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Performance evaluation of twelve low-cost $PM_{2.5}$ sensors at an ambient air monitoring site

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ABSTRACT

A variety of low-cost sensors are now available on the consumer market for measuring air pollutants. The use of these low-cost sensors for ambient air monitoring applications is increasing and includes fence-line or near-source monitoring, community monitoring, emergency response, hot-spot identification, mobile monitoring, epidemiological studies, and supplemental monitoring to improve the spatial-temporal resolution of current monitoring networks. Evaluating and understanding the performance of these devices is necessary to properly interpret the results and reduce confusion when low-cost sensor measurements are not in agreement with measurements from regulatory-grade instrumentation. Systematic and comprehensive field and laboratory studies comparing low-cost sensors with regulatory-grade instrumentation are necessary to characterize sensor performance. This paper presents the results of 12 particulate matter (PM) sensors measurement of $PM_{2.5}$ (particles with aerodynamic diameter less than 2.5 µm) tested under ambient conditions against a federally equivalent method (FEM) instrument at an ambient air monitoring station in Riverside, CA spanning over a 3-year period from 02/05/15 to 03/27/18. Sensors were evaluated in triplicate with a typical time duration of 8-week. Performance evaluation results found 6 of the 12 sensor triplicates with average R^2 values ≥ 0.70 for $PM_{2.5}$ concentrations less than 50 µg/m^3. Within this subset, the Mean Absolute Error (MAE) ranged from 4.4 to 7.0 µg/m^3 indicating the need for caution when interpreting data from these sensors. Additional analysis revealed that the impact of relative humidity on sensor performance varied between models with several models exhibiting increased bias error with increasing humidity. Results indicate that a number of these sensors have potential as useful tools for characterizing $PM_{2.5}$ levels in ambient environments when data is interpreted and understood correctly with regard to existing ambient air quality networks. The performance evaluation results are specific for Riverside, CA under non-repeatable ambient weather conditions and particle properties with the expectation that performance evaluation testing at other locations with different particle properties and weather conditions would yield similar but non-identical results.

1. Introduction

1.1. Particle pollution

Particulate matter (PM) is a ubiquitous environmental pollutant that has been linked to a host of health issues. Fine Particulate matter ($PM_{2.5}$; particles with aerodynamic diameter less than 2.5 µm) have been linked to respiratory illness, cardiovascular disease, stroke, lung cancer, reproductive issues, and premature death (Pope et al., 2002, 2009; Harris et al., 2014; Apte et al., 2015) In 2015, an estimated 4.2 million people died prematurely due to $PM_{2.5}$ exposure putting it in the top five mortality risk factors worldwide (Cohen et al., 2017). Based on modelled data, the World Health Organization (WHO) estimates 92% of people are exposed to $PM_{2.5}$ concentrations exceeding WHO's recommended annual mean of 10 µg/m^3 (World Health Organization, 2016). In addition to health impacts, PM pollution can impair visibility, damage the environment, and cause material damage (Al-Thani et al., 2018; Wu et al., 2018).

PM is regulated by the United States Environmental Protection Agency (U.S. EPA) under the Clean Air Act (U.S. Environmental Protection Agency, 2018). The National Ambient Air Quality Standards (NAAQS) are set to protect public health and the environment. For

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$PM_{2.5}$ concentrations, the NAAQS is set at 12.0 μg/m^3 (annual mean) and 35 μg/m^3 (24-hr daily). Compliance with the NAAQS is determined by stationary ambient air monitoring sites (AMS) utilizing instrumentation operated as U.S. EPA Federal Reference Method (FRM) or Federal Equivalent Method (FEM). Networks of monitoring stations are typically designed to monitor air pollutants at a regional level to determine attainment of the NAAQS at a regional scale. An increasing number of studies have found the spatial and temporal resolution of these regional sites to be insufficient to characterize air pollutants at a community or neighborhood scale for pollutants that exhibit high spatial variability such as traffic-related PM (Apte et al., 2017; Gu et al., 2018; Ye et al., 2018).

1.2. Low-cost sensors

Technological advancements have initiated a paradigm shift in the way air quality data is measured and shared to the public. This shift has been driven by the emergence of "low-cost" sensors for measuring both gas and particle pollutants. Numerous sensor models with prices ranging from $150 to $3000 USD are available to the public with some vendors offering open data access and visualization (Snyder et al., 2013). These low-cost sensors can provide real or near-real time pollutant information at increased spatial resolutions with the potential to complement and expand the capabilities of existing ambient air monitoring networks and provide meaningful measurements at the local scale (Sadighi et al., 2018). While the utility of these measurements depends on the performance of the sensor in a specific environment, sensors with low intra-model variability could be spatially deployed in a community to supplement existing regulatory-grade measurements and obtain hyper local measurements that could support emission reduction strategies such as those that will be designed for the California Assembly Bill (AB) 617. AB 617 was authored, passed, and signed to address the impacts of air pollution in disadvantaged neighborhoods by providing funding for emission reduction strategies and for air pollution monitoring at the local community scale.

Many low-cost sensors are sold to the public with minimal testing, maintenance recommendations, and standard operating procedures (Snyder et al., 2013; Lewis and Edwards, 2016). To date, there have been a limited number of systematic studies using an established protocol to characterize the performance of PM sensors in ambient conditions where end-users are likely to deploy these sensors (Morawska et al., 2018). Without systematic evaluation of the performance of these devices and dissemination of results in an easy-to-understand manner, the consumers are left to making purchasing decisions based on manufacturer marketing strategies, compatibility with cellular devices, exterior appearance of the sensor, and online product reviews. Some examples of marketing quotes for sensors evaluated in this paper include "Most Advanced Air Quality Sensor," "Professional grade, highly accurate indoor/outdoor air quality monitoring system," "Buy the Best Air Pollution Monitor," and "Tested by AQ-SPEC."

