Title
Long-term Evaluation of Low-Cost Air Sensors in Monitoring Indoor Air Quality at a California Community

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Long-term Evaluation of Low-Cost Air Sensors

in Monitoring Indoor Air Quality at a California Community

A thesis submitted in partial satisfaction

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in Environmental Health Sciences

by

Zemin Wang

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ABSTRACT OF THE THESIS

Long-term Evaluation of Low-Cost Air Sensors

in Monitoring Indoor Air Quality at a California Community

by

Zemin Wang

Master of Science in Environmental Health Sciences

University of California, Los Angeles, 2020

Professor Yifang Zhu, Chair

Introduction: In response to substantial evidence showing adverse health effects of long-term or short-term exposure to air pollutants, interest has grown in real-time monitoring of air quality in fine-grained geographic detail. The development and application of low-cost air sensors enable high spatial resolution air quality monitoring. The validity and consistency of those devices, however, still needs to be investigated. Previous literature suggests potential inaccuracy due to environmental factors. Our study aims to provide evidence that low-cost air sensors could be applied at a community scale to monitor indoor air quality over time and to alert communities and residents about air pollution issues.

Objectives: 1. Identify indoor particulate matter($PM_{2.5}$) sources using low-cost sensors at a community scale; 2. Identify and explore potential indoor PM mitigation measures; 3. Explore the impacts of ambient PM levels on indoor air quality; 4. Evaluate the long-term performance of low-cost air sensors

Methods: We have operated 30 PurpleAir II (PA-II) sensors (12 outdoor and 18 indoor) at a California community located adjacent to a major interstate freeway vicinity since May 2017. $PM_{2.5}$ data were recorded and uploaded automatically by the sensor network. We also collected one-week indoor human activity logs (i.e., whether cooking, opening windows, or using air purifiers at each hour) from 9 recruited residents using questionnaires during the PM monitoring campaign. The indoor PM data were matched with activity logs based on the monitoring location and time. We then assessed the impacts of ambient air quality, microclimatic factors (e.g., temperature and relative humidity (RH)), and indoor human activities on indoor $PM_{2.5}$ concentrations using t-tests and a linear mixed-effects regression model.

Results: Indoor sensors had greater data completeness than outdoor sensors. The average of $PM_{2.5}$ Indoor/Outdoor (I/O) ratio during cooking hours was 7.3, significantly greater ($p < 0.01$) than the average of 1.4 during non-cooking hours. The fitted linear mixed-effects model can explain 86.4% of the variation in indoor PM levels. The model shows that indoor $PM_{2.5}$ was positively influenced by ambient $PM_{2.5}$ and indoor cooking and negatively influenced by window opening and using an air purifier. Moreover, ambient PM and window opening had an interaction effect on indoor PM levels.

Conclusions: PA-II sensors could effectively monitor indoor PM concentrations over a long-time span and detect the impacts of indoor activities on IAQ. PA-II sensors deployed indoors performed better than those deployed outdoors. Ambient PM levels had a significant positive

effect on IAQ. Residential cooking was a strong indoor PM emission source, which could be influenced by effective ventilation and mitigation measures.

The thesis of Zemin Wang is approved.

Brian Cole

Michael Jerrett

Yifang Zhu, Committee Chair

University of California, Los Angeles

2020

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1. Introduction

According to the World Health Organization, 91% of people worldwide were breathing air containing high levels of pollutants in 2016 (WHO, 2016). Particularly, particulate matter (PM) pollution was predicted to be associated with more than 8 million nonaccidental deaths in 2015 (Burnett et al., 2018). As a complex mixture of particles suspended in air, PM is considered responsible for many of the most harmful health effects of ambient air pollution (Mukherjee & Agrawal, 2017). A recent study shows that PM-associated mortality in California in 2012 was estimated to 12,700-26,700, which is comparable to the ozone-associated mortality (Wang et al., 2019). Numerous studies have shown strong associations between PM pollution and various adverse health effects, such as respiratory, cardiovascular and cerebrovascular diseases, and cancers. When PM is combined with other air pollutants in the air, adverse health effects could accumulate (Farraj et al., 2015; Ku et al., 2017; Siddika et al., 2019; Thompson et al., 2019). A multi-city study has shown that the median death rate attributable to $PM_{2.5}$ was 39 deaths per 100,000 people in 2016 (Anenberg et al., 2019). Pascal et al. have also confirmed the short-term increases in mortality risk, even at PM exposure levels at concentrations under European regulation (Pascal et al., 2014). Schwartz et al. have concluded a causal association of air pollution with daily deaths at a concentration under U.S. EPA standards (Schwartz et al., 2017). Identification of possible PM sources will provide a foundation for control measures to reduce the adverse health impacts of air pollution (Mukherjee & Agrawal, 2017).

Since people spend 80-90% of their daily time in the indoor environment (Simoni et al., 2003), most human exposure to PM occurs indoors. Previous studies have highlighted the critical impacts of indoor air quality (IAQ) on working performance (Wargocki & Wyon, 2017) and human health symptoms such as respiratory diseases (Lanthier-Veilleux et al., 2016) and cardiovascular diseases (Snider et al., 2018). Indoor particles include the ambient infiltrated as well as the indoor generated through indoor human activities. A recent study in China (Snider et al., 2018) shows that outdoor $PM_{2.5}$ contributed an estimated 20-44% of indoor $PM_{2.5}$. Indoor air quality could be also influenced by a wide and varied range of indoor emission sources (e.g. cooking and heating with natural gas, tobacco and electronic cigarettes) (Li et al., 2019; Snider et al., 2018). Hence, traditional assessment based on fixed-site air quality monitoring networks is inadequate and problematic for personal or domestic exposure to air pollutants. Residential indoor monitoring sensors can provide a more representative measure of personal or domestic exposure. Moreover, controlling IAQ is presently recognized as more efficient and economic than decreasing outdoor pollutant concentrations (Liu & Zhang, 2019), which makes it necessary to accurately quantify indoor pollutant levels.

Attempts to collect indoor real-time and high-resolution air quality data have been encumbered by the limitations of air monitoring devices. Given the high cost of current air monitoring instruments, air pollution exposure is usually measured outdoors by central-site air quality monitoring stations (Faridi et al., 2018; Guo et al., 2017; Pun et al., 2017). Existing expensive and sophisticated air quality monitoring networks could provide limited data, especially lacking IAQ information for residents and communities. With technological advancements in the areas of electrical engineering and wireless networking, "low-cost" air quality sensors have been developed and shifted traditional air monitoring towards a more affordable and portable direction. South Coast Air Quality Management District has evaluated dozens of commercially available low-cost air quality sensors under ambient (field) and controlled (laboratory) conditions (Polidori et al., 2017). According to the evaluation reports, some low-cost sensors had a good performance under laboratory conditions and showed a good correlation in the field compared with Federal Reference Methods (FRM) or Federal Equivalent Methods (FEM). Previous studies, however, have suggested that a number of low-cost sensors had poor reliability and did not perform well under actual ambient conditions. Also, there is no generally accepted evidence on the long-term performance of the commercially available air quality sensors and their actual applications for individuals, local environment groups, or communities.

