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# Unexpected Performance Improvements of Nitrogen Dioxide and Ozone Sensors by Including Carbon Monoxide Sensor Signal

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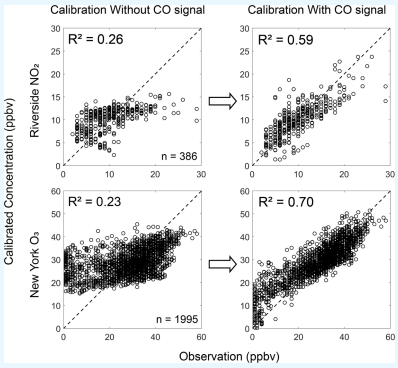
**ABSTRACT:** Low-cost air quality (LCAQ) sensors are increasingly being used for community air quality monitoring. However, data collected by low-cost sensors contain significant noise, and proper calibration of these sensors remains a widely discussed, but not yet fully addressed, area of concern. In this study, several LCAQ sensors measuring nitrogen dioxide ($NO_2$) and ozone ($O_3$) were deployed in six cities in the United States (Atlanta, GA; New York City, NY; Sacramento, CA; Riverside, CA; Portland, OR; Phoenix, AZ) to evaluate the impacts of different climatic and geographical conditions on their performance and calibration. Three calibration methods were applied, including regression via linear and polynomial models and random forest methods. When signals from carbon monoxide (CO) sensors were included in the calibration models for $NO_2$ and $O_3$ sensors, model performance generally increased, with pronounced improvements in selected cities such as Riverside and New York City. Such improvements may be due to (1) temporal co-variation between concentrations of CO and $NO_2$ and/or between CO and $O_3$; (2) different performance levels of low-cost CO, $NO_2$, and $O_3$ sensors; and (3) different impacts of environmental conditions on sensor performance. The results showed an innovative approach for improving the calibration of $NO_2$ and $O_3$ sensors by including CO sensor signals into the calibration models. Community users of LCAQ sensors may be able to apply these findings further to enhance the data quality of their deployed $NO_2$ and $O_3$ monitors.

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## ■ INTRODUCTION

Exposure to ambient air pollution is one of the most significant environmental health risk factors worldwide.[1−3] Air pollution exposures are associated with numerous adverse health effects, ranging from minor discomfort to increased mortality.[4−10] Traditional urban air quality management and many previous air pollution health studies have relied heavily on reported pollutant concentrations at sparse locations using monitors that are designated federal reference methods (FRM) or federal equivalent methods (FEM). These instruments have been extensively evaluated using strict testing protocols[11] and can provide reliable measurement data. However, FRM/FEM instruments are generally bulky, expensive, and require specialized personnel to operate. Due to the cost involved, the number of measurement locations is often limited. However, higher spatial and temporal measurement data are usually desired[12,13] to meet both regulatory and epidemiological needs.

Recent advancements in pollution measurement and Internet-of-Things (IoT) technologies have enabled the rapid evolution of low-cost air pollution sensors, which have gained tremendous attention in recent years,[11,14] allowing a paradigm shift in air quality monitoring.[15] For less than $2500 per pollutant, these low-cost air quality (LCAQ) sensors can be deployed in significantly greater numbers to expand the capabilities of the existing air pollution monitoring network, thereby extending the spatial and temporal resolution of estimated pollutant concentrations.[11,14−19] In addition, LCAQ sensors are easier to deploy and have lower up-front capital and maintenance costs per unit, thus making them ideal for citizen engagement, providing new avenues for public education on environmental science and technology, advancing citizen science, and contributing to sustainable social development.[20,21]

Despite the aforementioned advantages, the measurement data collected from LCAQ sensors also contain substantial uncertainties.[22−24] Although the performance of many LCAQ sensors is favorable under controlled laboratory conditions,[25,26] their accuracy in the ambient environment could vary substantially among deployment locations.[26−29] The impact of environmental conditions, such as temperature, humidity, and the presence of interfering chemical species, has proven to contribute most to these uncertainties.[26,27,30−33] In addition, most past studies on sensor uncertainties focused on a single pollutant at a single geographical location.[26,27,30−33] For example, field evaluations performed by the well-known Air

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Quality Sensor Performance Evaluation Center (AQ-SPEC) program (http://www.aqmd.gov/aq-spec) were conducted at a single site in southern California. On the other hand, FRM/FEM instruments are required to be evaluated in at least four sites with distinct climatological conditions.[34] Studies on how LCAQ sensors with the capability of multi-pollutant monitoring perform across locations with different climate conditions remain limited.[35−39] A better understanding of how LCAQ sensors perform under different environmental conditions and how to develop proper calibration models for LCAQ is critical for developing practical calibration algorithms and improving the data quality of connected sensor networks.

In this study, we evaluated and compared the performance of a commercially available LCAQ electrochemical sensor (Model SCI-608 monitor, Sailbri Cooper Inc., Portland, Oregon) at six locations with different climate conditions across the continental United States, with temperatures ranging from 24.8 to 111.5 °F and relative humidity (RH) ranging from 12 to 101%. The SCI-608 is capable of measuring six pollutants and meteorological parameters, including particulate matter with an aerodynamic diameter less than or equal to 10 $\mu$m ($PM_{10}$) and less than or equal to 2.5 $\mu$m ($PM_{2.5}$), ozone ($O_3$), carbon monoxide (CO), nitrogen dioxide ($NO_2$), sulfur dioxide ($SO_2$), temperature, and RH. It has been used in several previous ambient measurement studies.[40,41] In this paper, we focus our discussion on the measurements of gaseous pollutants, specifically CO, $NO_2$, and $O_3$. $SO_2$ is not discussed in the manuscript due to the low ambient concentration in most cities (below the instrument detection limit). $PM_{2.5}$ and $PM_{10}$ are not discussed here as they are irrelevant to the topic of this paper, which focuses on gaseous pollutants.

## ■ RESULTS AND DISCUSSION

**Field Deployment and Conditions.** The six deployment cities have significantly different climate conditions (Figure 1).