Prior published studies have evaluated the performance of several low-cost PM sensors under ambient conditions that are also evaluated in this paper. To the best of our knowledge, these include the AirBeam (Jiao et al., 2016; Mukherjee et al., 2017; Borghi et al., 2018), Alphasense OPC-N2 (Mukherjee et al., 2017; Crilley et al., 2018), PurpleAir (Kim et al., 2019; Magi et al., 2019), and Foobot for indoor air quality (Moreno-Rangel et al., 2018). This represents a small fraction of the PM sensors currently available to consumers and with many of the evaluations performed to evaluate the fit for purpose of a sensor for a specific project or deployment. The U.S. EPA has also evaluated the performance of low-cost sensors in ambient environments using a standard protocol with evaluation results for the TSI AirAssure, AirBeam, Alphasense OPC-N2, and Shinyei PM Evaluation kit which are also evaluated in this work (Williams et al., 2014; Jiao et al., 2016; Feinberg et al., 2018; U.S. Environmental Protection Agency, 2019). While this paper focuses on commercially available end user products, other researchers have evaluated the performance of the Original Equipment Manufacturer (OEM) PM sensors that include Plantower, Shinyei, and Nova Fitness OEM sensors (Austin et al., 2015; Kelly et al., 2017; Badura et al., 2018; Johnson et al., 2018; Zheng et al., 2018; Bulot et al., 2019; Liu et al., 2019; Sayahi et al., 2019; Zamora et al., 2019). A comprehensive review of low-cost sensors technology, applications, and outcomes is available in the literature (Morawska et al., 2018) and a comprehensive review of air sensor performance metrics and targets has been published (Williams et al., 2018). These reviews point out the diversity of work currently being published with differences in performance metrics used, types and duration of performance evaluations, and types of reference equipment by which sensors are evaluated against. This work differs from prior studies in that it presents the results of a large number of PM sensors evaluated in triplicate under a systematic protocol at one location. Many of these sensors have not been previously evaluated for performance and published in the literature.

As low-cost sensors become increasingly popular for both researchers and the general public, characterizing the performance of these sensors and educating the public about their appropriate applications, limitations, and data interpretation has become extremely important. Performance characterization will minimize confusion particularly when low-cost sensors report information that conflicts with data generated from reference-grade instrumentation operated by the local air pollution control districts (APCD). The South Coast Air Quality Management District (South Coast AQMD) established the Air Quality Sensor Performance Evaluation Center (AQ-SPEC; www.aqmd.gov/aq-spec) in mid-2014 to provide the public with unbiased information about the performance of commercially available low-cost sensors. AQ-SPEC performs a systematic and thorough performance evaluation of commercially available sensors in both field- and laboratory-based testing. In the field, air quality sensors are evaluated in triplicate for a period of two months to provide adequate statistical information to evaluate overall sensor performance against reference-grade instrumentation (Polidori et al., 2017). In the laboratory, a state-of-the-art characterization chamber is used to challenge the sensors with known concentrations of particle and gaseous pollutants under controlled environmental conditions (Papapostolou et al., 2017). AQ-SPEC has succeeded in providing potential end users (consumers and scientific researchers) with the necessary information to make informed product selections from a wide variety of commercially available products. This paper presents the field evaluations results of 12 commercially available low-cost PM sensors under ambient conditions as part of the ongoing AQ-SPEC sensor evaluation work. Sensor performance is evaluated systematically according to a documented evaluation protocol.

2. Methodology

2.1. Field deployment

The methods used to evaluate low-cost sensors in the field are described in detail in the AQ-SPEC Field Testing Protocol (Polidori et al., 2017). Briefly, low-cost air quality sensors are evaluated under ambient conditions for an 8-week field deployment at a fully instrumented AMS. Commercialized sensors are typically tested as off-the-shelf and out-of-the-box products without prior modification or calibration (i.e., zero, span). Sensors are operated according to the sensor manufacturer's user guide or manual if available. The low-cost sensors are deployed in triplicate so that intra-model variability can be examined and to provide the ability to detect potential malfunctions or sensor failures in a single unit. Sensors that are ruggedized for inclement weather (designed for ambient air monitoring) are typically mounted outside on the protective railing of the AMS. Sensors that are not ruggedized (designed for indoor air monitoring) are deployed in a custom-built sensor shelter. During the field evaluations, sensors were checked roughly once per week to confirm normal sensor operation and continuous data collection.

2.2. Site location and characteristics

The sensors evaluations took place at the South Coast AQMD Riverside-Rubidoux Air Monitoring Station (RIVR AMS) as part of the ongoing AQ-SPEC sensor evaluations. RIVR AMS, shown in appendix Figure S-1 (a), is a fully equipped regulatory air monitoring station with particulate matter instrumentation operating as FRMs and FEMs. This monitoring station is an inland location that is downwind of the Los Angeles Air Basin and is heavily impacted by transported PM from upwind sources as well as a nearby highway. The nearest major highway to the site is the California State Route 60 (SR-60) located 0.8 km to the north/northeast of the site. In the general vicinity of the station, land use includes apartment complexes and single-family residences, school grounds, retail outlets, and vacant lots. Figure S-2 shows the typical seasonal average chemical composition of $PM_{2.5}$ at RIVR AMS. Ambient $PM_{2.5}$ in this area is mainly comprised of secondary inorganic aerosols (i.e., nitrate, sulfate, ammonia) which accounts for 49–68% of the total $PM_{2.5}$ mass depending on the season. Organic matter is the second major contributor to $PM_{2.5}$ mass in this area (19–32%), followed by elemental carbon (4–10%), crustal material (dust, 4–6%), trace ions (e.g., sodium, potassium; 1–3%), and other trace elements (e.g., arsenic, barium; ~1%) (Hasheminassab et al., 2014).

2.3. Sensor selection and evaluation timing

The 12 commercially available low-cost sensors were tested between February 2015 and March 2018. These sensors vary in cost from approximately \$150 to \$3000 USD. Table 1 provides a description of the 12 sensors with make, model, time resolution, estimated cost, and pollutants measured. Even though several of these sensors are developed for indoor air quality monitoring and not specifically for outdoor ambient monitoring, the evaluation of the technology provides valuable insights into the emerging market of air quality sensors with regards to their use in ambient air monitoring applications.

While more than 12 PM sensors have been evaluated in the AQ-SPEC program, the selection of these 12 sensors was based on whether the sensor is commercially available, measures $PM_{2.5}$ (μg/m^3), tested within the three-year time span, and exhibited acceptable data recovery during the evaluation time period. The sensors were exposed to ambient air for a period of approximately 30–60 days. The timing of the evaluation was dependent on when the sensors were received and when space was available at RIVR AMS or in the sensor shelter.

Table 1
List of sensors evaluated and sensor specifications.