The PurpleAir II air quality sensor (PA-II) is a low-cost and indoor-friendly optical particle counter. The sensor was designed for monitoring not only outdoor but also indoor particulate matter levels compared with many current air monitoring sensors that could be only deployed outdoors. The sensor could also provide information on relative humidity (RH) and temperature for reference. A study on laboratory and field evaluation of low-cost sensors conducted by SCAQMD (Polidori et al., 2016, 2017) suggested that PA-II sensors showed good to excellent accuracy for monitoring $PM_{2.5.}$ The laboratory and in-field measurements of $PM_{1.0}$ and $PM_{2.5}$ from PA-II showed strong correlations (lab R^2>0.99, field R^2>0.93) compared with the FEM. The sensors, however, underestimated PM_{10} concentration as measured by the reference (field R^2>0.66), and as PM_{10} concentration increased, sensors' accuracy decreased.

Recent studies have tested the validity of PA-II sensors for assessing local or regional air pollutant exposure (Kim et al., 2019), monitoring indoor or outdoor PM emissions (Gupta et al., 2018), and measuring PM concentrations at a large scale (Bi et al., 2020). However, some researchers still doubt the real-world performance of low-cost air sensors. While various correction functions have been proposed (Magi et al., 2020; Malings et al., 2020), there are problematic because the proposed correction formulas were studied based on specific environmental conditions and the number of sensors used in these studies are limited. There is a great need for generally accepted evidence on the real-world performance and potential correction formulas for PA-II sensors. Therefore, this study aims to (1) evaluate the real-world performance and (2) explore the potential applications of commercially available air sensors in a local community using PA-II sensors.

2. Method

2.1. Study sites

We deployed a PA-II sensor network in a California neighborhood that straddles the 405 Freeway along the 3200 blocks of two major streets, Sawtelle and Sepulveda Boulevards, on the west and east of the freeway, respectively. A map of the sampling locations is attached in the Appendix (Figure A1). A total of 30 PA-II air sensors were installed and equally distributed at the two sides of the freeway since November 2017. Eighteen indoor sensors were installed in residents' apartments and twelve outdoor sensors were installed on the roof of the apartment buildings. Occupants of apartments recruited for indoor installations were recruited based on location, and they gave consent for data collection. Each recruited apartment was required to complete a one-week activity log to record their indoor activities along with a survey for their home characteristics during the first month of the investigation campaign.

2.2. Instrumentation

The PA-II sensor is a low-cost optical particle counter, which could measure number concentrations of suspended particles with diameters ranging from 0.3 to 10 μm and estimate the size-specific mass concentrations of particles such as $PM_{1.0}$, $PM_{2.5}$, PM_{10}. The sensors could also monitor ambient relative RH and temperature for reference. Each sensor has two identical monitoring units in case of either one not working. All the data collected by PA-II were automatically uploaded to and recorded on the PurpleAir server through a Wi-Fi connection. All sensors information in this study is available to the public on the PurpleAir website, and the datasets could be exported and downloaded upon request (https://www.purpleair.com/sensorlist).

2.3. Indoor activity logs

We collected information about residents' indoor activities logs from 9 out of the total of 30 recruited residents using questionnaires. Indoor cooking, window opening, and use of air purifiers were recorded hourly for seven days for each study participant.

2.4. Data processing

In this study, we used the average of the measurements monitored by two internal channels to represent one PA-II sensor. We excluded measurements with abnormal temperature records (i.e., greater than 200°F or less than 0°F) and smoothed the data by taking hourly, daily, and monthly averages, respectively. The hourly data were used for exploring the variation in Indoor/Outdoor ratios (I/O ratios) before/during various indoor activities. The daily and monthly data were used for showing the long-term trends of PM concentration and data collection validity.

2.5. Data analysis

2.5.1. Data completeness

Data completeness was used for assessing the data collection efficiency and indicating partial performance of a sensor. We calculated data completeness by taking the ratio between the number of available hourly data and the total hours that a sensor had been assumed to work (Zheng et al., 2018).

2.5.2. Calculation of indoor/outdoor ratios of PMs

Indoor/Outdoor Ratios of PM (I/O ratios) were used to compare indoor air quality with ambient air quality at a given location (Deng et al., 2015). I/O ratios were calculated by dividing indoor PM concentration level by outdoor PM concentration level recorded at the nearest outdoor sensor (the maximum distance between the paired sensors is 200 meters). I/O ratios above 1.2 suggest that indoor PM concentration is higher than the outdoors and could be due to indoor PM sources. I/O ratios above 0.8 and at or below 1.2 suggest that indoor concentration is equilibrating with outdoor concentration. I/O ratios less than 0.8 indicate that indoor concentration is lower than the outdoors and illustrates possible outdoor influence (Deng et al., 2015). To assess the overall difference between indoor and outdoor PM concentrations, we used a paired t-test to calculate the test statistic, t-value.

2.5.3. Effects of indoor activities on I/O ratio

We also examined how specific indoor activities affected indoor air quality, comparing the I/O ratios before and during a specific indoor activity. To test the statistical significance of differences in I/O ratios, we used a Welch two-sample t-test assuming unequal variances of two samples to calculate the t-value.

2.5.4. Effects of indoor factors and ambient air quality on indoor PMs

To further evaluate the performance of low-cost air sensors on assessing impacts of various indoor factors and ambient air quality on indoor PM levels, a linear mixed-effects regression model was developed utilizing questionnaire responses and observation data. The response variable was set as monitored hourly indoor $PM_{2.5}$ concentration. The input variables comprised current ambient PM concentration, indoor emission term (i.e., cooking), indoor ventilation term (i.e., window opening), indoor mitigation measure term(i.e., air purifier used), current microclimatic influence terms (e.g., temperature and RH). Since indoor air pollutants accumulate in indoor spaces and then continue to affect indoor air quality, past concentrations of indoor PM were added into the model to better predict the current indoor PM concentration (Lim et al., 2012). For the linearity assumption of modeling, regression models used the natural log of measured PM concentrations. Apart from these main effects, an interaction effect of window opening with the ambient $PM_{2.5}$ concentration was also taken into consideration. To take into account unobserved heterogeneity between monitoring devices, building structures, residents' characteristics, and residents' daily activities, the sampling site was considered as a potential random effects term in the regression analysis. Past concentrations of indoor $PM_{2.5}$, outdoor $PM_{2.5}$, cooking, window opening, air purifier using, temperature, RH, and interaction effect of window opening with the ambient $PM_{2.5}$ were selected as input (X) variables, and the concentrations of current indoor $PM_{2.5}$ were regarded as output (Y) variables, as listed in Table 1.