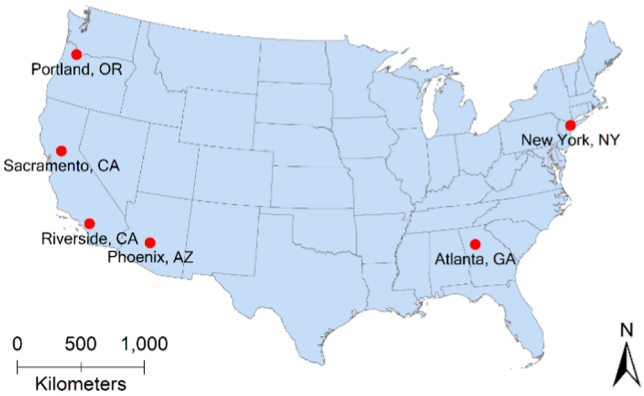


**Figure 1.** Locations of the six cities where the SCI-608 low-cost monitors were deployed.

Atlanta and New York City have a humid subtropical climate. Sacramento and Portland have a hot-summer and a warm-summer Mediterranean climate, respectively. On the other hand, Riverside's climate is semi-arid and Phoenix has a hot desert climate. Naturally, during deployment, meteorological conditions among the six cities varied considerably (Table 1). Hourly mean temperatures were relatively high in Atlanta (28.3 °C) and Riverside (26.9 °C) but low in New York (7.5 °C). Hourly mean relative humidity (RH) ranged from a moderate value of 48% (in Sacramento) to a relatively high value of 72% in Atlanta. The drastically different climates among the six cities make them ideal for comparing the performance of low-cost sensors under different environmental conditions.

Pollution concentration levels are relatively similar for CO and $NO_2$ but differ for $O_3$ among the six cities (Table 1). Moderate $NO_2$ levels were observed, with mean levels ranging from 7.4 ppbv (Atlanta) to 15.5 ppbv (Phoenix). Elevated $O_3$ levels were observed in Riverside (up to 126 ppbv, substantially higher than in the other five cities). CO concentration levels are generally low among all five cities where data are available.

**Sensor Performance.** All sensors in the SCI-608 monitor were directly exposed to ambient air, with no pre-conditioning. We performed sensor calibration using three different methods: linear, third-order polynomial, and random forest (RF). We evaluated model performance by comparing the coefficient of determination ($R^2$) and root-mean-square error (RMSE) for each model. Figure 2 provides a time-series plot of hourly $NO_2$ concentration at Portland, as collected by FRM/FEM equipment and from low-cost sensors calibrated using three different methods. The performances of the three methods are different, particularly with regard to their capability of capturing low and high concentrations. The linear calibration method even resulted in negative concentrations. Time-series plots of FRM/FEM data and calibrated concentrations for other pollutants and at other cities are provided in Figures S1 through S11. Further information on final calibration models is provided in Table S4. Note that in the RF model, the maximum number of trees was kept at 100 across all sites.

Performances of the six SCI-608 monitiors varied considerably among the six cities (Table 2 for $R^2$ and Table S2 for RMSE) and were not consistent for $NO_2$ and $O_3$. For example, the Atlanta and Riverside LCAQ sensors perform relatively poorly against the reference data for $NO_2$, with $R^2$s of only 0.34 and 0.26, respectively, when using linear calibration. On the other hand, these two sensors perform relatively well for $O_3$ (linear $R^2$ = 0.81 at Atlanta and 0.97 at Riverside). On the contrary, the Sacramento and New York monitors perform well for $NO_2$ (linear $R^2$ = 0.83 and 0.84, respectively) but relatively poor for $O_3$ (linear $R^2$ = 0.59 and 0.23, respectively). In Portland and Phoenix, the performances of the two sensors are relatively consistent between $NO_2$ and $O_3$. In Atlanta and Riverside, the relatively poor $NO_2$ sensor performances may be attributable to high temperature and humidity conditions, the impacts of which on the performances of electrochemical $NO_2$ sensors have been reported in other studies.[31,32,42] Relatively high $R^2$ values may be partially due to the considerable $O_3$ concentration reported at the two cities (maximum 1 h ozone concentration of 77 ppbv at Atlanta and 126 ppbv at Riverside) during summertime.

Among the three different sensor calibration methods, the RF method performs the best (Table 2 for $R^2$ and Table S2 for RMSE). However, using different methods did not change the inconsistent performances between $NO_2$ and $O_3$ sensors. Scientists from AQ-SPEC have conducted batch field tests of $NO_2$ and $O_3$ sensors from various manufacturers, 11 of which are based on electrochemical technology. According to the results summarized in Table S5, the performance of the $O_3$ sensor is consistently better than the $NO_2$ one. However, our findings indicate that their performance varied by location,


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**Table 1. Details of Deployments, Including Duration and Measurement Ranges, by City[a,b]**

| | SCI-608 | | | FRM/FEM | | | | |
|---|---|---|---|---|---|---|---|---|
| city | start time | end time | days | temperature (°C) | RH | $NO_2$ (ppbv) | $O_3$ (ppbv) | CO (ppmv) |
| Atlanta, GA | 6/28/2019 | 8/9/2019 | 42 | 28.3 (17−40.5) | 72 (31.7−97.4) | 7.4 (1−38) | 28.5 (1−77) | 0.3 (0.1−1.4) |
| New York City, NY | 1/28/2020 | 4/22/2020 | 85 | 7.5 (−9−23.9) | 62.5 (22.2−101) | 13.9 (1.1−53.7) | 28.8 (1−58) | 0.2 (0.1−1.4) |
| Phoenix, AZ | 12/11/2019 | 4/14/2020 | 125 | 15.7 (0−34.3) | 52.3 (16.9−98.3) | 15.5 (2−50) | 20.6 (1−56) | 0.4 (0−2.3) |
| Portland, OR | 1/4/2019 | 10/31/2019 | 301 | 14.7 (−4−40.2) | 68.9 (17−103) | 7.5 (1−42) | 23.2 (1−77) | 0.4 (0.1−14.9) |
| Riverside, CA | 8/2/2019 | 8/22/2019 | 20 | 26.9 (16.1−44.2) | 54.8 (15.3−90.1) | 10.2 (2−31) | 42.1 (2−126) | 0.2 (0.1−0.7) |
| Sacramento, CA | 9/27/2019 | 11/8/2019 | 43 | 17.6 (3−34.2) | 48.1 (12−94.8) | 17.1 (1−62) | 23 (-2−66) | |

[a]Temperature, relative humidity, $NO_2$, $O_3$, and CO data are hourly averages. [b]All hourly pollutant concentrations shown were collected by onsite reference instruments (FEM/FRM) and obtained through the EPA Air Quality System (https://www.epa.gov/outdoor-air-quality-data).