Manufacturer	Model	Pollutants Measured	Time Resolution	Cost
Shinyei	PM Evaluation Kit	$PM_{2.5}$	1-min	\$1000
Alphasense	OPC-N2	$PM_{2.5}$	< 1-min	\$450
TSI	AirAssure	$PM_{2.5}$	5-min	\$1000
Hanvon	N1	$PM_{2.5}$, HCHO	1-min	\$200
Airboxlab	Foobot	$PM_{2.5}$, CO_2, VOC	5-min	\$200
Kaiterra	LaserEgg	$PM_{2.5}$	< 1-min	\$200
PurpleAir	PA-II	$PM_{2.5}$, PM_{10}, $PM_{1.0}$	< 1-min	\$230
HabitatMap	Air Beam 1	$PM_{2.5}$	1-min	\$200
SainSmart	Pure Morning P3	$PM_{2.5}$, CO_2, HCHO	< 1-min	\$170
IQAir	AirVisual Pro	$PM_{2.5}$, CO_2,	< 1-min	\$270
Uhoo	uhoo	$PM_{2.5}$, O_3, NO_2, CO, CO_2, TVOC	1-min	\$300
Aeroqual	AQY	$PM_{2.5}$, O_3, NO_2	1-min	\$3000

2.4. Reference instrumentation

While the RIVR AMS is equipped with both FRM and FEM instrumentation, the performance of the PM sensors selected for this study are evaluated against 1-h FEM measurements of $PM_{2.5}$. The gravimetric FRM 24-h integrated filter mass measurements do not capture the high time resolution of low-cost sensors. For the purposes of this paper, a Met One Beta Attenuation Monitor (BAM), U.S. EPA designated Class III FEM (EQPM-0308-170) for monitoring $PM_{2.5}$, was used to compare against the low-cost sensor measurements. The Met One BAM provides 1-hr average $PM_{2.5}$ concentrations and is shown in Figure S-1 (b & c).

2.5. Principle of operation of particulate matter sensors

The 12 $PM_{2.5}$ sensors evaluated in this paper are categorized as optical sensors with regards to their principle of operation. Optical methods are based on the light scattering of aerosols which is a function of the wavelength of the light source along with the size, composition, and refractive index of the aerosol. Aerosols flow across a focused beam of light and a photodetector records the intensity of the scattered light. These sensors can be categorized into volume scattering devices and optical particle counters (OPCs). In volume scattering devices, light is scattered by the ensemble of particles and detected by a photodetector which provides a single digital or analog output. This output is converted to particle mass concentrations by a prior calibration with a test aerosol and collocation with some reference or research grade instrumentation. In OPCs, the aerosol particles are counted and categorized into distinct size bins. Particle mass concentrations are then calculated based on number, size, and assumptions with regards to the shape, density, and refractive index of the aerosol (Morawska et al., 2018). The OEM sensor manufacturer and/or end-product integrator often develops software algorithms to provide a corrected value for particle mass concentration and consider these algorithms as proprietary technology.

2.6. Sensor shelter

A louvered aluminum shelter was designed and constructed to house and protect the non-ruggedized air quality sensors from inclement weather conditions, such as rain, wind, and direct sunlight. The shelter is shown in appendix Figure S-1 (d & e). The main compartment of the shelter is approximately 1 × 1 × 1 m and designed with louvered vents and a mesh floor to allow for air circulation. The shelter has three aluminum mesh shelves upon which the sensors are placed for the field deployment. The shelter is designed in a manner to provide maximum movement of air through the enclosure and a sensing environment that is near-ambient conditions for pollutants and weather conditions.

2.7. Data analysis

Upon completion of the field deployment, the data was collected and joined for analysis. Data from the sensor triplicate was first validated following basic QA/QC procedures in which obvious time-series outliers, negative values, continuing zeros, and invalid data points (text, symbols, and blanks) were removed. Obvious time-series outliers were typically extremely high values that were found to be outside of the measurement range of a sensor or outside the bounds of typical ambient $PM_{2.5}$ concentrations. The remaining data were then averaged over 1-h time intervals and matched by date and time to the hourly FEM BAM $PM_{2.5}$ data. Data recovery of at least 75% of the sub hourly raw sensor data was required for a 1-hr average data point to be considered valid. The 1-hr average reduces the noise associated with measurements at shorter time resolutions.

Statistical analysis was conducted on the 1-hr time matched data to examine data completeness, intra-model variability, least-squares linear regression statistics, measurement error, and impact of environmental conditions. Following the data recovery calculations, the 1-hr time matched data sets were subjected to two data reduction filters to improve inter- and cross-model comparability. First, all rows with a missing $PM_{2.5}$ concentration for either the reference instrument or one of the three sensors was dropped from further analysis. Secondly, as regression statistics can be dependent on the range of PM experienced during the evaluation, data rows where the FEM BAM $PM_{2.5}$ concentration exceeded 50 μg/m^3 were removed from further analysis. The $PM_{2.5}$ concentration of 50 μg/m^3 was selected to include nearly four average standard deviations (8.9 μg/m^3) from the mean of means BAM $PM_{2.5}$ concentration (14.2 μg/m^3, Tables S–1) experienced during the 12 evaluations periods. This filter excludes only a small fraction (< 3% filtered per data set) and improves the comparability between the sensor evaluations. The equations for data recovery are provided in the appendix as Eq. S-1 and S-2.

Intra-model variability within a triplicate of sensors is defined as the degree to which the three sensors agree with one another. This is determined by calculating the mean $PM_{2.5}$ concentrations as measured by individual sensors within a triplicate and comparing with the mean of means and standard deviation (SD) for the mean of means. The SD for the mean of means provides a metric for intra-model variability. A high SD for the mean of means indicates high intra-model variability whereas a low SD indicates low intra-model variability.

Accuracy is defined as the degree to which the 1-hr average $PM_{2.5}$ concentrations generated from the low-cost sensors conforms to the $PM_{2.5}$ measurements from the FEM BAM instrument. Accuracy can be examined by looking at the regression statistics and measurement error between sensor and reference instruments. When reviewing the slope and intercept of the best fit line for determining accuracy, the importance of the R^2 statistic must not be overlooked. The least squares linear regression provides a best fit linear equation that is shown in Eq. S-3. In an ideal situation where the sensor perfectly matches the reference grade instrumentation, the slope (m) would be 1.0, intercept (b) 0.0, and the coefficient of determination (R^2) would be at or near 1.0. The R^2 statistic measures the scatter of the data points around the fitted linear regression line and provides a measure for how strongly variations in sensor-generated $PM_{2.5}$ concentrations are related to variations in BAM-generated $PM_{2.5}$ concentrations. When the R^2 value is below a certain threshold ($R^2 < 0.70$ for the purposes of this paper), examining the slope and intercept values to determine accuracy is not relevant due to the magnitude of scatter around the best fit line.