Table 1. Descriptions of X and Y variables of regression model on indoor PM

	Description
X variables	the past concentration of indoor $PM_{2.5}$, ambient $PM_{2.5}$ concentration, cooking, window opening, air purifier using, temperature, RH, the interaction effect of window opening with the ambient $PM_{2.5}$
Y variables	indoor $PM_{2.5}$ concentration

The indoor $PM_{2.5}$ prediction model can be expressed as follows:

$$LnCin_{ij} = \beta_0 + \beta_1 LnCin_{\ i-1,j} + \beta_2 LnCambient_{ij} + \beta_3 Cooking_{ij} + \beta_4 Window_{ij} + \beta_5 Purifier_{ij} + \beta_6 T_{ij} + \beta_7 R.H._{ij} + \beta_8 Window_{ij} * LnCambient_{ij} + u_j + \varepsilon_{ij} \quad (1)$$

The three indoor activities terms were determined from the previous part of the analysis and were coded as follows: 1 represents Yes (i.e., cooking, opening at least one window, or using at least one air purifier at the apartment), and 0 represents No (i.e., no cooking, closing windows, no air purifier used). In addition, the likelihood ratio test was used for testing the statistical significance of the potential random effect.

3. Results and Discussion

3.1. Outdoor and Indoor Sensors' Data Completeness

As shown in Figure 1 and Table 2, the performance of PA-II sensors on data completeness was different after deployed at different field locations. Each indoor sensor completed greater than 77% of data collection events during their sampling period (see Table 2). Incomplete indoor data mostly stemmed from the loss of stable Wi-Fi when residents went on vacation. Outdoor sensors provided less complete data than sensors deployed indoors. The outdoor sensor 2 had the lowest value of data completeness (24%). According to our records, sensor 2 was broken twice for unknown reasons. We suspect that possible detrimental conditions around the monitoring site (e.g., outlet failure) contributed to the malfunction of monitors. Sensor 10 also had extremely low data completeness (26%) probably due to the same issue.

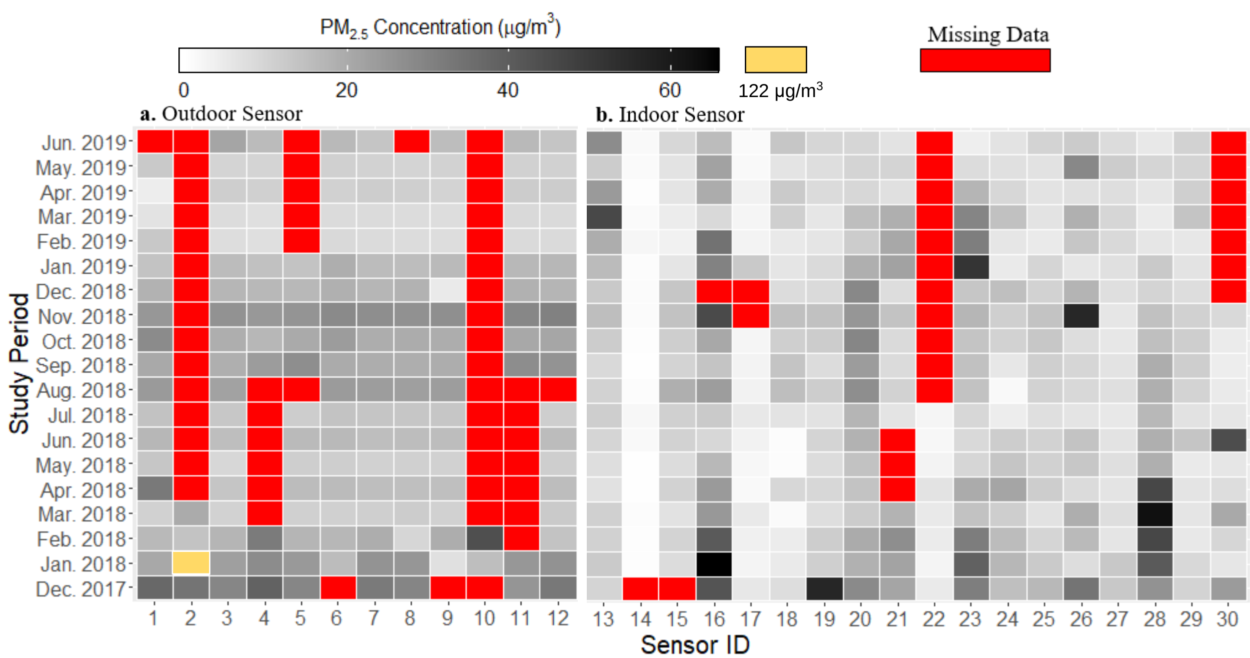

Figure 1. Data collected by the low-cost air monitoring network. The darkness of white-and-black boxes represents the monthly $PM_{2.5}$ concentration. The red boxes represent a monitoring month without available data from a sensor. The yellow box represents the average of $PM_{2.5}$ concentrations (121 μg/m^3) monitored by sensor 2 on January 1st, 2018, which was comprised of 19-hours measurements.

3.2. $PM_{2.5}$ concentration level, RH, and temperature on a 1-hour scale

Table 2 and Table 3 show the summary statistics for outdoor and indoor 1-hour averaged $PM_{2.5}$ concentrations, RH, and temperatures from November 2017 to June 2019. During the sampling period, the geometric mean (GM) of hourly indoor $PM_{2.5}$ concentration was 9.36 $\mu g/m^3$ (IQR: 1.16 – 10.57 $\mu g/m^3$) by 18 indoor PA-II sensors in the study community, compared to a GM of hourly outdoor $PM_{2.5}$ concentrations of 9.75 $\mu g/m^3$ (IQR: 4.90 – 21.45 $\mu g/m^3$) across 12 sensors. Based on the paired t-test results, the mean indoor $PM_{2.5}$ concentration was significantly lower than the average of outdoor $PM_{2.5}$ concentrations reported by the nearest sensor (difference = 4.18 $\mu g/m^3$, $p<0.001$), suggesting a possible protective role of buildings in the reduction of air pollution, which is consistent with previous findings (Snider et al., 2018). This effect was found to be more significant when the local ambient PM concentration increased in winter (Figure 2). On the contrary, most of the maximum hourly $PM_{2.5}$ levels reported by a single indoor sensor were much higher than outdoor $PM_{2.5}$ concentrations (Table 2 and Table 3), and the three highest hourly $PM_{2.5}$ concentrations were reported by indoor sensor 20 (1292 $\mu g/m^3$ and 965 $\mu g/m^3$) and indoor sensor 24 (938 $\mu g/m^3$). While the outdoor mean $PM_{2.5}$ levels monitored by different sensors were relatively close to each other, measurements by indoor sensors varied dramatically among sensors and logging time of a day. There could be potential influences of residence location and human activities on indoor PM levels.

