Performance and Feasibility of Low-Cost Air Sensors for Community and Occupational Exposure Assessment

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LIST OF ABBREVIATIONS

AGSL/SL	Alliance for a Greener South Loop
BAM	Beta Attenuation Method
CARB	California Air Resource Board
CBPR	Community-Based Participatory Research
C_b	Bias Correction Factor
CCC	Lin’s Concordance Correlation Coefficient
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EC	Electrochemical
FEM	Federal Equivalent Method
FRM	Federal Reference Method
HDVs	Heavy-Duty Vehicles
IEPA	Illinois Environmental Protection Agency
LDVs	Light-Duty Vehicles
LVEJO/LV	Little Village Environmental Justice Organization
MAE	Mean Absolute Error
MBE	Mean Bias Error

LIST OF ABBREVIATIONS (continued)

MLR	Multiple Linear Regression
MOS	Metal Oxide Semiconductor
$\mu g/m^3$	microgram per cubic meter
NAAQS	National Ambient Air Quality Standards
NDIR	Nondispersive Infrared
NO	Nitric Oxide
NO_2	Nitrogen Dioxide
NO_y	Total Reactive Nitrogen
OEHHA	Office of Environmental Health Hazard Assessment
O_3	Ozone
PCR/PC	People for Community Recovery
PM	Particulate Matter
PM2.5	Fine inhalable particles, with diameters ≤ 2.5 micrometers
PM10	Inhalable particles, with diameters ≤ 10 micrometers
ppm	part per million
ppb	part per billion
%RH	% Relative Humidity

LIST OF ABBREVIATIONS (continued)

RMSE	Root Mean Square Error
RCS	Relative Compliance Scores
SASA	Shared Air/Shared Action
SCAQMD	South Coast Air Quality Management District
SETF/SE	Southeast Environmental Task Force
UIC	University of Illinois at Chicago
USEPA	United States Environmental Protection Agency
UPAS	Ultrasonic Personal Aerosol Sampler
WINS	Well Impactor Ninety-Six

SUMMARY

The present study examined the performance of low-cost air monitoring sensors in environmental and occupational settings and the performance of these sensors against Illinois Environmental Protection Agency (IEPA) monitors at Northbrook, Illinois. The inter- and intra-variability of these sensors were assessed in order to gain an understanding of their reliability for future exposure assessment studies. The feasibility of employing these sensors with participation of citizen scientists (i.e., community members and workers) was determined. The understanding of performance characteristics and the feasibility of using these new generation sensors would expand the capacity of real-time air quality data for personal and sub-regional exposure concentrations. Since these sensors are low-cost and they provide real-time exposure data, incorporating them into air quality monitoring would similarly revolutionize the field of environmental and occupational exposure assessment by enabling access to real-time view of exposure concentrations and devising exposure/risk reduction exposures to improve community members' and workers' health, in addition to increasing the capacity of environmental justice organizations and socio-economically disadvantages subpopulations for air quality monitoring and air quality data interpretation for grassroots level community engagement and empowerment. This study provided valuable scientific data on the quality control parameters of these sensors, which are needed for exposure monitoring plan developments and exposure data collection efforts.

Our study demonstrates that it is feasible to employ the sensors for local air quality assessment in support of citizen science projects, when the citizen scientists are properly trained on how to operate and interact with air sensors and a collaborative relationship is established between the research team and community in each phase of the project. In addition, it is feasible to employ the sensors for occupational air quality assessment in support of personal exposure studies, when the workers are properly trained on how to operate and interact with air sensors. Our collocation study demonstrated that all investigated low-cost sensors had a very high degree of precision and sufficient accuracy in obtaining air pollutant concentrations at various locations to assess the relative air quality. The low-cost sensors had some degree of correlation and agreement with their Federal Reference Method/Federal Equivalent Method monitors; therefore, the low-cost sensors should not be used for compliance assessment. However, theyThe are very useful tools in determining the hot spots, and for public education, outreach, and advocacy efforts. The low-cost sensors were observed to be impacted by the temperature and humidity, which vary among locations and time periods; therefore, an additional correction of sensor measurements for the specific meteorological conditions need to be investigated in order to develop more appropriate and representative correction algorithms for specific locations.