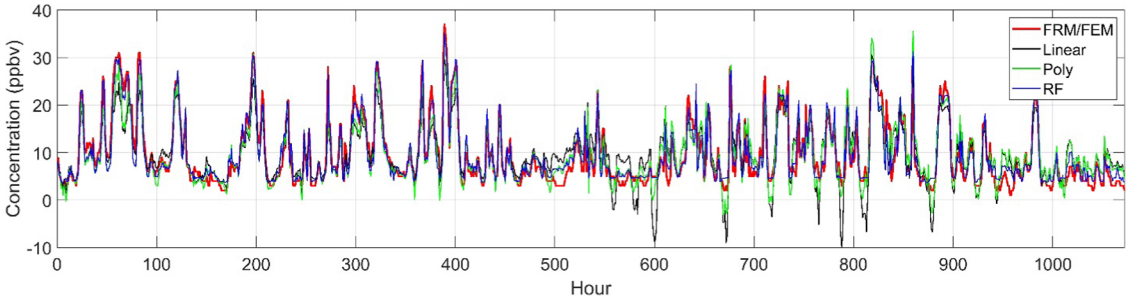


**Figure 2.** Example time-series plot of hourly $NO_2$ concentrations at Portland as collected by FRM/FEM equipment and from low-cost sensors with linear, polynomial, and random forest calibration.

**Table 2. Sensor Performance ($R^2$) at Corresponding Cities, without CO Data[a]**

| Pollutant | | Portland | Atlanta | Riverside | Sacramento | New York | Phoenix |
|---|---|---|---|---|---|---|---|
| $NO_2$ | linear | 0.73 | 0.34 | 0.26 | **0.83** | **0.84** | 0.51 |
| | polynomial | **0.83** | 0.37 | 0.20 | **0.88** | **0.88** | 0.62 |
| | RF | **0.84** | 0.65 | 0.48 | **0.93** | **0.90** | 0.74 |
| $O_3$ | linear | 0.63 | **0.81** | **0.97** | 0.59 | 0.23 | 0.58 |
| | polynomial | 0.65 | 0.79 | **0.95** | 0.55 | 0.18 | 0.53 |
| | RF | **0.81** | **0.86** | **0.97** | **0.82** | 0.39 | 0.70 |
| CO | linear | **0.91** | 0.74 | 0.4 | n/a | **0.94** | **0.97** |
| | polynomial | **0.9** | 0.74 | 0.46 | | **0.94** | **0.97** |
| | RF | **0.96** | **0.93** | **0.87** | | **0.96** | **0.98** |

[a]Excellent performance ($R^2 > 0.8$) is shown in bold.

**Table 3. Sensor Performance ($R^2$) at Corresponding Cities, with CO Data Introduced as an Independent Variable[a,b]**

| Pollutant | | Portland | Atlanta | Riverside | Sacramento | New York | Phoenix |
|---|---|---|---|---|---|---|---|
| $NO_2$ | linear | 0.80(+0.07) | 0.45(+0.11) | **0.59(+0.33)** | 0.89(+0.06) | 0.86(+0.02) | **0.76(+0.25)** |
| | polynomial | 0.84(+0.01) | 0.45(+0.08) | **0.48(+0.28)** | 0.89(+0.01) | 0.85(−0.03) | 0.72(+0.1) |
| | RF | 0.86(+0.02) | 0.74(+0.09) | **0.68(+0.2)** | 0.97(+0.04) | 0.92(+0.02) | 0.90(+0.16) |
| $O_3$ | linear | 0.78(+0.15) | 0.83(+0.02) | 0.97(+0) | **0.80(+0.21)** | **0.70(+0.47)** | **0.79(+0.21)** |
| | polynomial | 0.77(+0.12) | 0.77(−0.02) | 0.95(+0) | **0.76(+0.21)** | **0.60(+0.42)** | **0.73(+0.2)** |
| | RF | 0.93(+0.12) | 0.89(+0.03) | 0.97(+0) | 0.94(+0.12) | **0.81(+0.42)** | **0.91(+0.21)** |

[a]Data shown in parentheses are changes in $R^2$ value when CO data were included in the modela. [b]Substantial improvements ($R^2$ improvements ≥+0.2) are shown in bold.

highlighting the benefits of multiple location deployment during sensor evaluation.

**Impact of CO Data on $NO_2$ and $O_3$ Sensor Performances.** After we included the CO sensor signal (voltage) as an independent variable in the three calibration models for $NO_2$ and $O_3$ sensors, the performances of calibration models generally increased (Table 3 for $R^2$ and Table S3 for RMSE). This finding is consistent for both $NO_2$ and $O_3$, primarily when the original calibration model (without CO data) performs poorly. With included CO data, the mean linear $R^2$ values were improved by 24% from 0.59 to 0.72 for $NO_2$ and 28% from 0.64 to 0.81 for $O_3$ across all sites. The mean RMSE values for the linear method were reduced by 17% for $NO_2$ and 21% for $O_3$. The inclusion of CO data works well at New York for $O_3$ (linear $R^2$ values increased from 0.23 to 0.7, RMSE reduced by 38%), at Riverside for $NO_2$ (linear $R^2$ increased from 0.26 to 0.59, RMSE reduced by 26%), at Phoenix for both $NO_2$ and $O_3$, and at Sacramento for $O_3$. Similar findings are also observed when using polynomial and RF calibration methods.