Table 2. Summary Statistics for 1-hour Averaged Measurements of Outdoor Sensors

Sensor ID	Number of Hours of Data	$PM_{2.5}$ (μg/m^3)			R.H.[a] (%)	Temp.[b] (°F)	Data Completeness
		Mean ± SD[c]	GM[d]	IQR[e]	Mean ± SD[c]	Mean ± SD[c]	
1	12445	18 ± 18	10.3	18.2	50 ± 16	70 ± 9	52%
2	2265	35 ± 35	19.2	36.5	44 ± 20	63 ± 8	24%
3	13320	16 ± 18	8.9	16.4	53 ± 18	68 ± 9	96%
4	13495	17 ± 20	8.4	17.7	51 ± 17	68 ± 9	56%
5	10728	18 ± 20	10.0	18.3	51 ± 19	68 ± 10	82%
6	12843	16 ± 16	9.2	15.5	54 ± 16	69 ± 10	85%
7	13722	17 ± 18	9.6	16.8	50 ± 16	71 ± 10	100%
8	12874	16 ± 17	9.7	15.6	49 ± 15	71 ± 10	92%
9	12535	15 ± 15	8.9	14.1	51 ± 15	73 ± 9	95%
10	2190	23 ± 21	11.4	34.7	39 ± 17	69 ± 10	29%
11	14379	17 ± 20	9.1	18.0	51 ± 18	68 ± 10	57%
12	13166	17 ± 20	8.7	15.7	55 ± 19	67 ± 9	78%

Note: [a] R.H. represents relative humidity; [b] Temp. represents temperature; [c] SD represents standard deviation; [d] GM represents geometric mean; [e] IQR represents interquartile range.

Table 3. Summary Statistics for 1-hour Averaged Measurements of Indoor Sensors

Senor ID	Number of Hours of Data	$PM_{2.5}$ (μg/m^3)			R.H.[a] (%)	Temp.[b] (°F)	Data Completeness
		Mean ± SD[c]	GM[d]	IQR[e]	Mean ± SD[c]	Mean ± SD[c]	
13	13560	15 ± 45	4.3	8.2	41 ± 4	83 ± 2	100%
14	12511	1 ± 7	0.2	0.2	36 ± 3	85 ± 2	100%
15	12726	9 ± 14	5.7	8.6	45 ± 4	83 ± 3	99%
16	13468	25 ± 40	8.5	24.5	41 ± 3	82 ± 3	81%
17	13544	3 ± 19	0.8	1.7	43 ± 2	80 ± 2	84%
18	13111	8 ± 16	2.0	9.2	39 ± 5	80 ± 4	77%
19	13617	11 ± 29	6.5	8.3	40 ± 6	83 ± 3	100%
20	13736	18 ± 39	7.9	13.4	41 ± 6	83 ± 5	99%
21	13735	15 ± 38	4.2	8.8	39 ± 6	83 ± 3	78%
22	5284	4 ± 9	1.6	3.8	40 ± 4	83 ± 4	100%
23	13802	19 ± 40	6.0	13.6	41 ± 4	81 ± 4	98%
24	13806	11 ± 28	3.8	10.0	40 ± 5	82 ± 3	98%
25	13808	10 ± 14	5.7	8.9	41 ± 5	81 ± 3	100%
26	13830	16 ± 42	4.6	8.8	36 ± 6	83 ± 2	93%
27	13807	8 ± 32	1.4	3.9	46 ± 4	82 ± 3	100%
28	13848	21 ± 44	7.4	16.2	36 ± 6	85 ± 2	96%
29	13848	9 ± 19	4.1	7.4	40 ± 4	81 ± 3	100%
30	8403	11 ± 36	2.0	5.4	41 ± 4	85 ± 2	94%

Note: [a] R.H. represents relative humidity; [b] Temp. represents temperature; [c] SD represents standard deviation; [d] GM represents geometric mean; [e] IQR represents interquartile range.

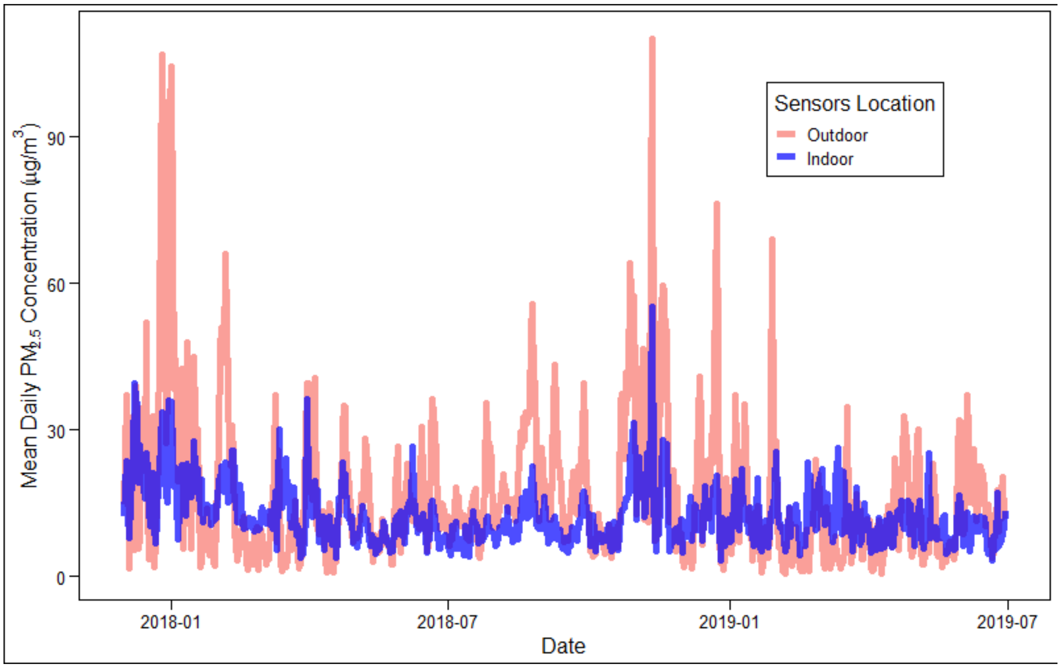

Figure 2. Outdoor and indoor $PM_{2.5}$ concentrations on a 1-day scale. The red line represents the daily average of outdoor $PM_{2.5}$ concentration. The green line represents the daily average of indoor $PM_{2.5}$ concentration.

3.3. Impacts of human activities on Indoor PM Emission Sources

Table 4 shows the summary of indoor activities reported, which could be related to PM emissions or mitigation, including cooking, opening window in the sensor room, and using an air purifier. According to the activity log records, 9 out of the total 30 residents reported their activity logs for seven days. Each of the nine residents reported at least one cooking activities with a total number of 59 cases. Window opening was reported 30 times from 7 residences and using an air purifier was reported 32 times from 5 residents. Each case lasted for a different number of hours.