Mean Bias Error (MBE) and Mean Absolute Error (MAE) are calculated in similar fashion with the MAE taking the absolute value of the hourly differences between the sensor and BAM measurements. The MBE between the sensor and the reference BAM instrument provides a metric that indicates the tendency of the sensor to either under- or over-estimate the reference $PM_{2.5}$ mass concentrations. The units of both MBE and MAE are calculated in μg/m^3 which is identical to the units of measurement for both sensor and FEM instrument. This provides a hands-on way to visualize the error especially with regards to identifying the cause of the error when reviewing the linear regression results. Care must be taken with the MBE statistic as over-estimated errors will cancel out under-estimated errors in the calculation of MBE. The MAE provides a better metric for actual measurement error between sensor and reference. The equations for MBE and MAE are found in equations (1) and (2), respectively. The Root Mean Square Error (RMSE) statistic is an additional metric for looking at the measurement error with the RMSE being disproportionately impacted by large errors. The equation for RMSE is found in equation (3).

$$\text{Mean Bias Error (MBE)} = \frac{1}{n}\sum_{i=1}^{n}(X_i - X_t) \tag{1}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\sum_{i=1}^{n}|(X_i - X_t)| \tag{2}$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - X_t)^2}{n}} \tag{3}$$

Where,

X_i is the 1-hr average measurement by the low-cost sensor
X_t is the 1-hr average measurement provided by the FEM $PM_{2.5}$ Met One BAM
n is the number of 1-hr time-matched data pairs

Some of the sensors have unique data recovery situations or unique methods for reporting data that require further attention and analysis. Due to a sensor malfunction, the Uhoo #2 sensor had a low data recovery of 47.2% and was therefore excluded from subsequent data analysis. The Purple Air PA-II has two OEM sensors and reports two similar but non-identical $PM_{2.5}$ concentrations. Data from these two OEM sensors were time matched and then averaged to provide a single $PM_{2.5}$ concentration per PA-II to compare with the reference instrumentation. The CF = atm measurement was selected for the Purple Air sensor based on the OEM sensor manufacturer's, Plantower, recommendation for ambient measurements according to their manual (Yong and Haoxin, 2016).

3. Results and discussion

3.1. Field conditions and data recovery

Twelve sensors were evaluated during specific and unique time periods taking place over three years: 02/05/15 to 03/27/18. The actual time periods of the evaluations are random and take place as the AQ-SPEC program receives sensors to evaluate and space is available in the sensor shelter. The ambient environment under which each triplicate of sensors is evaluated is characterized by specific, non-repeatable conditions for aerosol particles (size, count, shape, refractive index, speciation, and mass distribution) and climate conditions (temperature, relative humidity, wind, precipitation, etc.). Tables S–1 in appendix provides a summary of the field conditions for temperature, relative humidity, and hourly BAM FEM $PM_{2.5}$ mass concentrations experienced for the 12 distinct evaluation periods. The mean ambient temperature varies between the 12 evaluations and ranges between 12.3 and 25.2 °C indicating that seasonality differences in temperature do exist between the individual sensor evaluations. The mean RH between the 12 evaluations ranges from 48.1 to 67.9% with a mean of means at 54.3 ± 5.3%. The average SD for RH for the individual evaluations is ± 23.3% RH indicating that while moderate seasonal differences in RH exists between evaluations, the individual evaluations experienced a wide range of RH conditions. The BAM $PM_{2.5}$ mean concentration for the 12 evaluations ranged from 11.1 to 17.2 μg/m^3 with a mean of means at 14.2 ± 2.0 μg/m^3. The average SD for $PM_{2.5}$ individual evaluation periods is 8.9 μg/m^3 indicating that while moderate seasonality differences in $PM_{2.5}$ exist, the individual evaluation periods experienced a range of $PM_{2.5}$ concentrations. The max $PM_{2.5}$ values experienced during the 12 evaluations varied significantly between evaluations with max hourly concentrations ranging from 38 to 133 μg/m^3 indicating the need to filter out these higher $PM_{2.5}$ events to maintain a consistent concentration range between the evaluations.

The 1-hr average data recovery for the sensor triplicates is high with recovery > 79% for all sensors with most sensors nearing 99% data recovery as shown in Tables S–1. After processing the hourly matched data points for missing values (sensor triplicate or reference) and filtering out values for BAM $PM_{2.5}$ concentrations > 50 μg/m^3, the number of hourly matched data points (n) varied between the 12 evaluations ranging between 732 and 1917 data points with data recovery ranging from 71 to 98%.

Table 2
Summary statistics and intra-model variability for sensor triplicates.

	Sensor				Reference
	Mean ± SD (μg/m^3)			Mean of Means	BAM $PM_{2.5}$
Sensor	1	2	3	Mean ± SD (μg/m^3)	Mean ± SD (μg/m3)
Shinyei PM Evaluation Kit	14.8 ± 13.1	14.6 ± 12.7	13.0 ± 11.5	14.1 ± 0.80	15.2 ± 12.3
Alphasense OPC-N2	14.3 ± 6.2	10.1 ± 6.1	11.4 ± 7.0	11.9 ± 1.74	15.6 ± 6.6
TSI AirAssure	15.6 ± 13.4	17.4 ± 13.0	16.7 ± 12.4	16.6 ± 0.75	13.2 ± 11.3
Hanvon N1	32.0 ± 21.7	30.5 ± 19.7	27.6 ± 17.3	30.0 ± 1.80	15.2 ± 10.3
Airboxlab Foobot	19.7 ± 10.3	17.3 ± 8.6	24.0 ± 10.3	20.3 ± 2.75	14.4 ± 6.4
Kaiterra LaserEgg	15.6 ± 9.2	13.5 ± 8.2	12.9 ± 8.0	14.0 ± 1.16	14.0 ± 6.1
PurpleAir PA-II	16.9 ± 19.1	16.5 ± 18.6	16.7 ± 18.0	16.3 ± 0.13	12.1 ± 11.3
HabitatMap Air Beam 1	14.1 ± 9.3	17.0 ± 12.8	18.0 ± 14.5	16.4 ± 1.64	11.1 ± 6.6
SainSmart Pure Morning P3	14.6 ± 12.2	15.7 ± 12.8	14.7 ± 10.6	15.0 ± 0.51	11.1 ± 6.6
IQAir Air Visual Pro	17.5 ± 10.2	17.6 ± 10.2	20.7 ± 11.4	18.6 ± 1.51	17.2 ± 7.3
Uhoo	32.6 ± 14.9	–	20.1 ± 11.0	26.3 ± 6.23	17.1 ± 7.3
Aeroqual AQY	9.8 ± 11.5	9.7 ± 11.7	9.3 ± 10.8	9.6 ± 0.24	13.8 ± 14.4

3.2. Summary statistics and intra-model variability

Table 2 provides summary statistics with mean $PM_{2.5}$ concentrations measured for the three sensors, the mean of means, and the ± SD around the mean of means which provides a metric for intra-model variability. Four sensors, namely Aeroqual AQY, Purple Air PA-II, SainSmart P3, and TSI Air Assure, indicate low intra-model variability with the SD less than 0.75 with regards to the mean of means. Three sensors, namely the Laser Egg, Shinyei PM evaluation kit, and IQAir AirVisual Pro, indicate low to moderate intra-model variability with $0.76 \leq SD \leq 1.5$. Four sensors, namely Alphasense OPC-N2, Air Beam 1, Foobot, and Hanvon N1, indicate moderate to high intra-model variability with $1.51 \leq SD \leq 2.75$. The Uhoo indicates high intra-model variability with SD at ± 6.23.

