conditions.

Although this paper gives an exhaustive survey of the independent LCS evaluations, the concept of comparing LCS field tests from different studies can be difficult and may result in misleading conclusions. This is difficult because of the lack of uniformity in the metrics representing LCS data quality between studies and makes them difficult to compare. Comparing field tests of LCS may also be misleading, as in order to consider the highest number of studies it was necessary to rely on the coefficient of determination, R^2. However, R^2 is overly dependent on the range of reference measurements, on the duration of the test field, and on the season and location of the tests, meaning changes of R^2 are not completely dependent on LCS data quality or on calibration methods. This shortcoming makes the standardization of a protocol for evaluation of LCS at the international level a high priority, while inter-comparison exercises where LCS are gathered at the same test sites and at the same time are greatly needed.

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Appendix A

Table A1. Number of analyzed records and sensor models by averaging time.

Averaging Time	n. Records	n. OEMs and SSys
hourly	610	86
5 min	253	40
daily	248	42
1 min	214	33

Table A2. Model of OEMs by pollutant, type, openness, and price.

Model	Pollutant	Type	Reference	Open/Close	Living	Price
CO-B4	CO	electrochemical	Wei [59]	open source	N	50
CO 3E300	CO	electrochemical	Gerboles [23]	open source	Y	100
DataRAM pDR-1200	$PM_{2.5}$	nephelometer	Chakrabarti [70]	black box	N	-
DiscMini	PM	OPC	Viana [77]	open source	Y	11,000
DN7C3CA006	$PM_{2.5}$	nephelometer	Sousan [83]	open source	Y	10
DSM501A	$PM_{2.5}$	nephelometer	Wang [68], Alvarado [69]	open source	Y	15
FIS SP-61	O_3	MOs	Spinelle [26]	open source	Y	50
GP2Y1010AU0F	$PM_{2.5}$, PM_{10}	nephelometer	Olivares [71], Manikonda [54], Sousan [83], Alvarado [69], Wang [68]	open source	Y	10
MiCS-2710	NO_2	MOs	Spinelle [20], Williams [30]	open source	N	7
MICS-4514	CO, NO_2	MOs	Spinelle [20,24]	open source	Y	20
NO-3E100	NO	electrochemical	Spinelle [24], Gerboles [23]	open source	Y	120
NO-B4	NO	electrochemical	Wei [59]	open source	Y	50
NO2-3E50	NO_2	electrochemical	Spinelle [20], Gerboles [23]	open source	Y	100

Table A2. *Cont.*

Model	Pollutant	Type	Reference	Open/Close	Living	Price
NO2-A1	NO_2	electrochemical	Williams [30]	black box	Y	50
NO2-B4	NO_2	electrochemical	Spinelle [20,25]	open source	N	50
NO2-B42F	NO_2	electrochemical	Wei [59]	open source	N	50
NO2-B43F	NO_2	electrochemical	Sun [65]	open source	Y	50
O3-B4	O_3	electrochemical	Spinelle [20,25], Wei [59]	open source	N	50
O3-3E1F	O_3	electrochemical	Spinelle [20,25], Gerboles [23]	open source	Y	500
OPC-N2	PM_1, $PM_{2.5}$	OPC	AQ-SPEC [19], Mukherjee [35], Sousan [83], Feinberg [36], Crilley [84], Badura [49], Crunaire [33]	open source, black box	N	362
OPC-N3	PM_1, $PM_{2.5}$	OPC	AQ-SPEC [19]	open source	Y	338
PMS1003	$PM_{2.5}$	OPC	Kelly [75]	black box	Y	20
PMS3003	$PM_{2.5}$	OPC	Zheng [85], Kelly [75]	open source, black box	Y	30
PMS5003	$PM_{2.5}$	OPC	Laquai [48]	black box	Y	15
PMS7003	$PM_{2.5}$	OPC	Badura [49]	black box	Y	20
PPD42NS	$PM_{2.5}$, PM_3, PM_2	nephelometer	Wang [68], Holstius [51], Austin [73], Gao [74], Kelly [75]	open source	Y	15
SDS011	$PM_{2.5}$,	OPC	Budde [47], Laquai [48], Badura [49], Liu [52]	open source	Y	30
SM50	O_3	MOs	Feinberg [36]	open source	Y	500
TGS-5042	CO	MOs	Spinelle [24]	open source	Y	40
TZOA-PM Research Sensors	PM	nephelometer	Feinberg [36]	open source	Y	90
ZH03A	$PM_{2.5}$	nephelometer	Badura [49]	black box	Y	20

Table A3. Models of Sensor Systems by pollutant, type, openness, and price.

Model	Pollutant	Type	Reference	Open/Close	Living	Price
2B Tech. (POM)	O_3	UV	AQ-SPEC [19]	black box	Y	4500
Aeroqual-SM50	O_3	MOs	Jiao [39]	black box	Y	2000
AGT ATS-35 NO2	NO_2	MOs	Williams [30]	black box	N	-d
Air Quality Station	PM_1, $PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	2000
AirAssure	$PM_{2.5}$	nephelometer	AQ-SPEC [19], Feinberg [36], Manikonda [54]	black box	Y	1500
AirBeam	$PM_{2.5}$	OPC, nephelometer	AQ-SPEC [19], Mukherjee [35], Feinberg [36], Borghi [37], Jiao [39], Crunaire [33]	black box	Y	200
AirCube	NO_2, O_3, NO	electrochemical	Mueller [43], Bigi [42]	black box	Y	3538
AirMatrix	PM1, $PM_{2.5}$	nephelometer	Crunaire [33]	black box	Y	60
AirNut	$PM_{2.5}$	nephelometer	AQ-SPEC [19]	black box	Y	150
AIRQino	$PM_{2.5}$	OPC	Cavaliere [76]	open source	Y	1000
AirSensEUR (v.1)	NO, NO_2, O_3	electrochemical	Crunaire [33]	black box	Y	1600
AirSensEUR (v.2)	CO, NO, NO_2, O_3	electrochemical	Karagulian [22]	open source	Y	1600
AirSensorBox	NO_2, CO, O_3	electrochemical, MOs, nephelometer	Borrego [53]	black box	Y	280
AirThinx	PM_1, $PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	1000
AirVeraCity	CO, NO_2, O_3	electrochemical, MOs	Marjovi [57]	black box	Y	10000
AirVisual Pro	$PM_{2.5}$	nephelometer	AQ-SPEC [19]	black box	Y	270
AQMesh v.3.0	CO, NO	electrochemical	Jiao [39]	black box	N	10000
AQMesh v.4.0	NO_2, CO, NO, O_3	electrochemical	Cordero [63], AQ-SPEC [19], Castell [10], Borrego [53], Crunaire [33]	black box	updated	10000
AQT410 v.1.11	O_3	electrochemical	AQ-SPEC [19]	black box	Y	3700
AQT-420	NO_2,O_3, $PM_{2.5}$	electrochemical, OPC	Crunaire [33]	black box	Y	3256
AQY v0.5	$PM_{2.5}$, NO_2, O_3	OPC, electrochemical, MOs	AQ-SPEC [19]	black box	updated	3000
ARISense	NO_2, CO, NO, O_3	electrochemical	Cross [58]	black box	Y	-
Atmotrack	PM_1, $PM_{2.5}$	nephelometer	Crunaire [33]	black box	Y	2500
BAIRS	$PM_{2.5–0.5}$	OPC	Northcross [78]	open source	N	475