Table 4. Summary of indoor human activities related to indoor PM concentrations

Activities	No. of reported cases	No. of reported apartments
Cooking	59	9 out of 9
Opening window(s)	30	7 out of 9
Using air purifier(s)	32	5 out of 9

3.3.1.Cooking Activities

Cooking hours were defined as the reported cooking hours and one extra hour following the cooking activities. Out of 117 cooking hours with available air quality data, 61 hours (52%) had $PM_{2.5}$ I/O ratios less than 0.8, 7 hours (6%) had $PM_{2.5}$ I/O ratios between 0.8 to 1.2, and 49 hours (43%) had $PM_{2.5}$ I/O ratios greater than 1.2. The peak value of I/O ratios appeared as high as 183 during a residential cooking event and the simultaneous hourly $PM_{2.5}$ level was 194 $\mu g/m^3$, which indicates that cooking could lead to acute exposure to indoor $PM_{2.5}$. For some apartments, the low-cost sensor did not detect a noticeable increase of indoor $PM_{2.5}$ levels during cooking events. This may occur as a result of the varied type and scale of cooking activities, the distance from the cooking stove to the sensor, or good ventilation and mitigation measurements such as opening a window or using a range hood vent during a cooking activity.

Figure 3. Log-scale $PM_{2.5}$ I/O ratios during cooking and non-cooking hours. The solid horizontal line represents the median. The box represents the 25th to 75th percentiles, and the whiskers represent the outliers. The red solid line indicates where I/O ratio = 1.

The GM of $PM_{2.5}$ I/O ratios for cooking hours was approximately 1.0 (IQR: 0.3 - 3.2), and for non-cooking hours the GM of I/O ratios was approximately 0.3 (IQR: 0.1 – 0.8). As labeled in Figure 3, the $PM_{2.5}$ I/O ratios for cooking hours were significantly higher than the non-cooking hours ($p = 0.006$) using

Welch two-sample t-test. Both results indicate that during domestic cooking activities, the indoor PM was mostly generated indoors rather than infiltrated from the outdoor. When there were no cooking events in the residence, outdoor PM pollution apparently contributed more to indoor PM levels than indoor PM emissions. As cooking is an activity conducted daily in most homes, monitoring and mitigating the PM exposure during cooking is of great health importance. PA-II sensors used in this study were effective and economic for measuring indoor PM concentrations to identify potential acute exposure due to cooking. Based on the alerts from PA-II, residents could take good mitigation measures to decrease the indoor PM levels including the use of air cleaner, range hood, and natural ventilation or changing a cooking manner (Amouei Torkmahalleh et al., 2017; Kang et al., 2019; O'Leary et al., 2019; Sharma & Balasubramanian, 2020).

3.3.2.Opening window(s)

Comparing the window-opening and no-window-opening events, there is no statistically significant difference in I/O ratios ($p = 0.428$), but the center of the distribution of the I/O ratios during window openings seems to be closer to 1. As shown in Figure 4, the GM of I/O ratios from the window opening group was 0.9 (IQR: 0.6 – 1.1), and the GM of I/O ratios from the no window opening group was 0.3 (IQR: 0.1 – 0.8). This suggests that indoor air quality was influenced more by the ambient air quality when there was a window open because window openings could increase the outdoor-and-indoor ventilation rate. It indicates that the apartments were effectively ventilated by opening the window(s). Meanwhile, though, there was limited information on the number of windows opened or the opening area of the windows for further analysis of the ventilation effect of window openings.

Furthermore, we found an accelerated reduction of indoor PM when opening windows after cooking activities, which is consistent with the finding of a previous study (Kang et al., 2019). Figure 5 shows the normalized GMs trend of indoor $PM_{2.5}$ concentration in residences before, during, and after a cooking activity. The GMs of indoor background $PM_{2.5}$ concentrations (measured an hour before cooking) for the ventilation and the non-ventilation groups were 4.64 $\mu g/m^3$ and 1.79 $\mu g/m^3$, respectively. Data for both groups peaked during the cooking hour and gradually decreased to the background level. The GM of $PM_{2.5}$ concentrations for the ventilation group went back to the background level (4.53 μg/m^3) after 2 hours, and the GM of concentrations for the non-ventilation group (2.26 μg/m^3) was still slightly higher than the background level after 8 hours. This suggests that window opening could accelerate the decrease of indoor $PM_{2.5}$ concentrations to the background level after an indoor cooking activity, which is an effective ventilation measure to mitigating the cooking-derived PM exposure. The effect of the natural ventilation measure on indoor PM levels could be detected by the low-cost air sensor.

Figure 4. Log-scale $PM_{2.5}$ I/O ratios of ventilation group (window-opened hours) and non-ventilation group (no-window-opened hours). The solid horizontal line represents the median. The box represents the 25th to 75th percentiles, and the whiskers represent the outliers. The red solid line indicates where I/O ratio = 1.

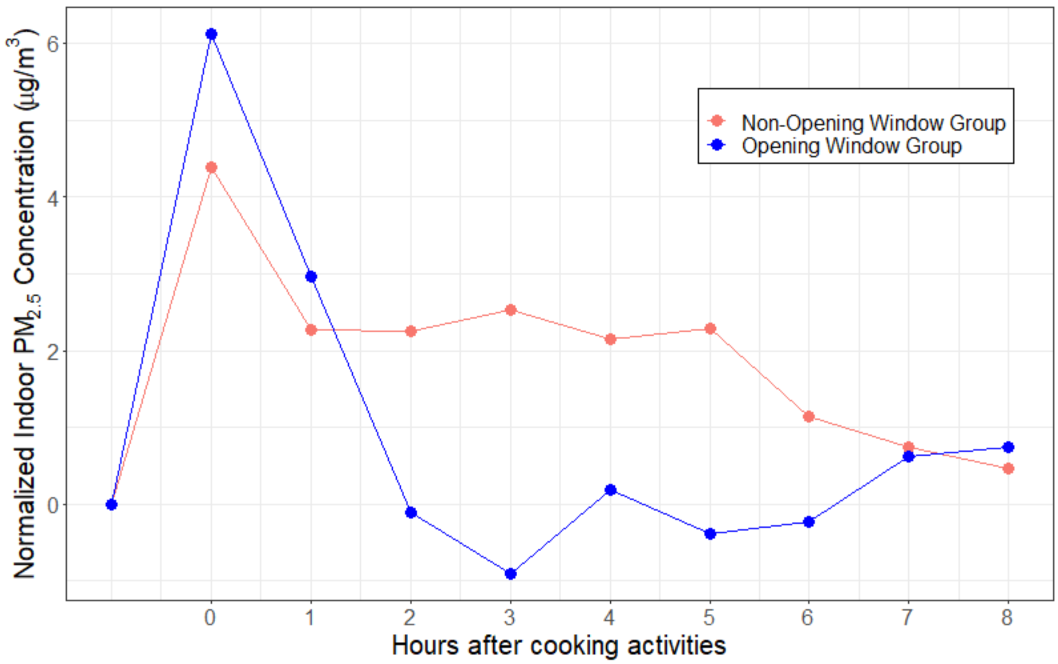

Figure 5. Normalized geometric mean of indoor $PM_{2.5}$ concentrations (μg/m^3) before, during, and after cooking activities with/without opening window. The green line represents the normalized GM of indoor $PM_{2.5}$ concentrations in residences with window opening. The red line represents the normalized GM of indoor $PM_{2.5}$ concentration in residences without window opened.