The improved model performances as a result of including CO data were included are primarily for three reasons: (1)


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**Table 4. Coefficient of Determination ($R^2$) between Hourly CO and $NO_2$ Data as Measured by Regulatory and SCI-608 Monitors**

| Pollutant | | Portland | Atlanta | Riverside | Sacramento[a] | New York | Phoenix |
|---|---|---|---|---|---|---|---|
| CO & $NO_2$ | between FRM/FEM | 0.45[b] | 0.45 | 0.79 | n/a | 0.72 | 0.65 |
| | between low-cost sensors | 0.22 | 0.37 | 0.26 | | 0.57 | 0.41 |
| CO & $O_3$ | between FRM/FEM | 0.27[c] | 0.07 | 0.11 | n/a | 0.56 | 0.56 |
| | between low-cost sensors | 0.22 | 0.01 | 0.04 | | 0.29 | 0.27 |

[a]No regulatory CO data available. [b]$R^2$ = 0.45 when all hourly CO concentration >2 ppm removed. $R^2$ = 0 when all hourly CO data are included. [c]$R^2$ = 0.27 when all hourly CO concentration >2 ppm removed. $R^2$ = 0.02 when all hourly CO data are included.

correlated temporal variation patterns between CO and $NO_2$ and between CO and $O_3$ concentrations; (2) different performances of low-cost CO, $NO_2$, and $O_3$ sensors; and (3) different impacts of environmental conditions on their performances. The rationale for the hypothesis is explained in the following paragraphs.

First, as shown in Table 4, the hourly concentrations of CO and $NO_2$ measured by colocated FRM/FEM instruments are moderate to relatively highly correlated in all cities. The highest $R^2$ values between CO and $NO_2$ are found at Riverside (0.79), followed by New York (0.72) and Phoenix (0.65). In these three cities, the temporal variations of CO are similar to those of $NO_2$, likely due to similar emission sources. Examination of the 2017 National Emission Inventory (NEI) data suggests CO and $NO_2$ emissions at all three monitoring stations are dominated by on-road and non-road mobile sources (on average 75% for $NO_2$ and 87% for CO).

Second, correlations between measurement data collected by low-cost CO and $NO_2$ sensors differed across cities (Table 4). Such differences are likely due to the performance differences between low-cost CO and $NO_2$ sensors and the different impacts of environmental conditions on their performances. In this study, electrochemical CO sensors used in the SCI-608 generally performed better than $NO_2$ sensors (Table 2), in part due to the $NO_2$ sensor design, which has room for improvement.[43] Additionally, AQ-SPEC (Collier-Oxandale et al., 2020[26]) evaluated the field performance of LCAQ sensors from different manufacturers, which have both electrochemical $NO_2$ and CO sensors onboard (Table S5). The averaged field $R^2$ values were between 0.59 and 0.66, with a maximum of 0.94 for CO. Meanwhile, the value for $NO_2$ was between 0.18 and 0.30, with a maximum of 0.58. Furthermore, the performance of low-cost electrochemical $NO_2$ sensors is known to degrade when the ambient temperature exceeds 30 °C but less so for the CO sensor.[31,44−46]

For these two reasons, a low-cost CO sensor may be able to capture temporal CO concentration variability reasonably. However, a low-cost $NO_2$ sensor may only capture a portion of the temporal $NO_2$ concentration variability or less at high temperatures. Since CO and $NO_2$ concentrations co-vary to some extent, a portion of the missing $NO_2$ concentration variability that was not captured by the low-cost $NO_2$ sensor is captured by the CO sensor. When we introduced the CO sensor as an independent variable in $NO_2$ calibration models, a portion of the missing $NO_2$ variability was reintroduced into the model, leading to better model performance. The $NO_2$ calibration model performance improved most in Riverside (summer deployment, mean and maximum temperatures of 26.9 and 44.2 °C, Table 1), moderately in Phoenix (winter/spring deployment, mean and maximum temperatures of 15.7 and 34.3 °C), and minimum in New York (winter/spring deployment, mean and maximum temperatures of 7.5 and 23.9 °C). Ambient CO and $NO_2$ concentrations in Portland and Atlanta are not as well correlated (Table 4). Therefore, including CO data in the $NO_2$ calibration model was not as beneficial as in Riverside. Similar phenomena were observed with improved $O_3$ calibration model performance when CO data were introduced as an independent variable. CO and $O_3$ concentrations measured by FRM/FEM instruments are moderately correlated in New York and Phoenix, but low-cost sensor measurements are not well correlated due potentially to sensor performance differences. The inclusion of CO data in the $O_3$ calibration model may reintroduce some missing temporal $O_3$ concentration variability not captured by the $O_3$ signal from the sensor but captured by the CO sensor, thus leading to improved model performance. We note that the impacts of environmental conditions on the performance of the $O_3$ sensor are not as substantial as those for the $NO_2$ sensor. In the SCI-608 monitor, two onboard electrochemical sensors were used for $O_3$ measurement. The first one measured $NO_2$ and $O_3$ (as $NO_2$ + $O_3$), and the second sensor measured only $NO_2$. The two sensors are fundamentally similar, but an $O_3$ removal apparatus is installed on the second sensor, so it does not respond to $O_3$. Naturally, environmental conditions that impact the $NO_2$ sensor will also affect the $O_3$ + $NO_2$ sensor. However, their impacts were mostly canceled out when subtracting the $NO_2$ sensor signal from the $O_3$ + $NO_2$ sensor signal to obtain the $O_3$ signal. Overall, our findings suggest that the signals from the onboard CO sensor may benefit $NO_2$ and $O_3$ sensor calibration, provided that CO and $NO_2$ and CO and $O_3$ concentrations are at least moderately correlated. It is worth mentioning that this study is not the first one that integrated the CO signal for the calibration of other sensors. For example, Cross et al.[46] explored using signals from CO, $CO_2$, NO, $NO_2$, and total oxidant ($O_x$) sensors to calibrate the NO sensor in the high-dimensional model representation method. To our knowledge, this study is the first that systematically investigated the mechanisms behind the calibration method.