Table A3. *Cont.*

Model	Pollutant	Type	Reference	Open/Close	Living	Price
Cair	$PM_{2.5}$, $PM_{10–2.5}$	OPC	AQ-SPEC [19]	black box	Y	200
CairClip O3/NO2	O_3, NO_2	electrochemical	Jiao [39], Spinelle [25], Williams [30], Duvall [64], Feinberg [36]	black box	Y	600
CairClip NO2-F	NO_2	electrochemical	Spinelle [20], Duvall [64], Crunaire [33]	black box	Y	600
CairClip PM2.5	$PM_{2.5}$	nephelometer	Williams [31]	black box	Y	1500
CAM	PM_{10}, $PM_{2.5}$, NO_2, CO, NO	OPC, electrochemical	Borrego [53]	black box	Y	-
CanarIT	PM	nephelometer	Williams [31]	black box	N	1500
Clarity Node	$PM_{2.5}$	nephelometer	AQ-SPEC [19]	black box	Y	1300
Dylos DC1100	$PM_{2.5–0.5}$	OPC	Jiao [39], Williams [31], Feinberg [36]	black box, open source	Y	300
Dylos DC1100 PRO	$PM_{2.5–0}$, $PM_{10–2.5}$, PM_{10}	OPC	Jiao [39], AQ-SPEC [19], Feinberg [36], Manikonda [54]	black box, open source	Y	300
Dylos DC1700	$PM_{2.5–0.5}$, PM_{10}, $PM_{10–2.5}$, PM_3, PM_2, $PM_{2.5}$	OPC	Manikonda [54], Sousan [83], Northcross [78], Holstius [51], Steinle [79], Han [80], Jovasevic [81], Dacunto [82]	open source	Y	475
e-PM	PM_{10}, $PM_{2.5}$	nephelometer	Crunaire [33]	black box	Y	2500
E-Sampler	$PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	5500
ECN_Box	PM_{10}, $PM_{2.5}$, NO_2, O_3	nephelometer, electrochemical	Borrego [53]	black box	Y	274
Eco PM	PM1	OPC	Williams [31]	black box	N	
ECOMSMART	NO_2, O_3, PM_1, PM_{10}, $PM_{2.5}$	electrochemical, OPC	Crunaire [33]	black box	Y	4560
Egg (2018)	PM_1, $PM_{2.5}$, PM_{10}	OPC	AQ-SPEC [19]	black box	Y	249
Egg v.1	CO, NO_2, O_3	MOs	AQ-SPEC [19]	black box	N	200
Egg v.2	CO, NO_2, O_3	electrochemical	AQ-SPEC [19]	black box	Y	240
Egg v.2 (PM)	$PM_{2.5}$, PM_{10}	nephelometer	AQ-SPEC [19]	black box	Y	280
ELM	NO_2, PM_{10}, O_3	MOs, nephelometer	AQ-SPEC [19], US-EPA [67]	black box	N	5200
EMMA	$PM_{2.5}$, CO, NO_2, NO	OPC, electrochemical	Gillooly [60]	black box	Y	-
ES-642	$PM_{2.5}$	OPC	Crunaire [33]	black box	Y	2600
Foobot	$PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	200
Hanvon N1	$PM_{2.5}$	nephelometer	AQ-SPEC [19]	black box	Y	200
Intel Berkeley Badge	NO_2, O_3	electrochemical, MOs	Vaughn [32]	open source	N	-
ISAG	NO_2, O_3	MOs	Borrego [53]	black box	N	-
Laser Egg	$PM_{2.5}$, PM_{10}	nephelometer	AQ-SPEC [19]	black box	Y	200
M-POD	CO, NO_2	MOs	Piedrahita [62]	black box	N	
MAS	CO, NO_2, O_3, $PM_{2.5}$	electrochemical, UV, nephelometer	Sun [40]	black box, open source	N, Y	5500
Met One-831	PM_{10}	OPC	Williams [31]	black box	Y	2050
Met One (NM)	$PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	1900
MicroPEM	$PM_{2.5}$	nephelometer	AQ-SPEC [19], Williams [31]	black box	Y	2000
NanoEnvi	NO_2, O_3, CO	electrochemical, MOs	Borrego [53]	black box	Y	-
PA-I	PM_1, $PM_{2.5}$, PM_{10}	OPC	AQ-SPEC [19]	black box	N	150
PA-I-Indoor	$PM_{2.5}$, PM_{10}	OPC	AQ-SPEC [19]	black box	Y	180
PA-II	PM_1, $PM_{2.5}$, PM_{10}	OPC	AQ-SPEC [19]	black box	Y	200
Partector	PM_1, $PM_{2.5}$	Electrical	AQ-SPEC [19]	black box	Y	7000
PATS+	$PM_{2.5}$	nephelometer	Pillarisetti [72]	black box	Y	500
Platypus NO2	NO_2	MOs	Williams [30]	black box	Y	50
PMS-SYS-1	$PM_{2.5}$	nephelometer	Jiao [39], AQ-SPEC [19], Williams [31], Feinberg [36]	black box	Y	1000
Portable AS-LUNG	PM_1, $PM_{2.5}$, PM_{10}	OPC	AQ-SPEC [19]	black box	Y	1000
Pure Morning P3	$PM_{2.5}$	OPC	AQ-SPEC [19]	black box	Y	170
RAMP	CO, NO_2	electrochemical	Zimmerman [61]	open source	Y	-
S-500	NO_2, O_3	MOs	Lin [66], AQ-SPEC [19], Vaughn [32]	black box	Y	500

Table A3. *Cont.*

Model	Pollutant	Type	Reference	Open/Close	Living	Price
SENS-IT	O_3, CO, NO_2	MOs	AQ-SPEC [19]	black box	N, Y	2200
SidePak AM510	$PM_{2.5}$	nephelometer	Karagulian [28]	open source	Y	3000
Smart Citizen Kit	CO	MOs	AQ-SPEC [19]	black box	Y	200
SNAQ	NO_2, CO, NO	electrochemical	Mead [44], Popoola [45]	black box	Y	-
Spec	CO, NO_2, O_3	electrochemical	AQ-SPEC [19]	black box	Y	500
Speck	$PM_{2.5}$	nephelometer	Feinberg [36], US-EPA [67], Williams [31], AQ-SPEC [19], Manikonda [54], Zikova [55]	black box	Y	150
UBAS	$PM_{2.5}$	nephelometer	Manikonda [54]	black box	N	100
uHoo	$PM_{2.5}$, O_3	nephelometer, MOs	AQ-SPEC [19]	black box	Y	300
Urban AirQ	NO_2	electrochemical	Mijling [41]	open source	N	-
Vaisala AQT410 v.1.11	CO, NO_2	electrochemical	AQ-SPEC [19]	black box	Y	3700
Vaisala AQT410 v.1.15	CO, NO_2	electrochemical	AQ-SPEC [19]	black box	Y	3700
Waspmote	NO, NO_2, PM_1, PM_{10}, $PM_{2.5}$	MOs, OPC	Crunaire [33]	black box	Y	1270
Watchtower 1	NO_2, PM_1, PM_{10}, $PM_{2.5}$, O_3	electrochemical, OPC	Crunaire [33]	black box	Y	5000

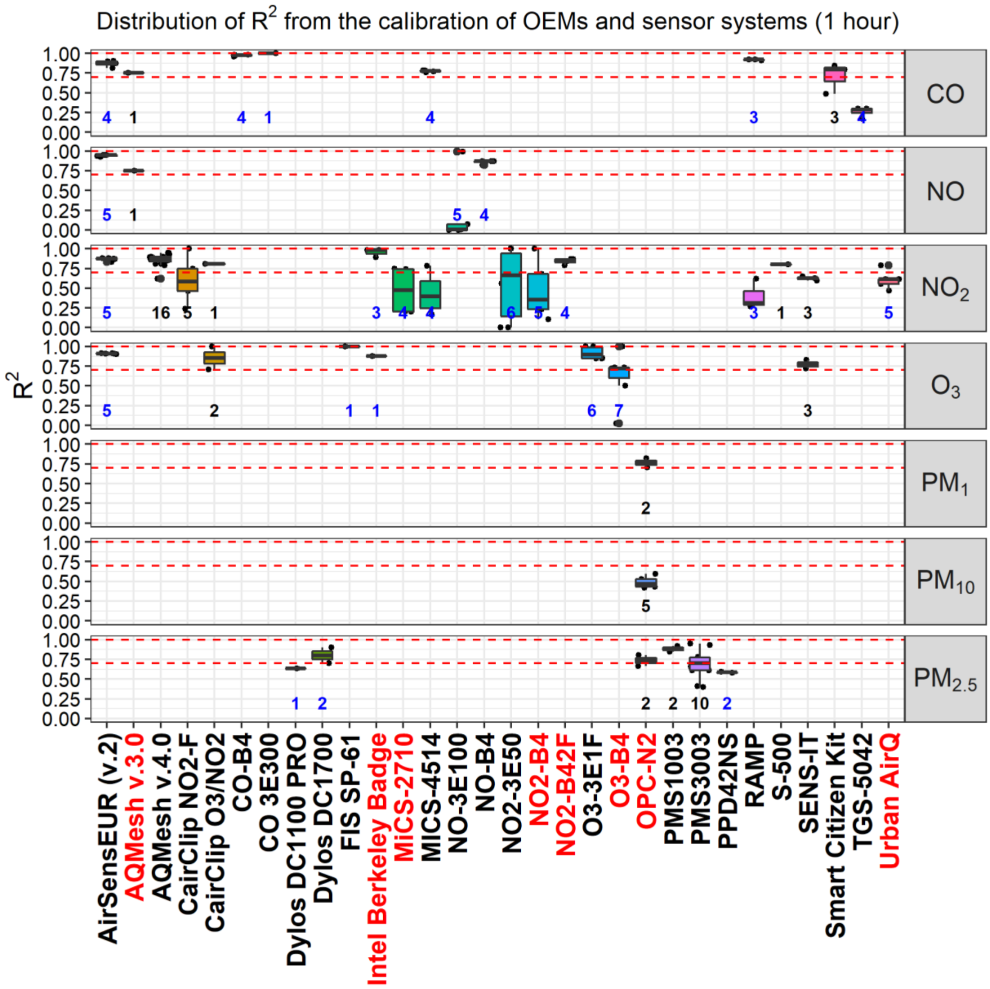

Figure A1. Distribution of R^2 for LCS hourly data against the reference for different pollutants. Dashed lines indicate the R^2 value of 0.7 and 1.0. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