3.3.3.Using air purifier(s)

Another potential mitigation measure that was evaluated in the study was the use of air purifiers. Among all the investigated residents, 5 out of 9 reported the utilization of air purifiers (56%) with a total of 32 cases. Residences with an air purifier in use had lower $PM_{2.5}$ I/O ratios (GM: 0.1, IQR: 0.0 – 0.3) compared with residence without any air purifier in use (GM: 0.8, IQR: 0.4 – 1.2), although the difference was not statistically significant (p = 0.769). This indicates that using an air purifier could decrease the effects of outdoor air quality on indoor PM levels to some extent. Further study is still needed to accurately measure the mitigation effect of air purifiers with different characteristics such as the air exchange flow and the type of air purifier. In Figure 5, there are several outliers in using purifiers group showing that indoor PM levels were over 100 times higher than the outdoor, which might occur due to the high associations between human indoor activities. For instance, people intuitively tend to use air purifier when they feel indoor air quality worse, or when they are doing some indoor PM-emitted activities. There is also a need for further study to confirm or refute the assumptions.

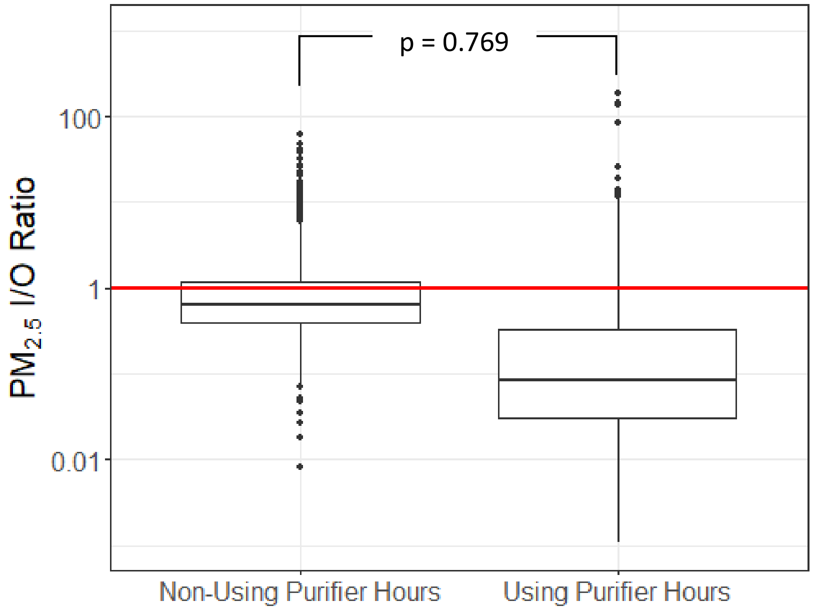

Figure 6. Log-scale boxplot of $PM_{2.5}$ I/O ratios during using and non-using air purifier hours. The red line indicates where the I/O ratio = 1.

3.4. Linear mixed-effects model for indoor $PM_{2.5}$ concentration

To further evaluate the performance of PA-II sensors, we developed a linear mixed-effects model for assessing the impacts of various indoor factors and ambient air quality on indoor $PM_{2.5}$ levels. The results of the fitted linear mixed-effects model are shown in Table 5 (fixed effects) and Figure 7 (random effect of sampling site). Based on this model, indoor $PM_{2.5}$ concentrations had positive associations with past indoor $PM_{2.5}$ concentrations ($p < 0.001$), current ambient $PM_{2.5}$ concentrations ($p < 0.001$), and indoor cooking activities ($p < 0.001$). Window opening ($p = 0.032$) and use of air purifiers ($p = 0.001$) had both significant negative impacts on indoor $PM_{2.5}$ concentrations, which had been identified as two effective household mitigation measures (Deng et al., 2015; Park et al., 2017; Sharma & Balasubramanian, 2020; Tong et al., 2020). Consistent with previous studies (Liu & Zhang, 2019; Snider et al., 2018; Tong et al., 2020; Zhao et al., 2015), ambient $PM_{2.5}$ levels were positively associated ($p < 0.001$) with indoor PM levels when all the other factors were controlled such as closing the window. These results indicate that $PM_{2.5}$ was always infiltrated from the outdoor to the indoor environment at a normal apartment even when the windows of the building were all closed. During window opening, the association between ambient $PM_{2.5}$ concentrations with IAQ would increase about two folds according to the value of interaction effect ($p = 0.046$). No microclimatic variable was significantly associated with indoor $PM_{2.5}$ concentrations in this study, and the measurements of temperature and RH reported by PA-II still need further studies to be evaluated for accuracy. In addition, previous studies found that meteorological factors have potential associations with the increased bias of low-cost sensors (Bi et al., 2020; Zheng et al., 2018), but the effect is still not clear and needs further evidence to confirm or refute these associations.

Unmeasured factors contributed to significant differences in PM levels between sites. As shown in Figure 7, varied intercepts were found for the $PM_{2.5}$ prediction model for each sampling site or monitoring sensor, and the likelihood ratio test comparing models with/without the random effect term demonstrates that sampling site or sensor was a significant random effect ($p = 0.03$), suggesting unobserved heterogeneity across residences and/or sensors deployed. Since all the low-cost sensors used in the present study were firstly deployed in the field without laboratory evaluation, there was probably some differences in factory calibration. On the other hand, differences between sites might also be attributable to microclimatic factors, as described above, leading to variation in sensor performance, as well as other factors of each residence (e.g., unrecorded activities of residents, building structure characteristics, the number of residents living in an apartment) that varied between sampling sites.