Given the tremendous potential of LCAQ sensors, the number of studies on LCAQ sensors and sensor networks has grown explosively in the past decade. Calibration methods for LCAQ to improve their performances in the harsh ambient environment are undoubtedly one of the most discussed topics. Researchers have approached this problem from various angles, such as hierarchical network design,[47] modeling,[48,49] sensor hardware design,[43] and diverse calibration approaches.[50,51] The presented method is intuitive and easy to implement and has great potential to improve the performances of selected LCAQ sensors.

This study does have several limitations. First, electrochemical sensors are known to respond to interfering gases, which will lead to worse sensor performance relative to a gold standard method; it is likely that varying amounts of interfering


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gases existed at the six monitoring stations during the study. However, without detailed measurement data, it is difficult to quantify the impact of interfering gases on the low-cost sensors deployed in this study. Second, due mostly to logistics, the deployments of all SCI-608 monitors did not occur at the same time, making a direct comparison across all six locations difficult. Third, due to length limitations, we focused our discussion on the coefficient of determination ($R^2$), which is not the ideal metric for comparing sensor performance across cities with varying pollution levels. For example, $R^2$ values are expected to be higher at locations with a wider range of concentrations. Including more metrics, such as mean absolute error or mean fractional error, would be more indicative of model performances.[52,53] We nonetheless still choose to use $R^2$ because it is suitable for quantifying how much temporal pollution concentration variability is captured by the model. Fourth, we only used uncorrected voltage data collected from working and reference electrodes in this study as we do not have voltage data from other electrodes (e.g., auxiliary) readily available. If such additional data were to be used, the performances of calibration models are expected to be improved.[54] However, we do not anticipate the conclusions of this study to be changed by excluding additional voltage data. The previous study also showed that the auxiliary electrode in Alphasense electrochemical sensors did not function as desired.[46]

## ■ CONCLUSIONS

Six LCAQ sensors were deployed in six cities with diverse meteorological conditions across the U.S. to evaluate their performance using three different methods. We found that the performance of low-cost $NO_2$ and $O_3$ sensors varied among cities. The performance of calibration models generally improved (considerably in certain cities) when the signals from CO sensors were included. Such observations can be explained by (1) the temporal co-variation of CO and $NO_2$ and CO and $O_3$ concentrations; (2) different performance levels of CO, $NO_2$, and $O_3$ sensors; and (3) different impacts of environmental conditions on low-cost sensors. Low-cost electrochemical CO sensors performed better than $NO_2$ and $O_3$ sensors, particularly under high temperature and humidity conditions. Because CO and $NO_2$ and CO and $O_3$ concentrations co-vary to some extent, the temporal CO concentration variations captured by the CO sensor reflected the temporal $NO_2$ concentration variability. When signals from the low-cost CO sensor were included in calibration models for $NO_2$ and $O_3$ sensors, a portion of the temporal concentration variability not captured by $NO_2$ and $O_3$ sensors may have been reintroduced into the calibration model, thus leading to better model performances. However, such improvements are expected to vary among locations. To our best knowledge, this phenomenon has not been reported previously, and other researchers can use our findings to improve the performance of low-cost $NO_2$ and $O_3$ sensors.

## ■ EXPERIMENTAL METHODS

The SCI-608 monitor houses multiple sensors designed for particulate matter (PM) and gaseous pollutants. One laser optical particle counter (PM2005, Cubic Sensor and Instrument Co., China) was used for PM measurement, four electrochemical sensors (B4 series, Alphasense, U.K.) were used for gaseous pollutants, and one meteorological sensor (SHT21, Sensirion) was used for relative humidity and temperature. The optical particle counter (OPC) counts the number of particles within different size ranges based on the laser scattering principle. The OPC converts particle numbers to particle mass concentrations using proprietary algorithms. The electrochemical sensors estimate pollutant concentrations by measuring current changes within the sensor as induced by chemical reactions with the target gas. The monitor can be powered by an AC power source or an optional solar panel. Measurement data collected by the monitor are transmitted to a centralized server via the cellular network, and a web-based interface is used to manage and visualize the collected measurement data.[40]

In this study, we deployed six SCI-608 monitors to six regulatory monitoring stations located in six cities in the United States, including Portland, OR; Atlanta, GA; Riverside, CA; Sacramento, CA; New York, NY; and Phoenix, AZ. A map of the six cities is provided in Figure 1, with corresponding FEM/FRM equipment models listed in Supporting Information Table S1.

SailHero performed internal screening procedures to identify and discard sensors with abnormal responses.[55] As an additional precaution measurement prior to field deployment, all monitors were first tested in Portland, OR (Site ID 41-051-00804) by colocating with FEM/FRM instruments for at least one week as a part of sensor QA/QC and then transported to and deployed in each city. All onsite reference data (EPA FEM/FRM), including temperature and relative humidity in this research, were obtained through the EPA Air Quality System (AQS) application programming interface (API) (https://aqs.epa.gov/aqsweb/documents/data_api.html). Measurement data from sensors were collected continuously, and the hourly average was computed. No down-sampling or pre-processing (other than averaging) was performed.

Due primarily to logistic reasons, the six monitors were not deployed at the same time (Table 1, columns 1−4). The first monitor was installed in Portland on January 4, 2019, and the last monitor was installed in New York on January 28, 2020. The lengths of deployment varied, ranging from 20 days (Riverside) to 301 days (Portland), with an average deployment of 103 days due to site access and availability. All units were AC-powered, and no solar panels were used. Data completeness is 99% in Phoenix, AZ, and 100% in all other five cities.