3.3. Least squares linear regression and measurement error

Least squares linear regression was performed for each sensor within a triplicate with the results shown in Table 3. Six of the 12 sensors were found to have a triplicate average of $R^2 \geq 0.70$ and will be discussed further with regards to slope/intercept for accuracy. Four sensors, namely Aeroqual AQY, Purple Air PA-II, Sainsmart P3, and the Shinyei PM Evaluation kit indicated high linearity with $R^2 \geq 0.75$ and two sensors, namely TSI Air Assure and Air Visual pro, indicated linearity with $0.70 \geq R^2 \geq 0.74$. With regards to slope as a measure for accuracy, four of these six sensors, namely Aeroqual AQY, Shinyei PM Evaluation kit, TSI Air Assure, and IQAir Air Visual Pro, were found to have slope values within ± 0.25 of the 1.0 ideal value. The Purple Air PA-II and the SainSmart P3 were found to generally overestimate FEM $PM_{2.5}$ concentrations by roughly 50% with slope values between 1.31 and 1.68. With regards to intercept value as a measure for accuracy, three sensors, namely the Sainsmart P3, Shinyei, and IAQir Air Visual Pro were found to have intercept values $|b| < 2.5$ from the ideal 0.0 value. The remaining three sensors, namely the Aeroqual AQY, Purple Air PA-II, and TSI AirAssure, were found to have higher intercept values ranging from $2.6 < |b| < 4.0$.

The calculated measurement errors (MBE and MAE) between sensors and the BAM $PM_{2.5}$ measurements are shown in Table 3. Four sensors, namely the Aeroqual AQY, Kaiterra LaserEgg, Shinyei PM Kit, and IQAir AirVisual Pro, have MAE near or less than 5 μg/m^3. Five sensors, namely the Alphasense OPC, Air Beam 1, Purple Air PA-II, Sainsmart P3, and the TSI Air Assure, have MAE in the 5–7.5 μg/m^3 range. Three sensors, namely the Foobot, Hanvon N1, and the Uhoo, have MAE greater than 7.5 μg/m^3. For 8 of the 12 sensors, namely the Aeroqual, Foobot, Alphasense OPC, AirBeam 1, Hanvon N1, Purple Air PA-II, SainSmart P3, and TSI Air Assure, the proportion of MBE to MAE is greater than 0.65 indicating that the predominant error associated with these sensors is systematic in nature rather than random. Accounting for this systematic bias error could significantly reduce the measurement errors associated with low-cost sensors.

Several interesting observations can be made with regards to the regression statistics and measurement errors. The Aeroqual AQY bias error (triplicate average: 3.1 μg/m^3) is strikingly close to the linear regression intercept values (triplicate average: 2.8 μg/m^3) indicating that the sensor may suffer from a zero offset and that correcting for this offset may potentially reduce measurement error. For the Hanvon N1, the MBE accounts for over 95% of the MAE indicating a strong positive bias error which is confirmed with slope values > 1.73 with the sensor often overestimating BAM $PM_{2.5}$ concentrations by over 100%. The Kaiterra Laser Eggs regression statistics show near ideal slope and intercept values, but the R^2 was found to be less than 0.60. The MBE/MAE ratio for the Laser Eggs is less than 0.5 indicating that the measurement error is dominated by random error rather that systematic or bias error. This sensor highlights the importance of evaluating accuracy not only on slope/intercept values, but also with the R^2 statistic and measurement error to gain a more comprehensive understanding of sensor performance.

3.4. Comparison of results with previous sensor evaluations

Sensor performance evaluations from prior studies often differ with regards to methodology with differences in geographic locations, length of evaluation, meteorological conditions, particle properties, reference instrumentation, and purpose of evaluation. The most comparable sensor evaluations to this work have been performed by the U.S. EPA according to a standard protocol at a reference air monitoring site with non-ruggedized sensors housed in a sensor shelter. The comparison between the results of the AQ-SPEC and U.S. EPA sensor evaluations for the TSI AirAssure, Habitat Map AirBeam, Alphasense OPC-N2, and the Shinyei PM evaluation kit are provided in Table 4. The differences in slope, intercept, and correlation between these distinct geographic locations indicate that sensor performance may vary by geographic regions that experience different concentration ranges and aerosol optical properties (Feinberg et al., 2018).

The AirBeam and Alphasense OPC-N2 were also evaluated in Cuyama Valley, CA against a Grimm 11-R for 12 weeks. Average regression statistics for the AirBeam were slope of 0.38, intercept of 4.1, and R^2 of 0.66 and for the Alphasense OPC-N2 were slope of 0.14, intercept of 2.5, and R^2 of 0.41 for hourly data (Mukherjee et al., 2017). While the correlations are similar to the results presented in this study, the slope/intercepts between evaluations differ with the AirBeam overestimating $PM_{2.5}$ in Riverside and underestimating it in the Cuyama Valley. While both studies found the Alphasense OPC-N2 to underestimate $PM_{2.5}$ concentrations, the magnitude of the negative bias

Table 3
Linear Regression Statistics and measurement error for sensor triplicates.