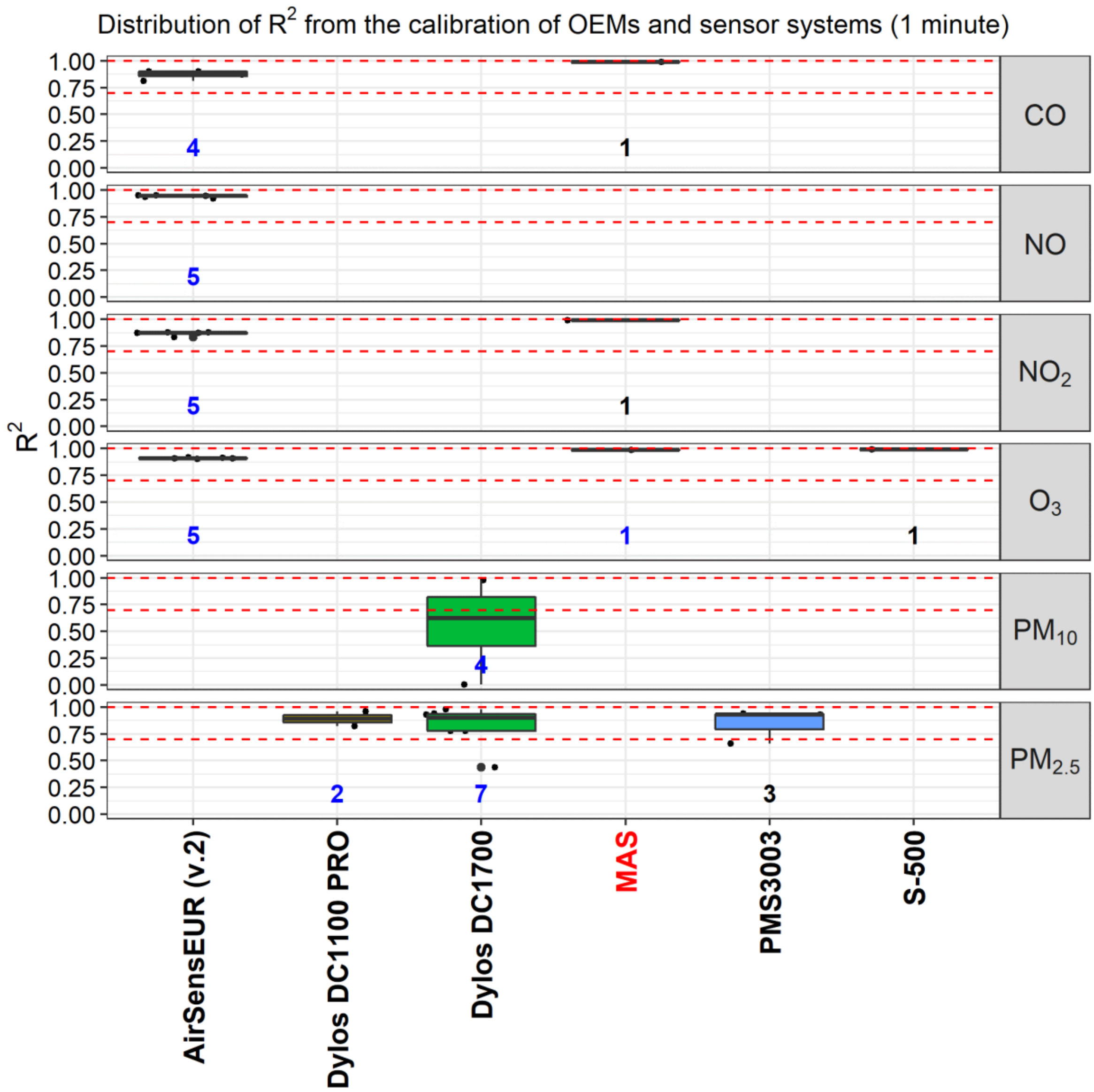

Figure A2. Distribution of R^2 for LCS minute data against the reference for different pollutants. Dashed lines indicate the R^2 value of 0.7 and 1.0. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated in black and red labels of the x-axis color, respectively.

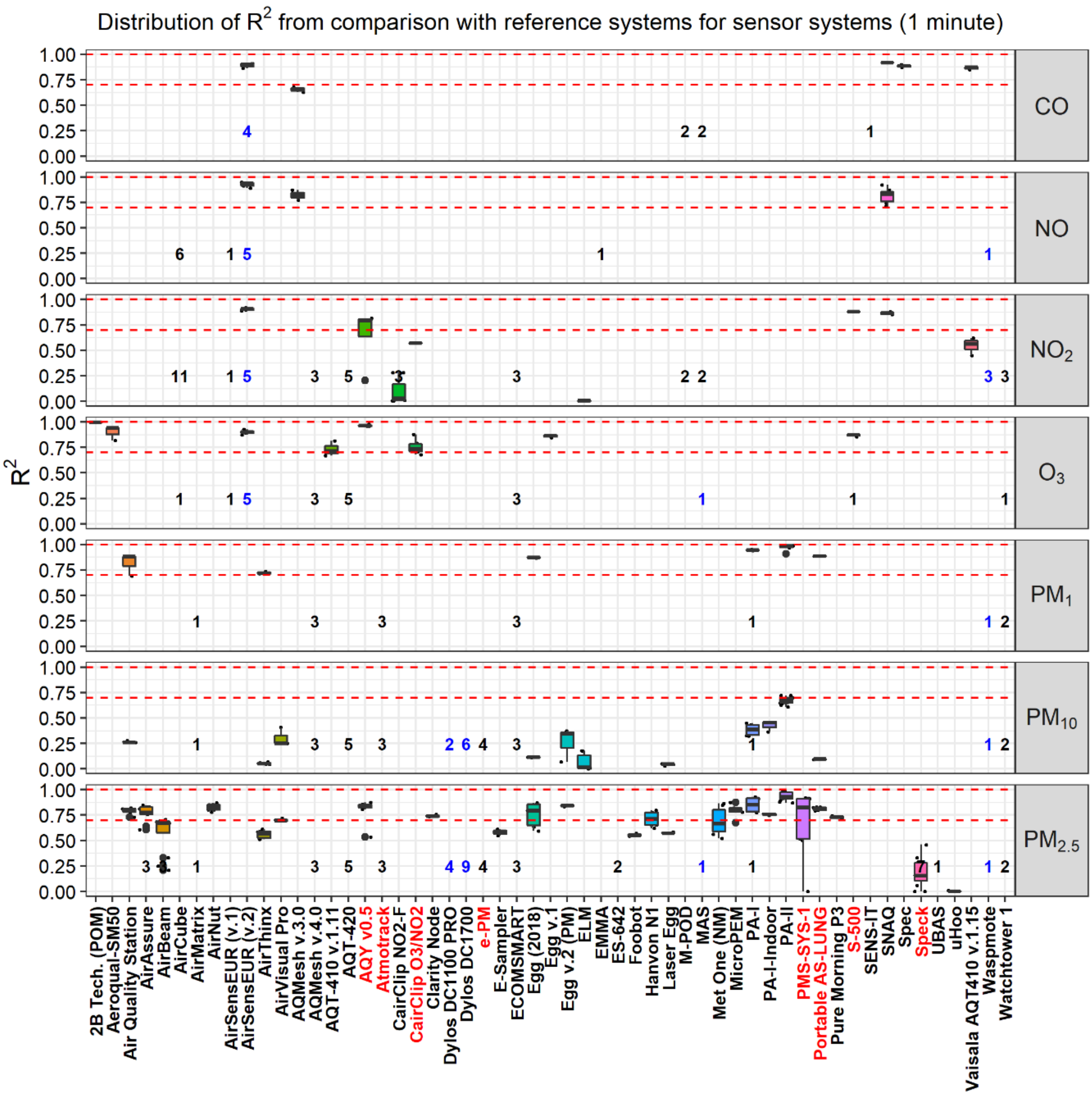

Figure A3. Distribution of R^2 from the comparison of SSys minute data against reference measurements. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