We applied three methods, separately at each location, to develop sensor calibration models: simple linear regression, third order polynomial regression, and random forest (RF), all of which have been used in recent studies of low-cost gaseous sensor calibrations.[56,57] In the linear method, we applied eq 1

$$C_p = aS_p + bT + c\mathrm{RH} + d \tag{1}$$

where $C_p$ is the concentration (ppbv) of pollutant p as measured by the FRM/FEM instrument; $S_p$ is the uncorrected electrode voltage (mV) from sensors, which was set to raw $NO_2$ sensor voltage for $NO_2$ calibration and $O_3$ sensor response with the $NO_2$ signal subtracted for $O_3$ calibration (done due to the physical design of electrochemical sensors used in SCI-608); $T$ is the temperature (°C); RH is the relative humidity; and $a$, $b$, $c$, and $d$ are the linear regression coefficients. To keep the data conformity, $T$ and RH data used in this study were measured by FRM/FEM equipment but not from low-cost sensors.


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In the polynomial method, we applied the following equation (eq 2)

$$C_p = aS_p^3 + bT^3 + c\mathrm{RH}^3 + d \quad (2)$$

In the random forest method, we selected 100 as the number of trees grown in each calibration model based on sensitivity analysis. All other parameters, such as maximum tree depth, were also selected based on sensitivity analysis.

## ■ ASSOCIATED CONTENT

### Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsomega.2c07734.

Additional experimental details and results; including monitoring site information; sensor performance metrics, and time-series plots of uncorrected and corrected concentration data (PDF)

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### Notes

The authors declare no competing financial interest.

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## ■ REFERENCES


(1) Neira, M.; Prüss-Ustün, A.; Mudu, P. Reduce air pollution to beat NCDs: from recognition to action. *Lancet* **2018**, *392*, 1178−1179.

(2) Burnett, R.; Chen, H.; Szyszkowicz, M.; Fann, N.; Hubbell, B.; Pope, C. A.; Apte, J. S.; Brauer, M.; Cohen, A.; Weichenthal, S.; et al. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proc. Natl. Acad. Sci. U.S.A.* **2018**, *115*, 9592−9597.

(3) Cohen, A. J.; Brauer, M.; Burnett, R.; Anderson, H. R.; Frostad, J.; Estep, K.; Balakrishnan, K.; Brunekreef, B.; Dandona, L.; Dandona, R.; et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *Lancet* **2017**, *389*, 1907−1918.

(4) Gakidou, E.; Afshin, A.; Abajobir, A. A.; Abate, K. H.; Abbafati, C.; Abbas, K. M.; Abd-Allah, F.; Abdulle, A. M.; Abera, S. F.; Aboyans, V.; et al. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990−2016: a systematic analysis for the Global Burden of Disease Study 2016. *Lancet.* **2017**, *390*, 1345−1422.

(5) Kampa, M.; Castanas, E. Human health effects of air pollution. *Environ. Pollut.* **2008**, *151*, 362−367.

(6) Pope, C. A., III; Dockery, D. W. Health effects of fine particulate air pollution: lines that connect. *J. Air Waste Manage. Assoc.* **2006**, *56*, 709−742.

(7) Bernstein, J. A.; Alexis, N.; Barnes, C.; Bernstein, I. L.; Nel, A.; Peden, D.; Diaz-Sanchez, D.; Tarlo, S. M.; Williams, P. B.; Bernstein, J. A. Health effects of air pollution. *J. Allergy Clin. Immunol.* **2004**, *114*, 1116−1123.

(8) Kim, J. Ambient air pollution: health hazards to children. *Pediatrics* **2004**, *114*, 1699−1707.

(9) de Zwart, F.; Brunekreef, B.; Timmermans, E.; Deeg, D.; Gehring, U. Air pollution and performance-based physical functioning in Dutch older adults. *Environ. Health Perspect.* **2018**, *126*, No. 017009.

(10) Münzel, T.; Sørensen, M.; Gori, T.; Schmidt, F. P.; Rao, X.; Brook, J.; Chen, L. C.; Brook, R. D.; Rajagopalan, S. Environmental stressors and cardio-metabolic disease: part I−epidemiologic evidence supporting a role for noise and air pollution and effects of mitigation strategies. *Eur. Heart J.* **2017**, *38*, 550−556.

(11) Hall, E. S.; Kaushik, S. M.; Vanderpool, R. W.; Duvall, R. M.; Beaver, M. R.; Long, R. W.; Solomon, P. A. Integrating sensor monitoring technology into the current air pollution regulatory support paradigm: Practical considerations. *Am. J. Environ. Eng.* **2014**, *4*, 147−154.

(12) Apte, J. S.; Messier, K. P.; Gani, S.; Brauer, M.; Kirchstetter, T. W.; Lunden, M. M.; Marshall, J. D.; Portier, C. J.; Vermeulen, R. C.; Hamburg, S. P. High-resolution air pollution mapping with Google street view cars: exploiting big data. *Environ. Sci. Technol.* **2017**, *51*, 6999−7008.

(13) Karner, A. A.; Eisinger, D. S.; Niemeier, D. A. Near-roadway air quality: synthesizing the findings from real-world data. *Environ. Sci. Technol.* **2010**, *44*, 5334−5344.

(14) Castell, N.; Dauge, F. R.; Schneider, P.; Vogt, M.; Lerner, U.; Fishbain, B.; Broday, D.; Bartonova, A. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environ. Int.* **2017**, *99*, 293−302.

(15) Snyder, E. G.; Watkins, T. H.; Solomon, P. A.; Thoma, E. D.; Williams, R. W.; Hagler, G. S.; Shelow, D.; Hindin, D. A.; Kilaru, V. J.; Preuss, P. W. The Changing Paradigm of Air Pollution Monitoring. *Environ. Sci. Technol.* **2013**, *47*, 11369−11377.

(16) Becnel, T.; Tingey, K.; Whitaker, J.; Sayahi, T.; K, L.; Goffin, P.; Butterfield, A.; Kelly, K.; Gaillardon, P. A Distributed Low-Cost Pollution Monitoring Platform. *IEEE Internet Things J.* **2019**, *6*, 10738−10748.

(17) Qin, X.; Hou, L.; Gao, J.; Si, S. The evaluation and optimization of calibration methods for low-cost particulate matter sensors: Inter-comparison between fixed and mobile methods. *Sci. Total Environ.* **2020**, *715*, No. 136791.