Sensor			Slope		Intercept		Measurement Error (μg/m^3)		
	#	R^2	Slope	95% CI	Intercept	95% CI	MBE	MAE	RMSE
Shinyei PM Evaluation Kit	1	0.75	1.18	0.04	−1.48	0.59	0.9	4.5	6.8
	2	0.73	1.13	0.04	−1.07	0.60	0.7	4.5	6.7
	3	0.75	1.03	0.03	−1.29	0.52	−0.9	4.2	5.8
Alphasense OPC-N2	1	0.67	0.78	0.04	2.08	0.67	−1.3	3.3	4.1
	2	0.38	0.57	0.05	1.18	0.90	−5.5	6.5	7.8
	3	0.40	0.67	0.06	1.03	1.01	−4.2	5.9	7.2
TSI AirAssure	1	0.73	1.10	0.04	1.61	0.60	2.9	5.1	7.6
	2	0.74	1.08	0.03	3.66	0.57	4.7	6.0	8.2
	3	0.72	1.01	0.03	3.81	0.56	4.0	5.6	7.6
Hanvon N1	1	0.56	2.13	0.10	0.91	1.71	17.4	18.1	24.1
	2	0.54	1.91	0.10	2.69	1.59	15.9	16.3	21.9
	3	0.58	1.73	0.08	2.39	1.34	13.1	13.5	18.1
Airboxlab Foobot	1	0.57	1.32	0.06	0.28	1.00	5.0	6.4	8.6
	2	0.54	1.08	0.05	1.35	0.86	2.6	4.7	6.4
	3	0.54	1.29	0.07	4.89	1.03	9.2	9.5	11.7
Kaiterra LaserEgg	1	0.57	1.15	0.06	−0.08	0.95	2.0	4.7	6.4
	2	0.56	1.02	0.06	−0.40	0.85	−0.1	4.1	5.4
	3	0.58	1.01	0.06	−0.80	0.82	−0.7	4.0	5.2
PurpleAir PA-II	1	0.95	1.68	0.03	−3.06	0.51	5.0	7.0	10.6
	2	0.95	1.63	0.03	−2.84	0.49	4.7	6.7	10.0
	3	0.95	1.58	0.03	−2.08	0.48	4.8	6.7	9.7
HabitatMap Air Beam 1	1	0.59	1.08	0.05	2.03	0.63	2.9	4.4	6.6
	2	0.57	1.47	0.07	0.46	0.90	5.7	6.5	10.6
	3	0.57	1.66	0.08	−0.62	1.01	6.8	7.5	12.4
SainSmart Pure Morning P3	1	0.76	1.52	0.05	−2.34	0.69	3.5	5.3	7.8
	2	0.77	1.61	0.05	−2.19	0.70	4.6	5.9	8.8
	3	0.74	1.31	0.05	0.06	0.62	3.5	5.0	6.8
IQAir AirVisual Pro	1	0.69	1.15	0.04	−2.38	0.73	0.2	4.4	5.8
	2	0.69	1.16	0.04	−2.42	0.73	0.3	4.4	5.8
	3	0.72	1.31	0.04	−1.97	0.77	3.4	5.3	7.3
Uhoo	1	0.00	0.09	0.11	31.11	2.03	15.4	17.7	22.4
	2	–	–	–	–	–	–	–	–
	3	0.00	0.02	0.08	19.74	1.51	2.9	10.1	13.5
Aeroqual AQY	1	0.78	0.99	0.02	−2.75	0.39	−2.9	4.5	6.1
	2	0.79	1.01	0.02	−3.08	0.38	−3.0	4.7	6.2
	3	0.79	0.94	0.02	−2.63	0.35	−3.4	4.6	6.1

was larger in the Cuyama Valley than in Riverside. In a long-term performance evaluation of the Purple Air PA-II sensor against a Met One BAM 1020 in Charlotte, North Carolina, regression statistics found slope at 2.2, intercept at 1.3, and R^2 at 0.54 (Magi et al., 2019). These long-term evaluation results differ from the findings in this study with 2-month evaluation average regression statistics finding a slope of 1.63, intercept of −2.66, and R^2 of 0.95. This significant difference between studies indicates that the length of the evaluation may also impact correlation against reference monitors especially if a sensor degrades or malfunctions during a long-term evaluation.

3.5. Impact of environmental conditions on bias error

A contributing factor for diminishing performance of low-cost

Table 4
Comparison between published sensor evaluation results.

	South Coast AQMD			U.S. EPA			U.S. EPA		
Location	Riverside, California			Denver, Colorado			Atlanta, Georgia		
Reference				Feinberg et al. (2018)			Jiao et al. (2016)		
Comparison Instrument	Met One BAM 1020			Grimm 180 EDM			Met One BAM 1020		
Time-period	~8 weeks			Long-term			> 30 days		
Time Average	1-HR			1-HR			12-HR		
	Avg Regression Stats			Avg Regression Stats			Avg Regression Stats		
Sensor	Slope	Intercept	R^2	Slope	Intercept	R^2	Slope	Intercept	R^2
TSI AirAssure	1.06	3.03	0.73	1.15	0.41	0.63	–	–	–
Habitat Map AirBeam	1.40	0.62	0.58	–	–	0.69	–	–	0.43
Alphasense OPC-N2	0.67	1.43	0.48	0.47	−1.48	0.16	–	–	–
Shinyei PM Evaluation Kit	1.11	−1.28	0.74	0.56	0.52	0.51	0.72	7.48	0.36