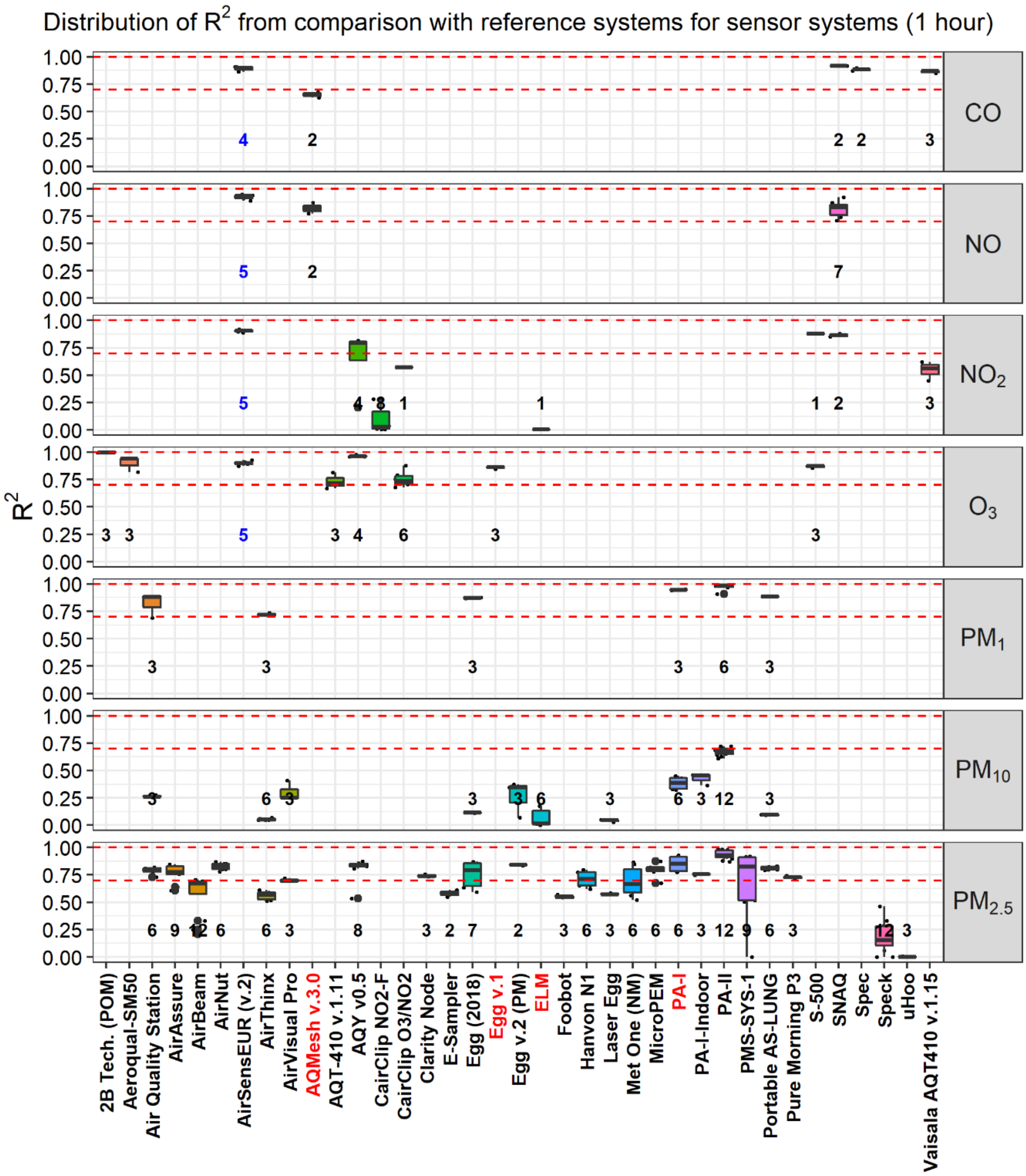

Figure A4. Distribution of R^2 from the comparison of SSys hourly data against reference measurements. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

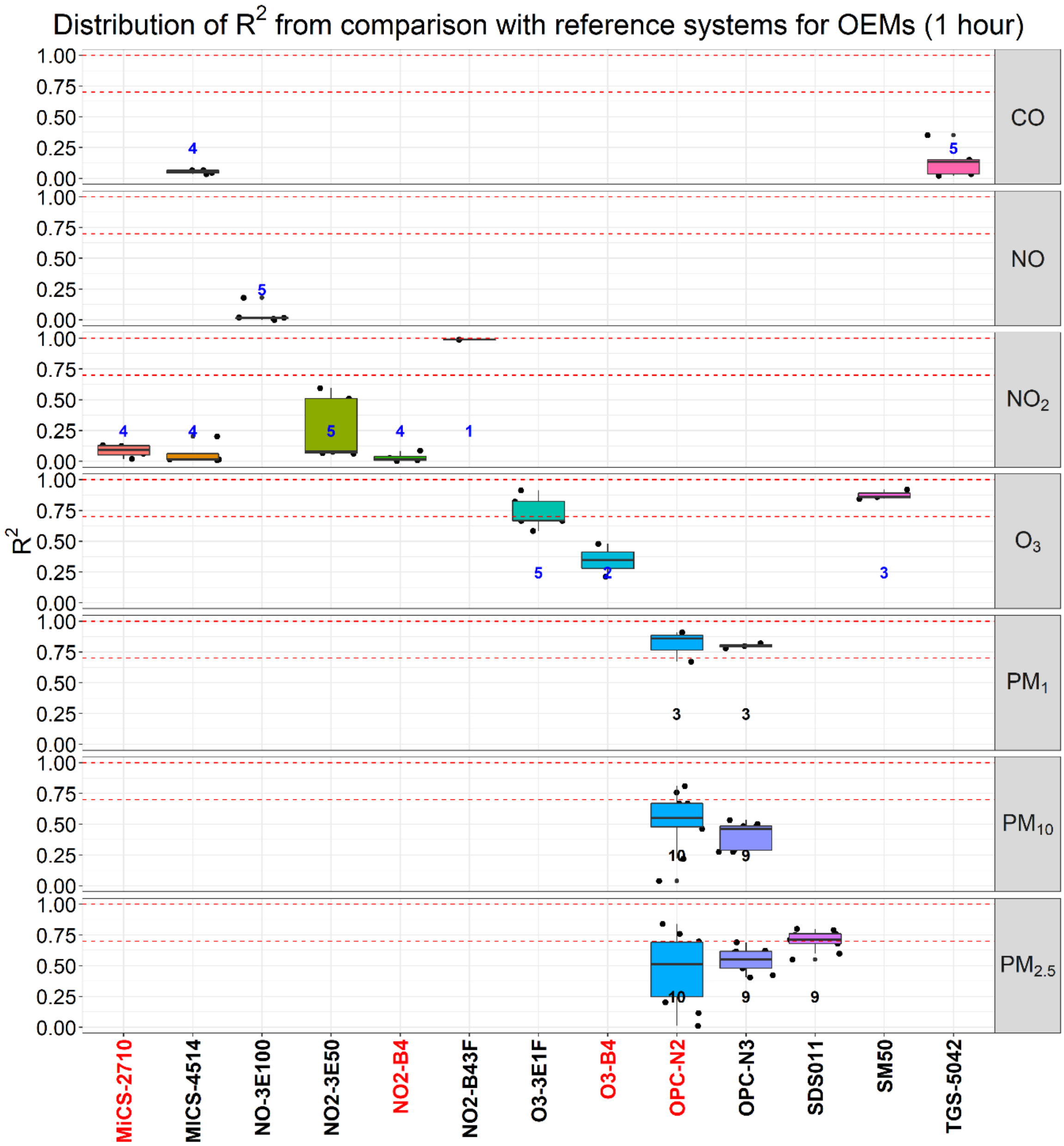

Figure A5. Distribution of R^2 from the comparison of all OEMs against reference systems. Records were averaged over a time-scale of 1 h. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