(18) Liu, Y.; Sarnat, J. A.; Kilaru, V.; Jacob, D. J.; Koutrakis, P. Estimating Ground-Level PM2.5 in the Eastern United States Using Satellite Remote Sensing. *Environ. Sci. Technol.* **2005**, *39*, 3269−3278.

(19) Caubel, J. J.; Cados, T. E.; Preble, C. V.; Kirchstetter, T. W. A Distributed Network of 100 Black Carbon Sensors for 100 Days of Air Quality Monitoring in West Oakland, California. *Environ. Sci. Technol.* **2019**, *53*, 7564−7573.

(20) Conrad, C. C.; Hilchey, K. G. A review of citizen science and community-based environmental monitoring: issues and opportunities. *Environmental monitoring and assessment,* **2011**, *176*, 273−291.

(21) Riesch, H.; Potter, C. Citizen science as seen by scientists: Methodological, epistemological and ethical dimensions. *Public Understanding Sci.* **2014**, *23*, 107−120.

(22) Karagulian, F.; Barbiere, M.; Kotsev, A.; Spinelle, L.; Gerboles, M.; Lagler, F.; Redon, N.; Crunaire, S.; Borowiak, A. Review of the performance of low-cost sensors for air quality monitoring. *Atmosphere* **2019**, *10*, No. 506.

(23) Morawska, L.; Thai, P. K.; Liu, X.; Asumadu-Sakyi, A.; Ayoko, G.; Bartonova, A.; Bedini, A.; Chai, F.; Christensen, B.; Dunbabin, M.; et al. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? *Environ. Int.* **2018**, *116*, 286−299.

(24) Bulot, F. M. J.; Johnston, S. J.; Basford, P. J.; Easton, N. H.; Apetroaie-Cristea, M.; Foster, G. L.; Morris, A. K.; Cox, S. J.; Loxham, M. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Sci. Rep.* **2019**, *9*, No. 7497.

(25) Zamora, M. L.; Xiong, F.; Gentner, D.; Kerkez, B.; Kohrman-Glaser, J.; Koehler, K. Field and laboratory evaluations of the low-cost plantower particulate matter sensor. *Environ. Sci. Technol.* **2019**, *53*, 838−849.

(26) Collier-Oxandale, A.; Feenstra, B.; Papapostolou, V.; Zhang, H.; Kuang, M.; Der Boghossian, B.; Polidori, A. Field and laboratory performance evaluations of 28 gas-phase air quality sensors by the AQ-SPEC program. *Atmos. Environ.* **2020**, *220*, No. 117092.

(27) Feenstra, B.; Papapostolou, V.; Hasheminassab, S.; Zhang, H.; Boghossian, B. D.; Cocker, D.; Polidori, A. Performance evaluation of twelve low-cost PM2.5 sensors at an ambient air monitoring site. *Atmos. Environ.* **2019**, *216*, No. 116946.

(28) Borrego, C.; Ginja, J.; Coutinho, M.; Ribeiro, C.; Karatzas, K.; Sioumis, T.; Katsifarakis, N.; Konstantinidis, K.; De Vito, S.; Esposito, E.; et al. Assessment of air quality microsensors versus reference methods: The EuNetAir Joint Exercise − Part II. *Atmos. Environ.* **2018**, *193*, 127−142.

(29) Borrego, C.; Costa, A. M.; Ginja, J.; Amorim, M.; Coutinho, M.; Karatzas, K.; Sioumis, T.; Katsifarakis, N.; Konstantinidis, K.; De Vito, S.; et al. Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. *Atmos. Environ.* **2016**, *147*, 246−263.

(30) Bulot, F. M. J.; Johnston, S. J.; Basford, P. J.; Easton, N. H. C.; Apetroaie-Cristea, M.; Foster, G. L.; Morris, A. K. R.; Cox, S. J.; Loxham, M. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Sci. Rep.* **2019**, *9*, No. 7497.

(31) Mijling, B.; Jiang, Q.; de Jonge, D.; Bocconi, S. Field calibration of electrochemical NO2 sensors in a citizen science context. *Atmos. Meas. Tech.* **2018**, *11*, 1297−1312.

(32) Lewis, A. C.; Lee, J. D.; Edwards, P. M.; Shaw, M. D.; Evans, M. J.; Moller, S. J.; Smith, K. R.; Buckley, J. W.; Ellis, M.; Gillot, S. R.; White, A. Evaluating the performance of low cost chemical sensors for air pollution research. *Faraday Discuss.* **2016**, *189*, 85−103.

(33) Smith, K. R.; Edwards, P. M.; Evans, M. J.; Lee, J. D.; Shaw, M. D.; Squires, F.; Wilde, S.; Lewis, A. C. Clustering approaches to improve the performance of low cost air pollution sensors. *Faraday Discuss.* **2017**, *200*, 621−637.

(34) *Pt. 53, Subpt. C, Table C-5, in Title 40 - Protection of Environment*; U.S.E.P. Agency, 2018.

(35) Malings, C.; Westervelt, D. M.; Hauryliuk, A.; Presto, A. A.; Grieshop, A.; Bittner, A.; Beekmann, M.; Subramanian, R. Application of low-cost fine particulate mass monitors to convert satellite aerosol optical depth to surface concentrations in North America and Africa. *Atmos. Meas. Tech.* **2020**, *13*, 3873−3892.

(36) Ripoll, A.; Viana, M.; Padrosa, M.; Querol, X.; Minutolo, A.; Hou, K. M.; Barcelo-Ordinas, J. M.; Garcia-Vidal, J. Testing the performance of sensors for ozone pollution monitoring in a citizen science approach. *Sci. Total Environ.* **2019**, *651*, 1166−1179.

(37) Zheng, T.; Bergin, M. H.; Johnson, K. K.; Tripathi, S. N.; Shirodkar, S.; Landis, M. S.; Sutaria, R.; Carlson, D. E. Field evaluation of low-cost particulate matter sensors in high- and low-concentration environments. *Atmos. Meas. Tech.* **2018**, *11*, 4823−4846.