Table 5. Fixed-effects variables and coefficients of the linear mixed-effects regression model

Fixed Effects	Description	Coefficient	Standard Error	p-value
$LnCin_{i-1,j}$	past concentration of indoor $PM_{2.5}$	0.839	0.014	<0.001
$LnCambient_{ij}$	ambient $PM_{2.5}$ concentration	0.097	0.021	<0.001
$Cooking_{ij}$	cooking	0.567	0.075	<0.001
$Window_{ij}$	window opening	-0.259	0.120	0.032
$Purifier_{ij}$	air purifier using	-0.333	0.077	0.001
T_{ij}	Temperature	-0.002	0.009	0.842
$R.H._{ij}$	Relative humidity	0.001	0.004	0.811
$Window_{ij} * LnCambient_{ij}$	Interaction effect of window opening and ambient $PM_{2.5}$	0.083	0.041	0.046

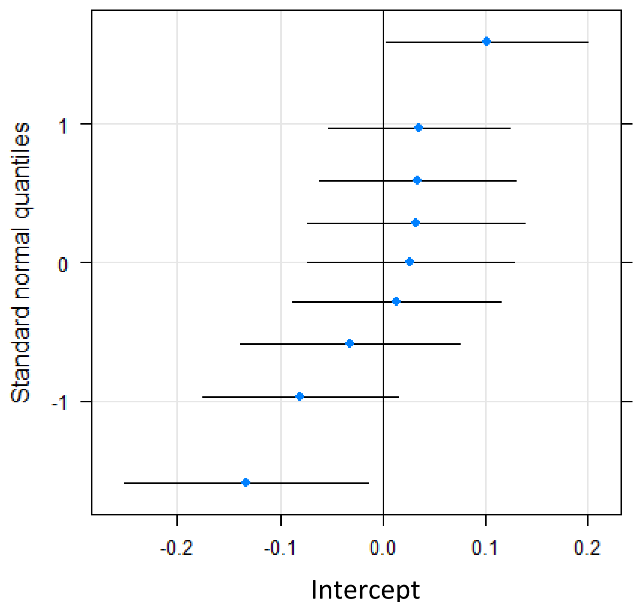

Figure 7. Random-effect of sampling site (intercepts) for the fitted linear mixed-effects regression model. Horizontal lines represent the 95% confidence intervals of the random intercepts at each sampling site.

The diagnostic graphs of the fitted regression model are attached in the Appendix (Figure A2). The residual plot and the histogram of residuals verify the assumptions of linearity and homoscedasticity, and the normal Q-Q plot proves the assumption of normality. The scatter plot of the fitted against the observed values of the natural logarithm of $PM_{2.5}$, as shown in Figure 8, suggests a good fit by this model. The conditional and marginal R^2 (0.864 and 0.862, respectively) of the fitted model reveal that this mixed-effects model could explain 86.4% of the variations in the indoor $PM_{2.5}$ concentrations and the model with fixed-effects could explain 86.2% of the variations. Compared to previous studies (Gaffin et al., 2017; Tong et al., 2020), this model has better performance in explaining the variations in indoor $PM_{2.5}$ levels with a greater value of R^2. Introducing past indoor $PM_{2.5}$ levels term into this model, however, could limit the generalization of the model. If we removed the past IAQ term from the model, the conditional and marginal R^2 would be 0.490 and 0.246, respectively. The fitted results of the partial regression model are attached in the Appendix (Table A1). Therefore, this model performed well with the data monitored by PA-II sensors, yielding reliable and reasonable predictions of indoor PM levels.

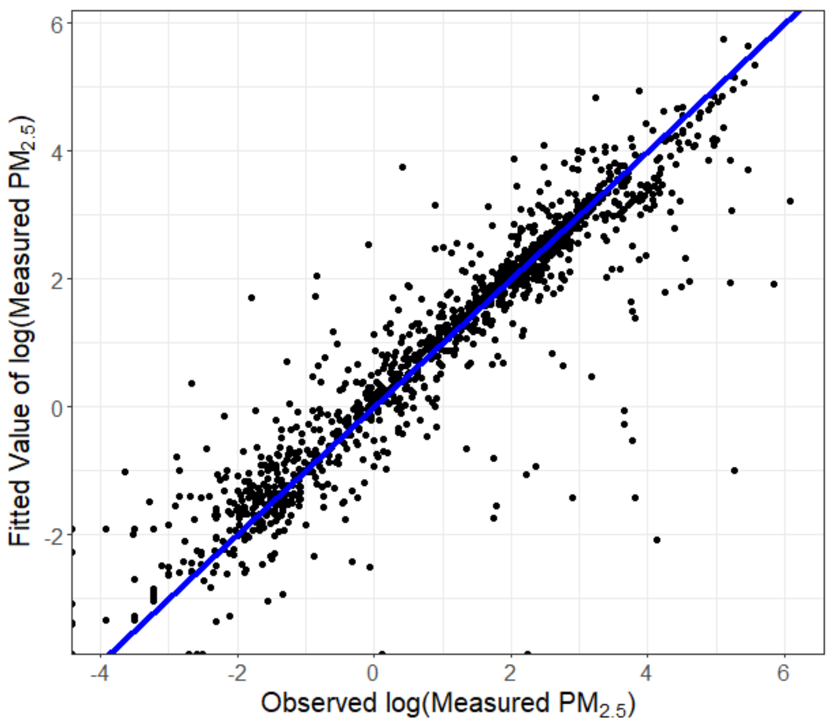

Figure 8. Scatter plot of the fitted value vs. observed value of the natural logarithm of indoor $PM_{2.5}$ concentrations. The blue line indicates where the fitted values equal to the observed values.

4. Limitations

This study has several limitations. First, the study was conducted at a single university-based community with a small sample size. The similarity of residents' routine, sampling location, and building design limited the generalizability of this study. Second, the activity logs were only collected for 7 days at each recruited residence and were recorded manually by the recruited participants. Individual memory errors and attention biases could happen. Third, this low-cost air quality sensor can detect size-specific PM, but performs poorly for PM with diameters less than 0.3 μm and greater than 10 μm. Since the particles emitted from gasoline vehicles distribute more in the range of diameter less than 0.5 μm, the PA-II sensor probably failed to detect part of the transportation pollution around this freeway-adjacent study site. In addition, the performance of PA-II sensor was highly affected by the outlet and wi-fi connection, which could introduce unknown bias. Lastly, the study investigated three indoor activities with limited control variables, while there are more than three types of indoor activities (e.g., burning candles, smoking, and putting on make-up) and influence factors (e.g., room area, number of residents, and ventilation system) relating to indoor PM concentrations.

5. Conclusions

This study provides evidence that the low-cost air quality sensor, PA-II sensor, could effectively monitor indoor PM concentrations and detect the impacts of indoor activities on IAQ.

As analyzed above, indoor sensors perform better compared with sensors deployed outdoors. Residential cooking is a major indoor PM emission source. Natural ventilation (opening window) can effectively bring back indoor elevated $PM_{2.5}$ concentration to the background level. Using an air purifier is another effective mitigation measure.

In addition, indoor PM levels are significantly associated with past PM levels, ambient PM levels, and indoor activities. Ambient PM levels and window opening have an interaction effect on indoor PM levels. In other words, when ambient PM pollution occurs, closing windows could significantly help to reduce indoor PM levels. When indoor PM emission occurs, opening windows could effectively help to dilute the indoor PM.