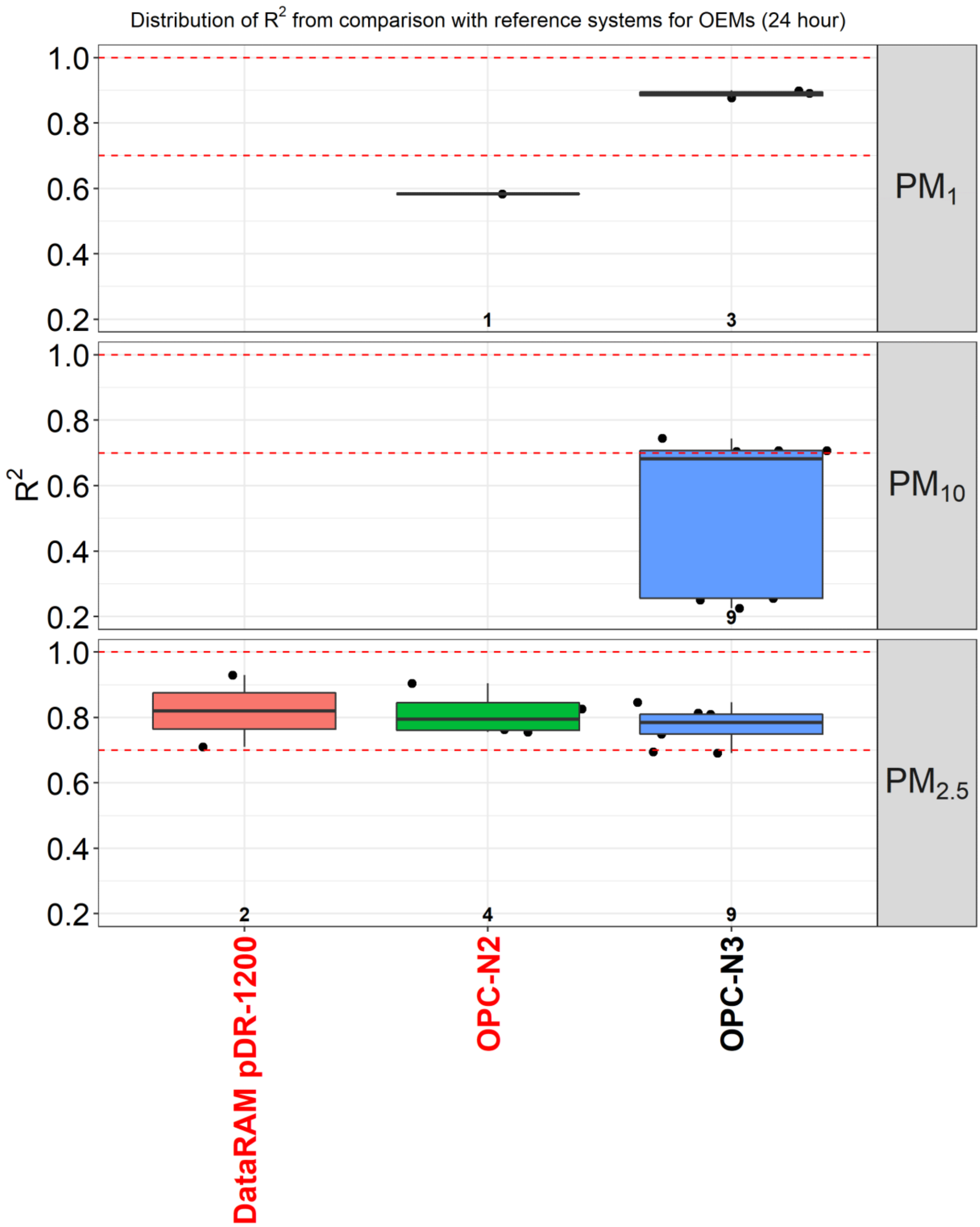

Figure A6. Distribution of R^2 from the comparison of all OEMs against reference systems. Records were averaged over a time-scale of daily data. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

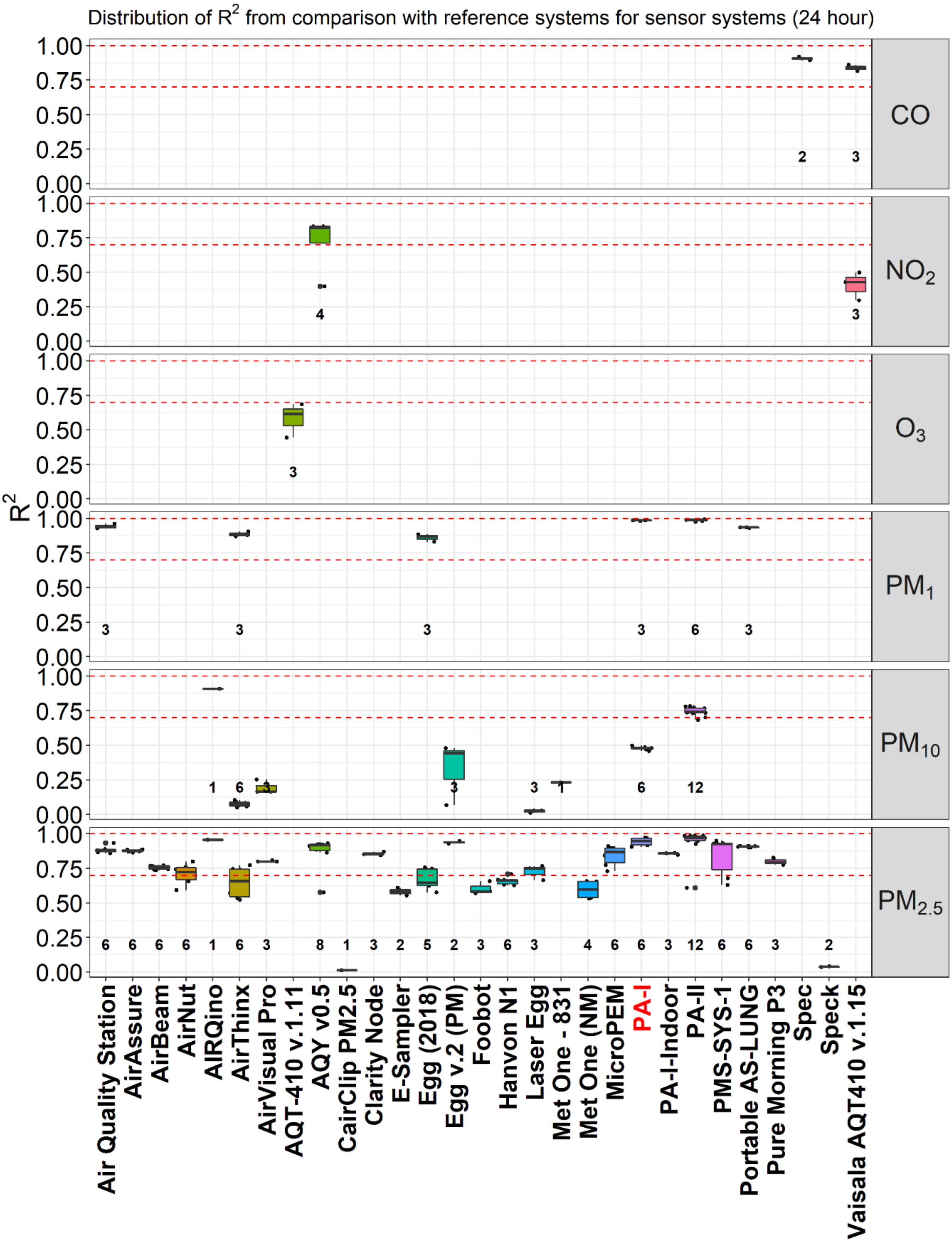

Figure A7. Distribution of R^2 from the comparison of all sensor systems against reference systems. Records were averaged over a time-scale of daily data. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