(38) Johnson, K. K.; Bergin, M. H.; Russell, A. G.; Hagler, G.S.W. Field Test of Several Low-Cost Particulate Matter Sensors in High and Low Concentration Urban Environments. *Aerosol Air Qual. Res.* **2018**, *18*, 565−578.

(39) Zusman, M.; Schumacher, C. S.; Gassett, A. J.; Spalt, E. W.; Austin, E.; Larson, T. V.; Carvlin, G.; Seto, E.; Kaufman, J. D.; Sheppard, L. Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. *Environ. Int.* **2020**, *134*, No. 105329.

(40) Li, Y.; Yuan, Z.; Chen, L.W.A.; Pillarisetti, A.; Yadav, V.; Wu, M.; Cui, H.; Zhao, C. From air quality sensors to sensor networks: Things we need to learn. *Sens. Actuators, B* **2022**, *351*, No. 130958.

(41) Chen, L.W.A.; Olawepo, J. O.; Bonanno, F.; Gebreselassie, A.; Zhang, M. Schoolchildren's exposure to PM2.5: a student club−based air quality monitoring campaign using low-cost sensors. *Air Qual., Atmos. Health* **2020**, *13*, 543−551.

(42) Wei, P.; Sun, L.; Anand, A.; Zhang, Q.; Huixin, Z.; Deng, Z.; Wang, Y.; Ning, Z. Development and evaluation of a robust temperature sensitive algorithm for long term NO2 gas sensor network data correction. *Atmos. Environ.* **2020**, *230*, No. 117509.

(43) Farquhar, A. K.; Henshaw, G. S.; Williams, D. E. Understanding and Correcting Unwanted Influences on the Signal from Electrochemical Gas Sensors. *ACS Sens.* **2021**, *6*, 1295−1304.

(44) Rogulski, M.; Badyda, A.; Gayer, A.; Reis, J. Improving the Quality of Measurements Made by Alphasense NO2 Non-Reference Sensors Using the Mathematical Methods. *Sensors* **2022**, *22*, No. 3619.

(45) Han, P.; Mei, H.; Liu, D.; Zeng, N.; Tang, X.; Wang, Y.; Pan, Y. Calibrations of low-cost air pollution monitoring sensors for CO, NO2, O3, and SO2. *Sensors* **2021**, *21*, No. 256.

(46) Cross, E. S.; Williams, L. R.; Lewis, D. K.; Magoon, G. R.; Onasch, T. B.; Kaminsky, M. L.; Worsnop, D. R.; Jayne, J. T. Use of electrochemical sensors for measurement of air pollution: Correcting interference response and validating measurements. *Atmos. Meas. Tech.* **2017**, *10*, 3575−3588.

(47) Weissert, L.; Miles, E.; Miskell, G.; Alberti, K.; Feenstra, B.; Henshaw, G. S.; Papapostolou, V.; Patel, H.; Polidori, A.; Salmond, J. A.; Williams, D. E. Hierarchical network design for nitrogen dioxide measurement in urban environments. *Atmos. Environ.* **2020**, *228*, No. 117428.

(48) Weissert, L.; Alberti, K.; Miles, E.; Miskell, G.; Feenstra, B.; Henshaw, G. S.; Papapostolou, V.; Patel, H.; Polidori, A.; Salmond, J. A.; Williams, D. E. Low-cost sensor networks and land-use regression: Interpolating nitrogen dioxide concentration at high temporal and spatial resolution in Southern California. *Atmos. Environ.* **2020**, *223*, No. 117287.

(49) Bisignano, A.; Carotenuto, F.; Zaldei, A.; Giovannini, L. Field calibration of a low-cost sensors network to assess traffic-related air


https://doi.org/10.1021/acsomega.2c07734
ACS Omega XXXX, XXX, XXX−XXX

pollution along the Brenner highway. *Atmos. Environ.* **2022**, *275*, No. 119008.

(50) De Vito, S.; Esposito, E.; Castell, N.; Schneider, P.; Bartonova, A. On the robustness of field calibration for smart air quality monitors. *Sens. Actuators, B* **2020**, *310*, No. 127869.

(51) Williams, D. E. Low Cost Sensor Networks: How Do We Know the Data Are Reliable? *ACS Sens.* **2019**, *4*, 2558−2565.

(52) Dharmalingam, S.; Senthilkumar, N.; D'Souza, R. R.; Hu, Y.; Chang, H. H.; Ebelt, S.; Yu, H.; Kim, C. S.; Rohr, A. Developing air pollution concentration fields for health studies using multiple methods: Cross-comparison and evaluation. *Environ. Res.* **2022**, *207*, No. 112207.

(53) Yu, H.; Russell, A.; Mulholland, J.; Odman, T.; Hu, Y.; Chang, H. H.; Kumar, N. Cross-comparison and evaluation of air pollution field estimation methods. *Atmos. Environ.* **2018**, *179*, 49−60.

(54) Liang, Y.; Wu, C.; Jiang, S.; Li, Y. J.; Wu, D.; Li, M.; Cheng, P.; Yang, W.; Cheng, C.; Li, L.; et al. Field comparison of electrochemical gas sensor data correction algorithms for ambient air measurements. *Sens. Actuators, B* **2021**, *327*, No. 128897.

(55) Cui, H.; Zhang, L.; Li, W.; Yuan, Z.; Wu, M.; Wang, C.; Ma, J.; Li, Y. A new calibration system for low-cost Sensor Network in air pollution monitoring. *Atmos. Pollut. Res.* **2021**, *12*, No. 101049.

(56) Bigi, A.; Mueller, M.; Grange, S. K.; Ghermandi, G.; Hueglin, C. Performance of NO, NO2 low cost sensors and three calibration approaches within a real world application. *Atmos. Meas. Tech.* **2018**, *11*, 3717−3735.

(57) van Zoest, V.; Osei, F. B.; Stein, A.; Hoek, G. Calibration of low-cost NO2 sensors in an urban air quality network. *Atmos. Environ.* **2019**, *210*, 66−75.



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