Given the inexpensive cost and good performance in this study, the PA-II sensor offers a cost-effective way to monitor real-time IAQ for individuals, communities, and other local environmental groups, and has the potential to provide a high-resolution dataset of PM for environment scientists and policymakers.

Appendices

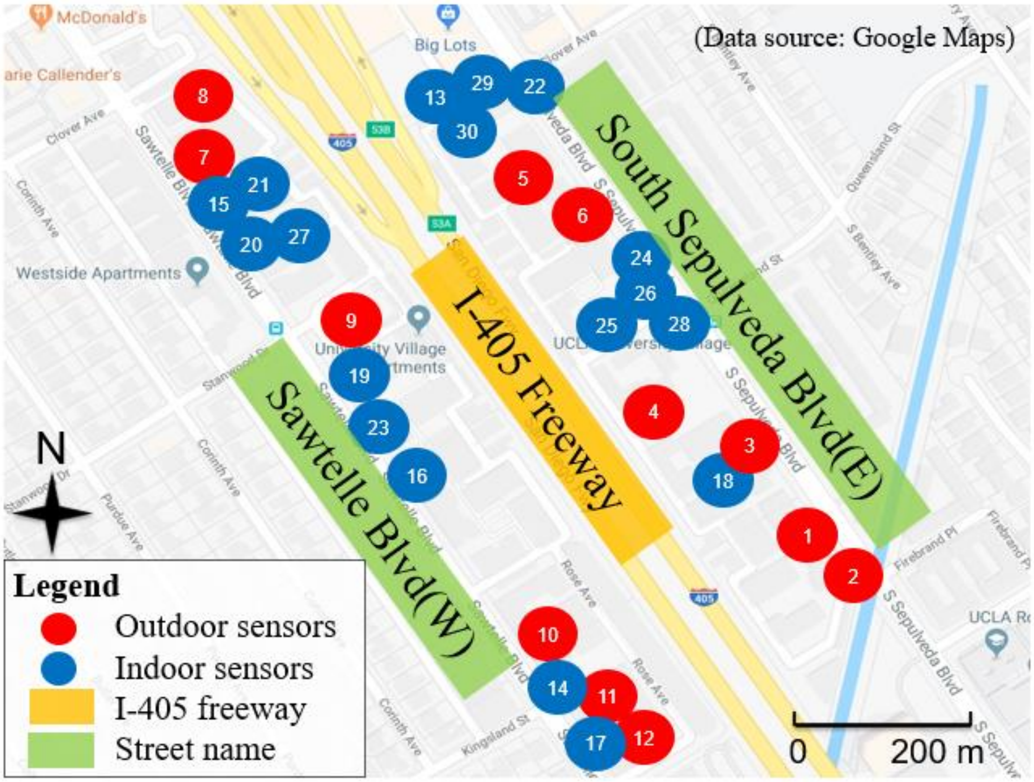

Figure A1. Map of Sampling Locations of PurpleAir II sensors in the university village apartments

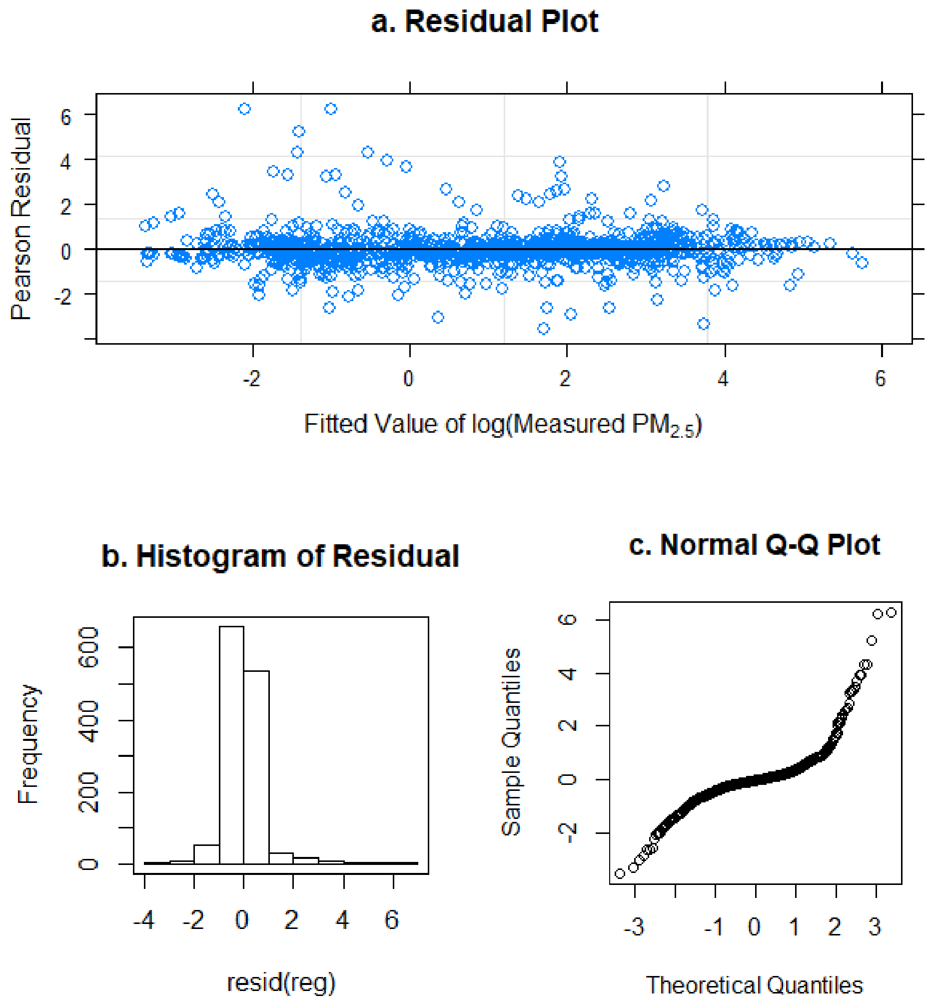

Figure A2. Diagnostic graphs of the fitted regression model.

Table A1. Fixed-effects variables and coefficients of the linear mixed-effects regression model

Fixed Effects	Description	Coefficient	Standard Error	p-value
$LnCambient_{ij}$	ambient $PM_{2.5}$ concentration	0.522	0.036	<0.001
$Cooking_{ij}$	cooking	0.852	0.140	<0.001
$Window_{ij}$	window opening	-0.384	0.240	0.110
$Purifier_{ij}$	air purifier using	-0.915	0.236	<0.001
T_{ij}	temperature	0.002	0.019	0.932
$R.H._{ij}$	Relative humidity	0.010	0.008	0.245
$Window_{ij} * LnCambient_{ij}$	Interaction effect of window opening and ambient $PM_{2.5}$	0.217	0.077	0.005

Note: conditional R^2 = 0.490, marginal R^2 = 0.246.

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