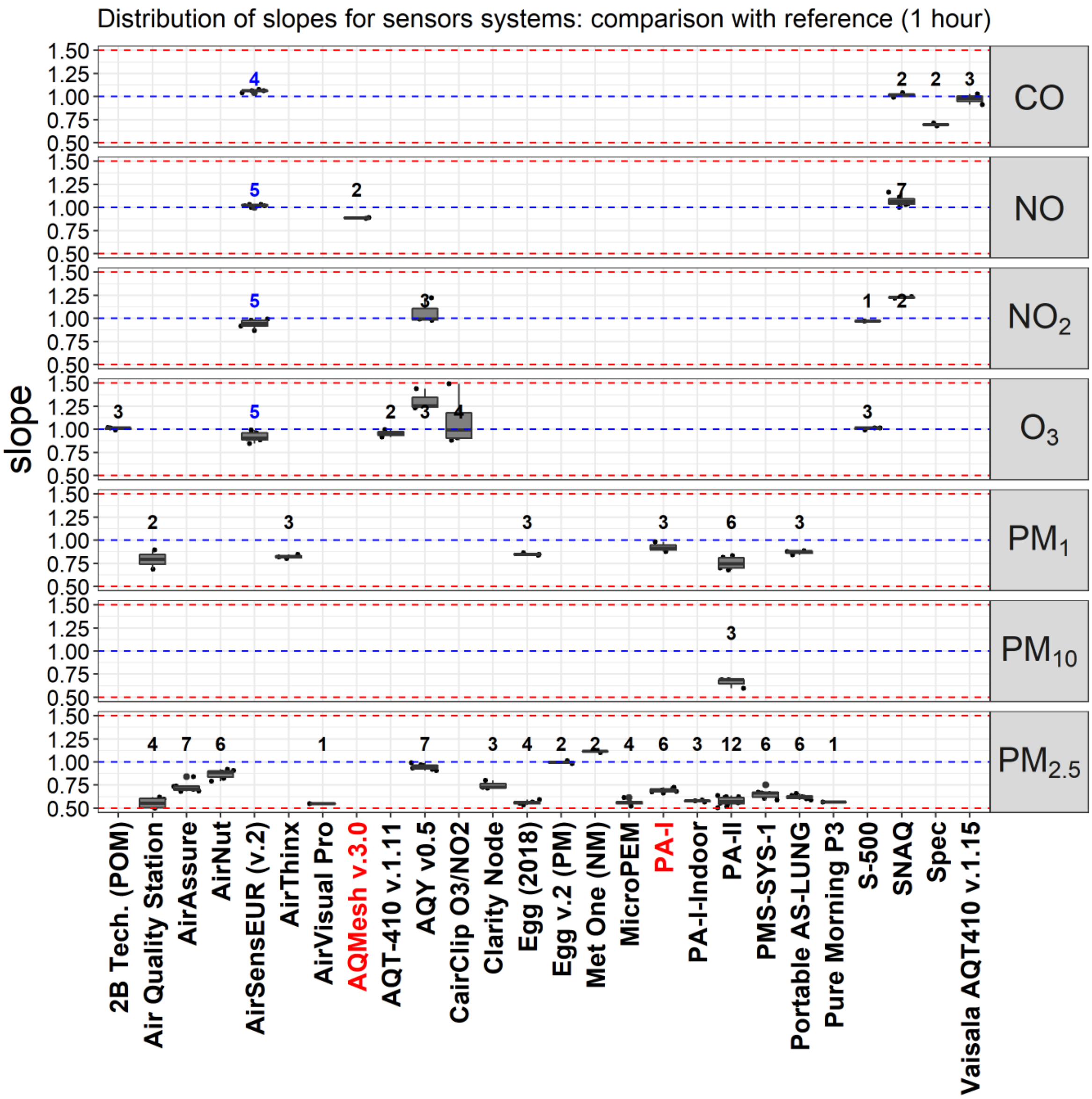

Figure A8. Distribution of slopes from the comparison of SSys against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of 1 h. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

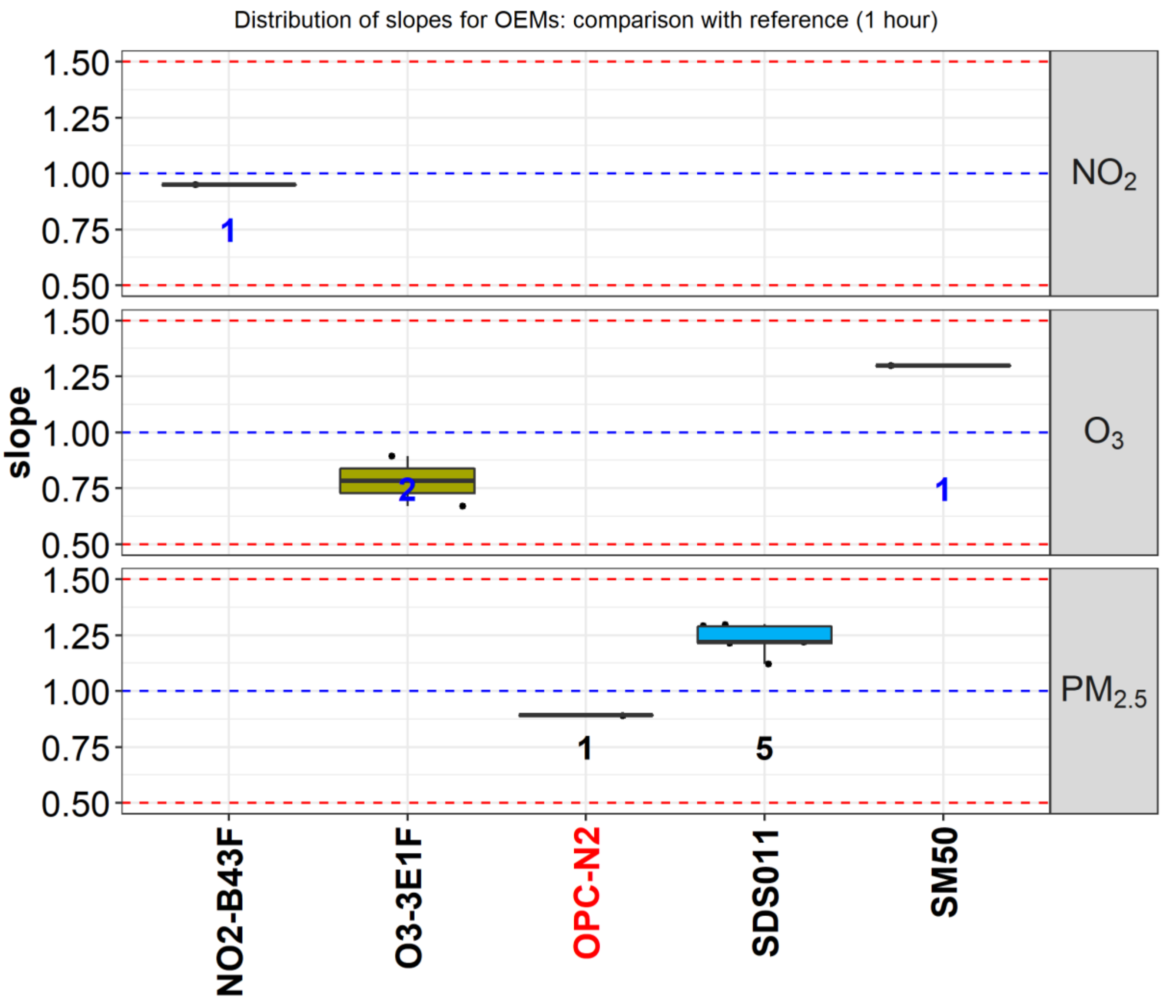

Figure A9. Distribution of slopes from the comparison of OEMs against the reference. Only hourly records with $R^2 > 0.7$ and $0.5 <$ slope < 1.5 are shown. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