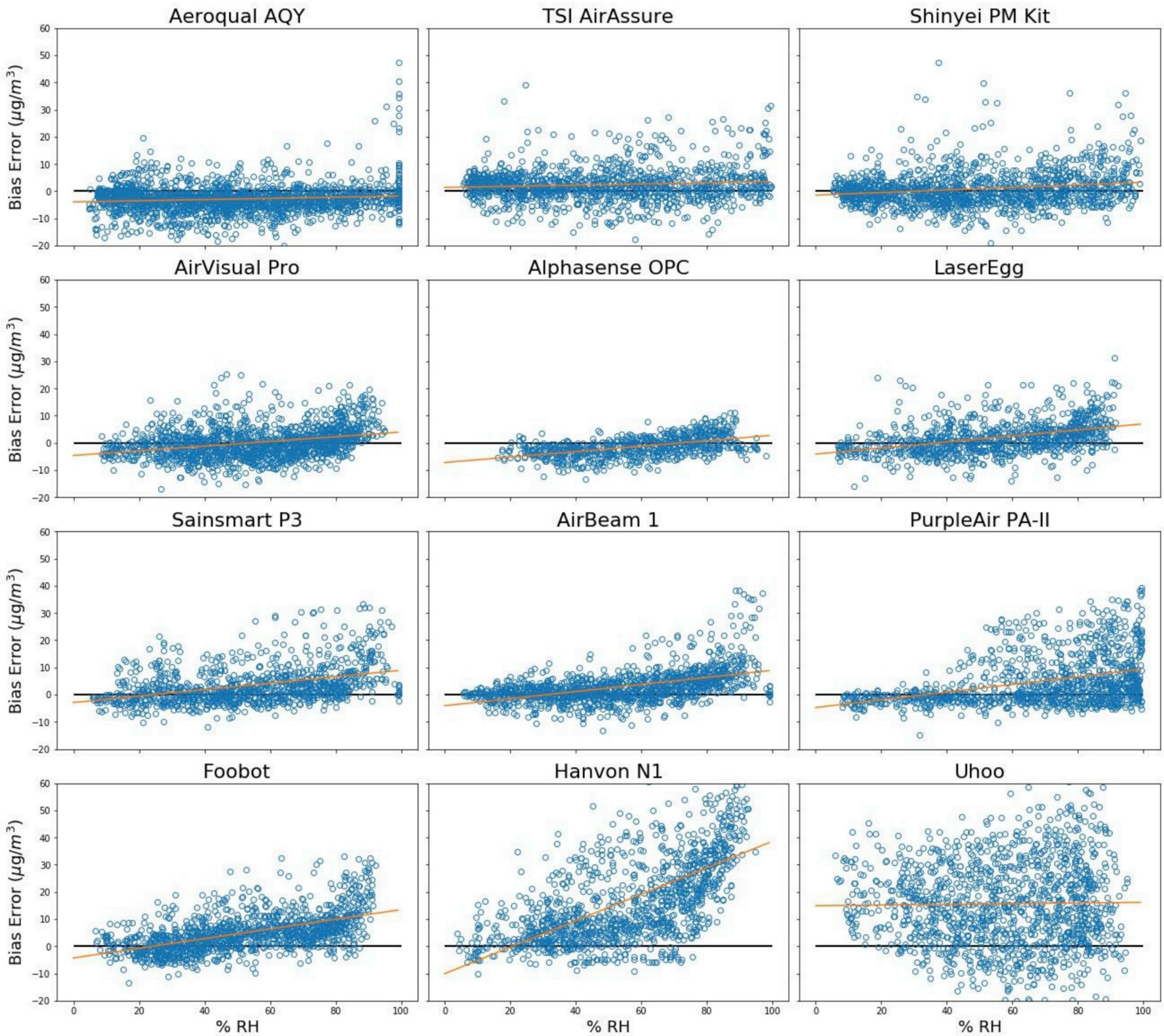

Fig. 1. Impact of Relative Humidity (RH) on the bias error between Sensor and Met One BAM.

sensors when compared against reference instrumentation is due to the impact of RH (Jayaratne et al., 2018). Some low-cost optical methods adjust or calibrate in real-time for the impacts of RH on the conversion from particle count to particle mass concentration (Hojaiji et al., 2017; Di Antonio et al., 2018). While the BAM FEM monitor is equipped with a heater to condition the aerosol to a set temperature and RH prior to sampling, the low-cost sensors measure PM at ambient temperature and RH. To examine the potential impact of RH on sensor response, hourly bias errors were plotted against the hourly RH for all 12 sensors (Fig. 1). Ideally, the slope of the best fit line would be zero and would be located on the y = 0 axis. The bias error by RH plot for the Aeroqual AQY, TSI AirAssure, and the Shinyei indicate that these sensors are not strongly impacted by increasing RH. The remaining 9 sensors, except for the Uhoo, indicate increasingly positive bias error as RH increases and are ordered from left to right and top to bottom by magnitude of slope of best fit line.

Addressing and correcting for the impact of RH on these optical devices, by either advancing OPC hardware or by developing software corrections algorithms for RH, would likely result in a reduction in the measurement error associated with low-cost sensors. Care should be taken when developing these software correction algorithms so that the model or algorithm developed is based on scientifically relevant inputs (i.e. ambient Temperature and RH collected in real-time) so as not to over-fit the models to limited training data sets and to ensure that the measurement is still a measurement (Hagler et al., 2018). Extensive field testing to capture seasonal variabilities for temperature and RH will help tremendously towards understanding the impacts of RH on low-cost optical particle counters. Additionally, laboratory testing with a sophisticated heating, ventilation, and air conditioning (HVAC) system to control temperature, RH, and the particles environment can provide valuable insights into the impacts of local weather conditions and interferants on these devices (Papapostolou et al., 2017).

To examine the potential impact of $PM_{2.5}$ concentrations on sensor response, hourly bias errors were plotted against the hourly BAM $PM_{2.5}$ for all 12 sensors (Fig. 2). No consistent trends are seen across the 12 sensors as $PM_{2.5}$ concentrations increase. Individually though, Fig. 2 provides a telling story of where shifts between systematic and random measurement error occur along the $PM_{2.5}$ measurement range. For example, the Purple Air sensor indicates predominant random error between 0 and 12 μg/m^3 with scatter almost evenly distributed between positive and negative bias. However, between 13 and 50 μg/m^3 the sensor indicates systematic positive bias error. On the other hand, the Aeroqual AQY indicates systematic negative error that increases as concentrations rise from 0 to 25 μg/m^3. Above 25 μg/m^3, the Aeroqual