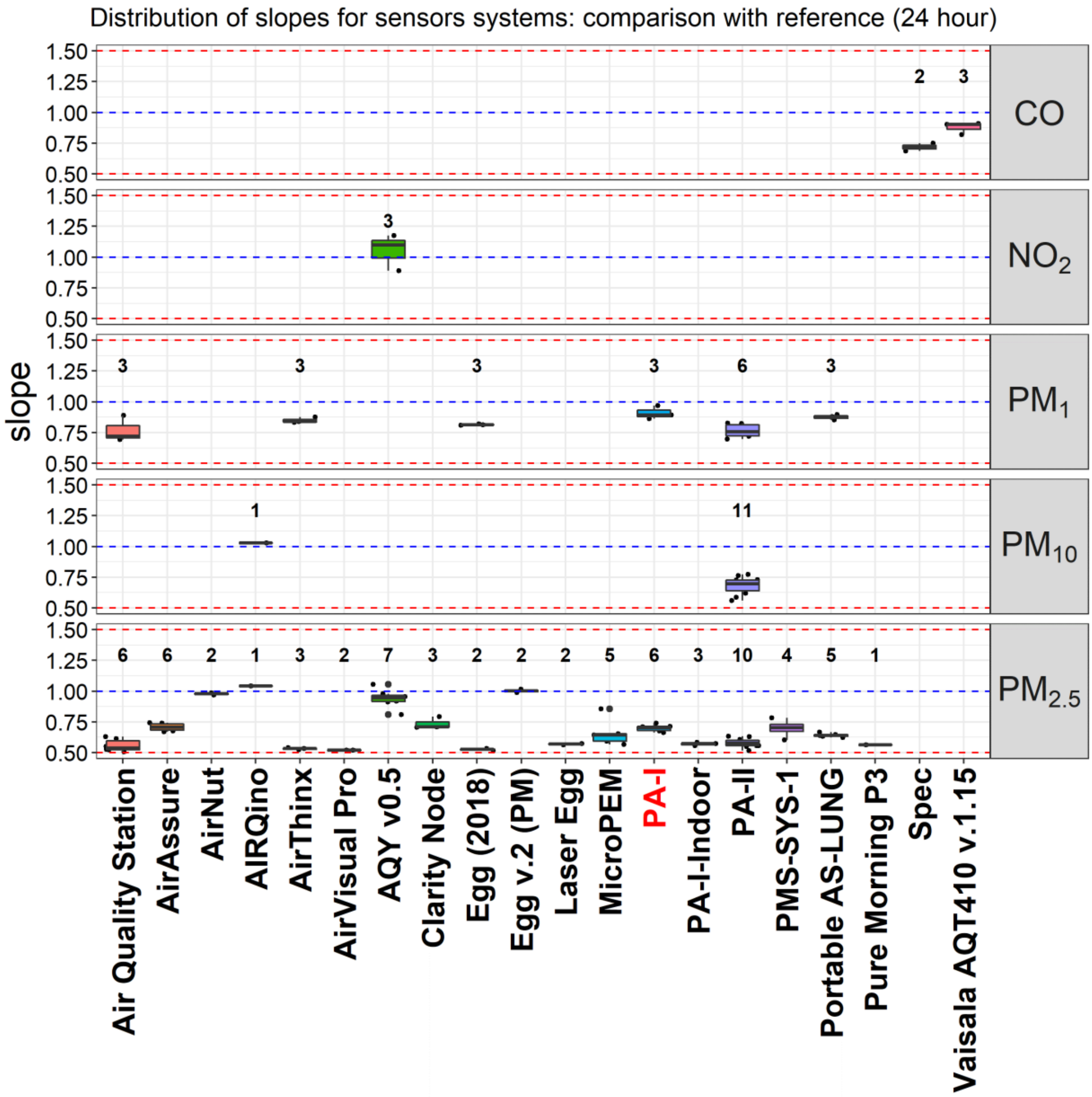

Figure A10. Distribution of slopes from the comparison of SSys against the reference. Only records with $R^2 > 0.7$ and $0.5 < \text{slope} < 1.5$ are shown. Records were averaged over a time-scale of daily data. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

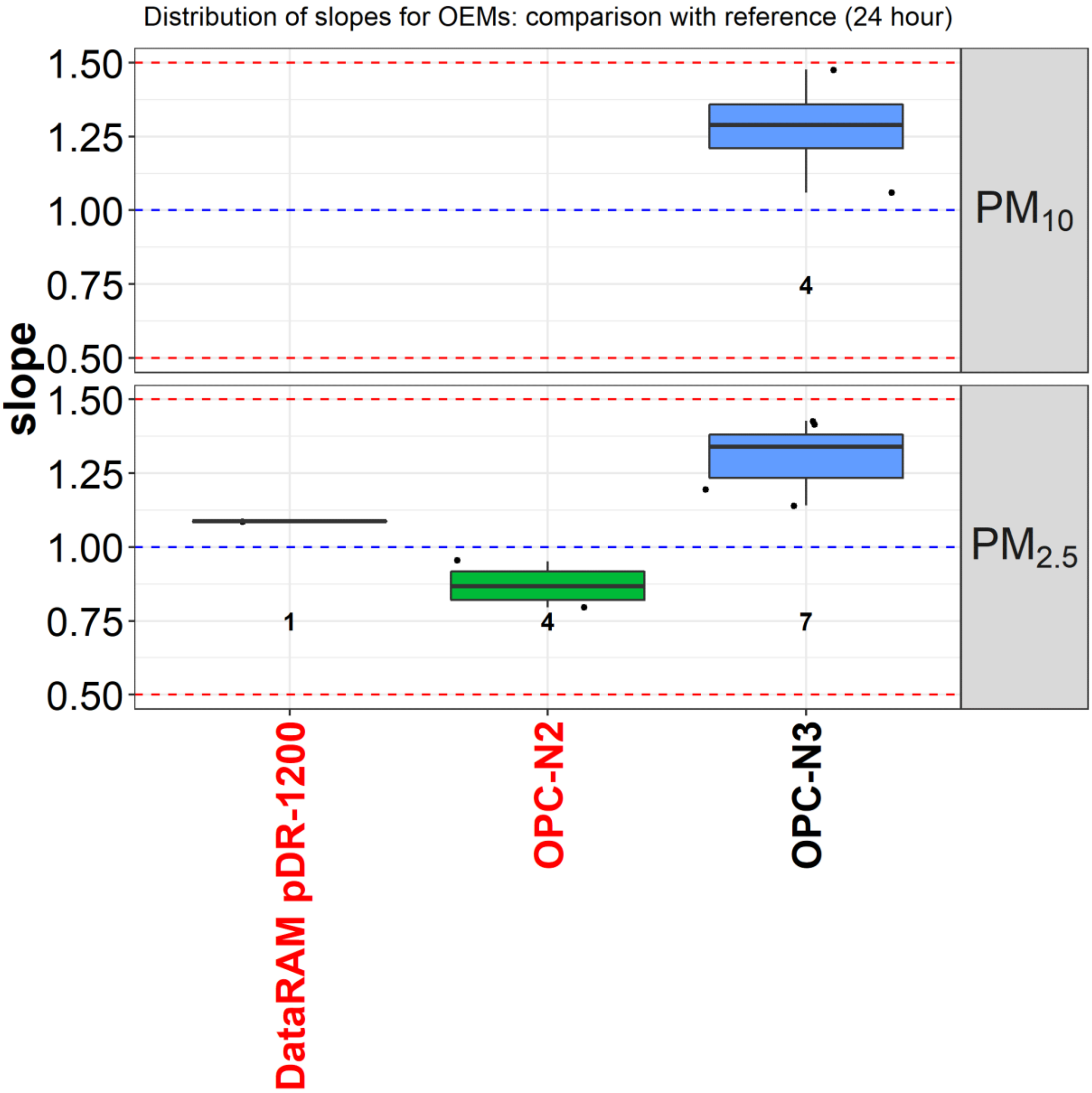

Figure A11. Distribution of slopes from the comparison of OEMs against the reference. Only records with $R^2 > 0.7$ and $0.5 <$ slope < 1.5 are shown. Records were averaged over a time-scale of daily data. Numbers in blue and black indicate the number of open source and black box records, respectively. Names of "living" and "non-living" sensors are indicated by black and red labels on the x-axis, respectively.