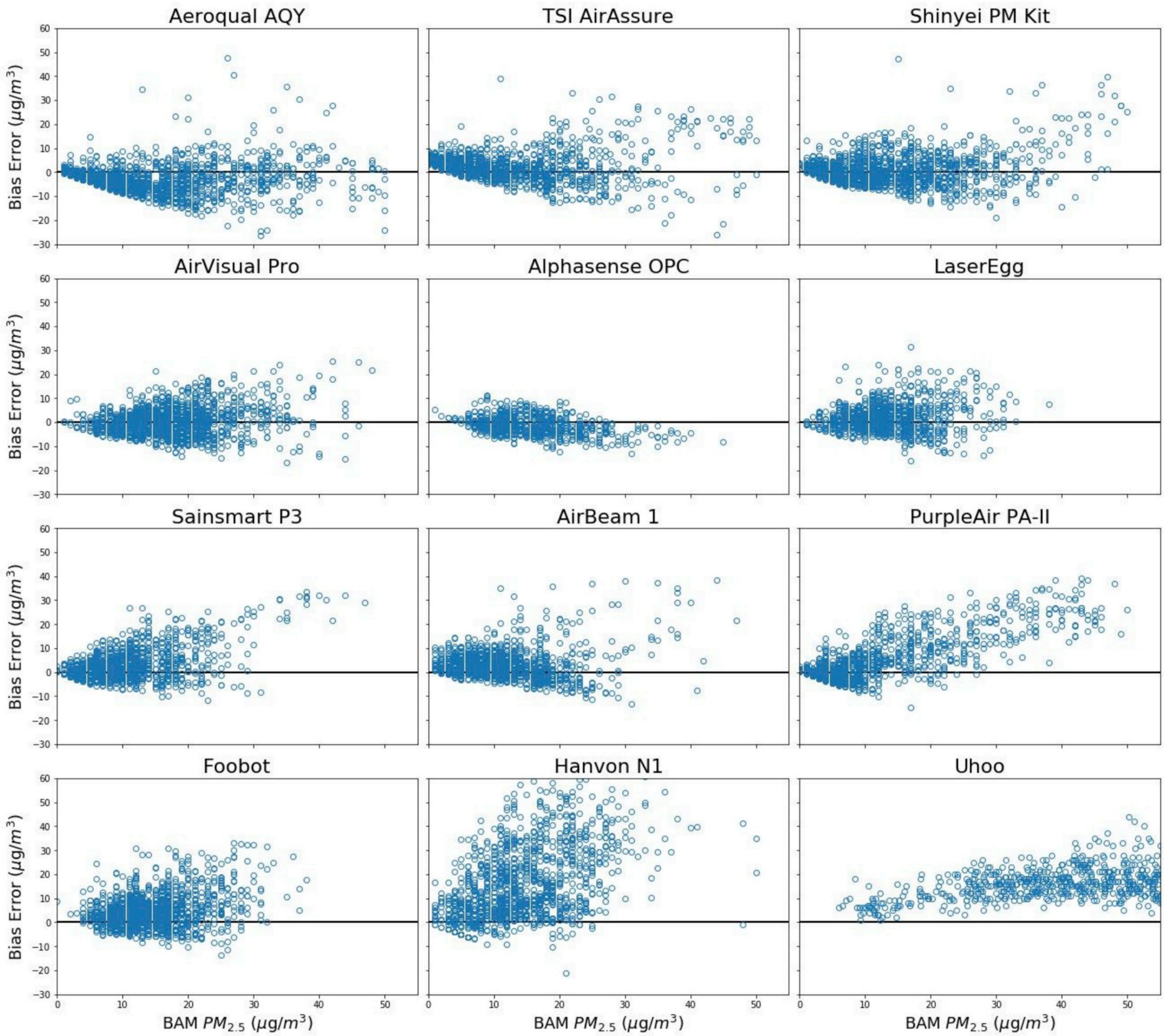

Fig. 2. Impact of PM concentration on the bias error between Sensor and Met One BAM.

AQY bias is scattered around the y = 0 line indicating random error. The Shinyei PM kit, AirVisual Pro, and Laser Egg indicate measurement error dominated by random error with scatter evenly distributed between positive and negative bias. These sensors also exhibit lower MBE/MAE ratios. Understanding when measurement error shifts between systematic and random error, can provide insights on how to model sensor response to regulatory-grade equipment. It should be noted that these observations are limited to the $PM_{2.5}$ concentration range of 0–50 μg/m^3 and sensors may behave differently outside of this range.

3.6. Limitations and future work

Evaluating the performance of low-cost air quality sensors has limitations that must be acknowledged and understood. First, the ambient field environment is specific to location, time of year, weather conditions, and the pollutant physical/chemical properties experienced during the evaluation. The ambient environment experienced by a sensor within an evaluation time period cannot be controlled or duplicated for subsequent tests. The results of this limited evaluation provide an indication of the sensors performance under specific conditions at the RIVR AMS. A performance evaluation of a sensor under different environmental conditions and particle properties would likely provide similar but non-identical results. To address these limitations of field performance evaluations, sensors that perform well in the field are submitted to the AQ-SPEC laboratory for testing in a characterization chamber (Papapostolou et al., 2017). Secondly, a number of the sensors evaluated are designed for indoor air quality and are not ruggedized for ambient monitoring. These non-ruggedized sensors are installed inside an aluminum shelter enclosure which protects the units from ambient weather conditions. While the enclosure minimizes the effect of extreme weather conditions and is designed to provide a near ambient environment, the shelter environment is not identical to the ambient environment sampled by the FEM BAM $PM_{2.5}$ instrument.

The future development of performance targets for low-cost air quality sensors would drive technology advancement and provide a pathway to generate an increase in understanding and trust in low-cost sensors. A sensor certification program could perform more rigorous field testing that incorporates multiple sites across the country and multiple seasons in a testing protocol similar to the process for instruments to achieve designation as a FRM or FEM. Rigorous field testing for PM sensors in various environments would be necessary as generating an aerosol environment in a laboratory identical to a local aerosol environment (e.g., in terms of particle count, shape, refractive index, speciation, source, size and mass distribution) is extremely difficult. A certification program with more rigorous field and laboratory studies can enhance the current understanding of how particle composition can impact low-cost sensor performance with understanding how these optical methods respond in environments dominated by regional specific aerosols like inland dust, course silt, coastline sea salt, secondary organic aerosol, and other regional specific aerosol compositions. A certification center could provide guidance and catalyze the evolution of this technology, identify key data quality indicators, set performance requirements, and increase trust in data generated by low-cost sensors.

4. Conclusions

This paper presents the results of 12 low-cost $PM_{2.5}$ sensors against reference instrumentation at the South Coast AQMD RIVR AMS in Southern California. The sensor products range in price from $150 to $3000 USD with varying performance for intra-model variability, linear regression statistics, and measurement errors. The high correlation coefficients between sensors and the FEM BAM indicate that a number of these low-cost units track the ambient PM concentrations of regulatory monitors well. For sensors that are highly correlated to the FEM BAM, the slope and intercept offsets of the regression statistics indicate that refinement or calibration of the sensors could be performed to improve sensor performance and reduce measurement error. Additionally, sensors with a high MBE/MAE ratio are impacted predominantly by systematic error which could potentially be accounted for to reduce measurement error. The impacts of environmental conditions (RH and PM concentration) were investigated and indicate that the bias error for many low-cost optical particulate sensors on the market are impacted by changing environmental conditions. Future development by sensor manufacturers and sensor integrators that address the positive bias error associated with RH will likely produce sensors with less measurement error and that generate higher trust in data collected. Not accounting for RH effects may lead to the collection of measurements with a large bias error and may limit the usefulness of these low-cost sensors and collected data. Due to the need for slope/intercept and potential RH corrections for some sensors, the actual utility of these devices may be limited to those who have access to reference grade instrumentation and the data science skill set to develop models and algorithms to correct the data. The technical requirements to develop and apply these corrections in real-time can potentially remove the usefulness of this technology from potential end-users and limit usefulness to those that are trained and able to perform the required corrections. For use by non-experts, low-cost sensors should be easily operated, installed, configured, and provide data with low measurement errors.

The overall state of the technology for measuring PM is improving and commercially available products have the potential to provide meaningful results to citizen scientists, communities, researchers, and regulatory agencies. As the market continues to expand, air quality measurement techniques and methodology is changing dramatically. Validating the performance of these sensors is a critical step as this new paradigm of low-cost sensing takes effect. The potential applications for low-cost sensors are vast and properly characterizing of the performance of these devices will provide insights into interpreting their results and reduce confusion especially when low-cost sensor data does not agree with regulatory-grade instrumentation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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