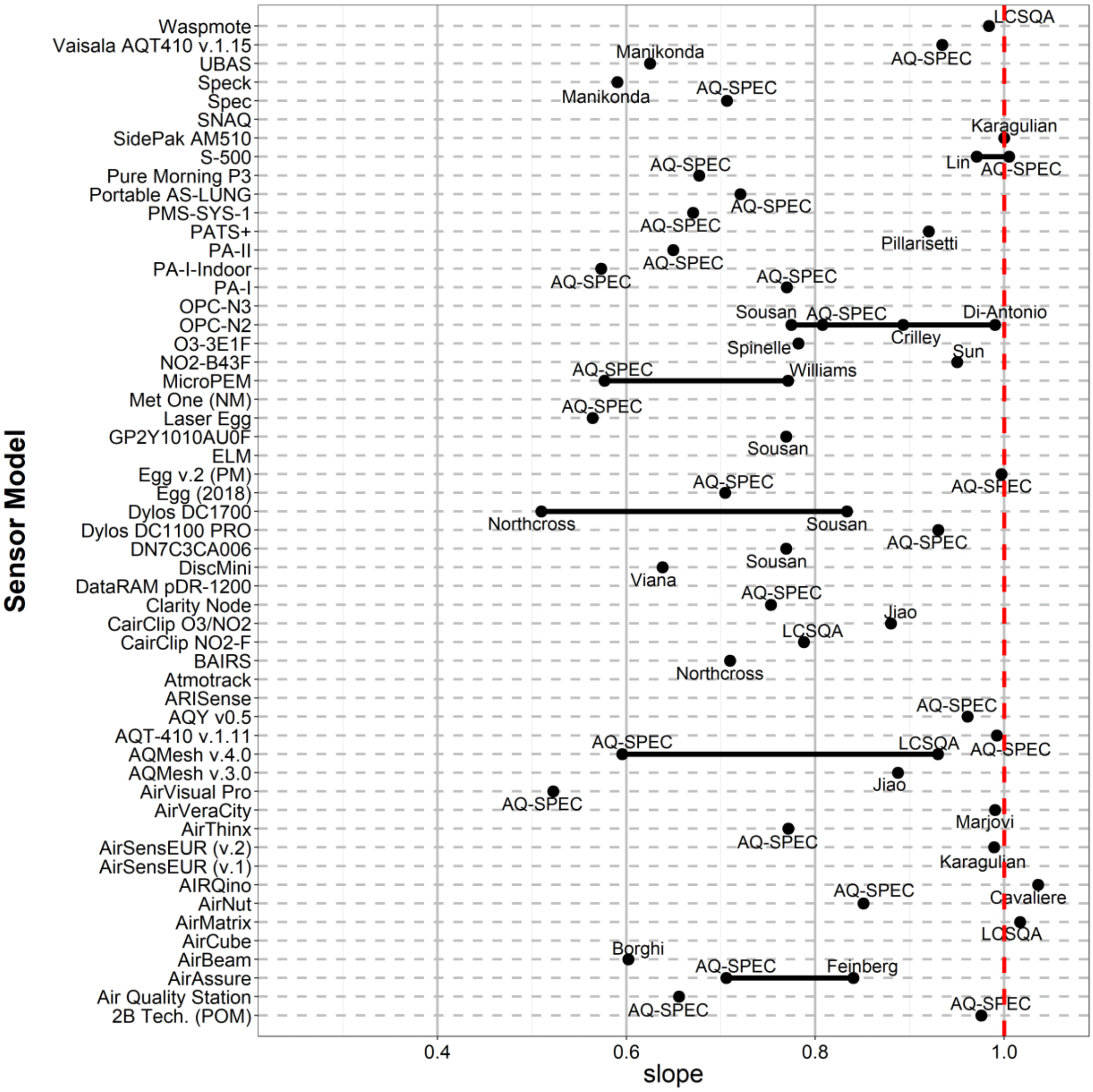

Figure A12. Mean slope obtained from the comparison of LCS against reference measurements.

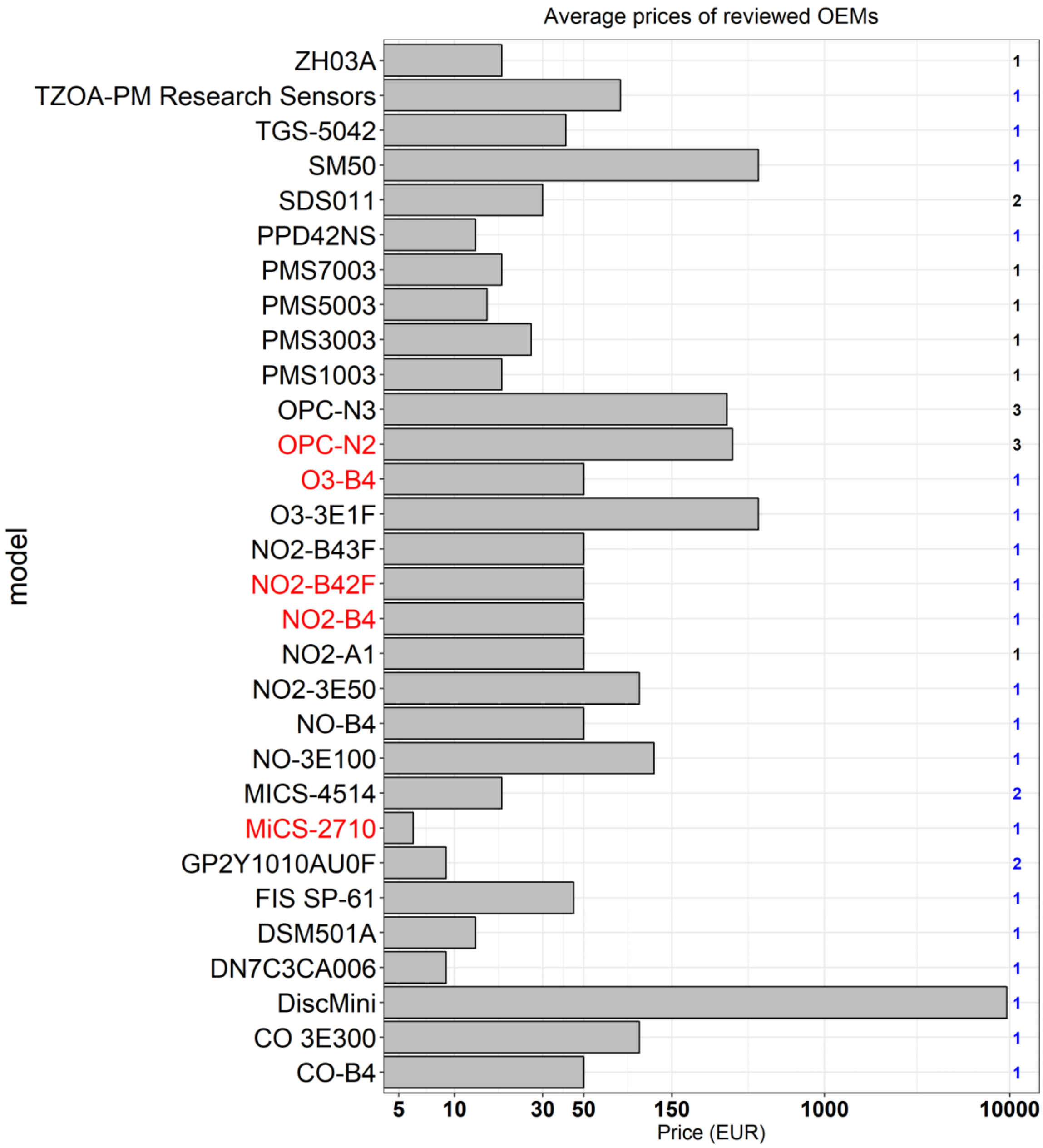

Figure A13. Prices of OEMs grouped by model. Numbers at right indicates the number of pollutants measured by each OEMs, with open source in blue and black box in black. The x-axis uses a logarithmic scale. Names of “living” and “non-living” OEMs are indicated by black and red for the labels on the y-axis, respectively.

Table A4. Shortlist of SSys showing good agreement with reference systems ($R^2 > 0.85$; $0.8 <$ slope < 1.2) for daily data.

Model	Pollutant	Mean	Mean Slope	Mean Absolute Intercept	Open/Close	Living	Commercial	Price (EUR)
PA-I	PM_1	0.99	0.9	0.47	black box	N	commercial	132
PA-II	PM_1	0.99	0.8	1.8	black box	Y	commercial	176
Egg (2018)	PM_1	0.88	0.8	0.33	black box	Y	commercial	219
Egg v.2 (PM)	$PM_{2.5}$	0.94	1	3.3	black box	Y	commercial	246
AirThinx	PM_1	0.89	0.8	1.3	black box	Y	commercial	880
Portable AS-LUNG	PM_1	0.93	0.9	1.5	black box	Y	non-commercial	880
AIRQino	$PM_{2.5}$, PM_{10}	0.91	1	1.1	open source	Y	non-commercial	1000
Air Quality Station	PM_1	0.94	0.9	1.1	black box	Y	non-commercial	1760
AQY v0.5	$PM_{2.5}$	0.91	0.9	4.0	black box	updated	commercial	2640
Vaisala AQT410 v.1.15	CO	0.86	0.9	0.25	black box	Y	commercial	3256

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