I. INTRODUCTION

Air pollution is a mixture of natural and anthropogenic substances in the air we breathe including both outdoor and indoor. Air pollution was the fifth leading mortality risk factor worldwide in 2017 (Health Effects Institute, 2019). Pollutants considered as public health concerns include particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). PM is one of the most known health threats. In 2013, it was classified as a human carcinogen by WHO's International Agency Research on Cancer (IARC). Particulate matter is a mixture of very small solid particles and liquid droplets in the air. It is typically measured as coarse, fine or ultrafine particles, designated as PM10, PM2.5, PM1.0 respectively, where the numeric subscript refers to the maximum particle aerodynamic diameter measured in micrometers. Several epidemiologic studies suggested PM can cause adverse health outcomes involving cardiovascular diseases, respiratory issues, lung cancer, and adverse birth outcomes (Brook et al., 2010; Madrigano et al., 2013; Pope et al., 2011; Ristovski et al., 2012; WHO, 2018). The Clean Air Act enacted in 1970 mandated USEPA to establish National Ambient Air Quality Standards (NAAQS) for six criteria air pollutants i.e., PM, ground-level O_3, CO, SO_2, NO_2, and lead which are ubiquitous across the U.S. and considered harmful to human health and the environment. These standards are periodically reviewed and may be revised according to updated scientific evidence (USEPA, 2014).

Overall, air quality has improved nationally across the U.S. since 1980; however, this is still an ongoing matter. Approximately, 137 million people have lived in counties with pollution level above the primary NAAQS for one or more pollutants (USEPA, 2016). In particular, PM2.5 level decreased by 2.4% from 2009 to 2016 and increased by 5.5% from 2016 to 2018, especially among West and Midwest regions (Clay & Muller, 2019). In 2017, the percentage of people worldwide living in areas that exceeded the most-stringent WHO air quality guideline for PM2.5 ($\leq 10\ \mu g/m^3$) and the least-stringent guideline ($\leq 35\ \mu g/m^3$) were 92% and 54%, respectively (Health Effects Institute, 2019). Creating better policies for a richer quality of life requires reliable information about exposure to and impact from air pollutants to meaningfully address air pollution concerns. Air quality monitoring has been shifted to more miniaturized and low-cost sensors due to an inadequate number of traditional fixed-site air monitoring stations conducted by government agencies. Some issues related to fixed-site air monitoring stations include: limited air quality data collected at high spatial and temporal resolutions; high cost and high demanding maintenance; and required technical infrastructures and well-trained personnel to properly operate the equipment (Borghi et al., 2018; Kumar et al., 2015). The shortage of air monitoring stations has occurred globally, including in the U.S. In the past decade, the numbers of air monitoring stations have decreased from 84 (in 2010) to 64 (in 2017) across Illinois (Illinois Environmental Protection Agency Bureau of Air, 2014; IEPA, 2013; IEPA, 2018). Another issue is that most regulatory stations are generally located away from roadsides and congested areas. Thus, point-based emission and personal exposure assessment are not feasibly and readily determined. The air quality data relies on a limited number of air monitoring stations capturing spatial concentrations rather than personal exposure concentrations. Within the last ten years, low-cost air monitoring sensors (<$2,500) have been commercially available. These low-cost sensors enhance the ability to understand air quality in a wide range of spatial and temporal conditions; in addition to advancing personal exposure assessment studies. These sensors will narrow the gap of accessibility to air quality data among communities and laypeople (Clements et al., 2017; Snyder et al., 2013). However, there are several challenges in employing low-cost sensors including the development of sensors producing high quality data and the evaluation of sensor performances in environmental and occupational settings (Snyder et al., 2013). Several studies have assessed performances of these commercial sensors in environmental and controlled laboratory settings against Federal Reference Method (FRM) and Federal Equivalent Method (FEM) monitors (Lin et al., 2017; Liu, Zhang, Jiang, & Chen, 2017; Manikonda, Zíková, Hopke, & Ferro, 2016; Rai et al., 2017; SCAQMD, n.d.). However, these low-cost mobile sensors have not been used in occupational settings and their practicality has not been determined. The present study examined the performance of low-cost air monitoring sensors in environmental and occupational settings and the performance of these sensors against USEPA monitors. The inter- and intra-variability of these sensors were assessed in order to gain an understanding of their reliability for future exposure assessment studies. The feasibility of employing these sensors was determined. The strengths, weaknesses, and limitations of using them in the field were documented. The understanding of performance characteristics and the feasibility of using these new generation sensors would expand the capacity of real-time air quality data for personal and sub-regional exposure concentrations. The new generation of these sensors has facilitated citizen-science projects with respect to outdoor air pollution characterization across communities in the U.S. but have been limitedly used in occupational exposure assessments. Since these sensors are low-cost and they provide real-time exposure data, incorporating them into air quality monitoring would similarly revolutionize the field of environmental and occupational exposure assessment by enabling access to real-time view of exposure concentrations and devising exposure/risk reduction measures in an expeditious fashion. This is expected to result in improved health and safety for community members and workers exposed to air pollutants, in addition to increasing the capacity of environmental justice organizations and socio-economically disadvantages subpopulations for air quality monitoring and air quality data interpretation for grassroots level community engagement and empowerment. Moreover, this study aims to provide valuable scientific data on the quality control parameters of these sensors, which are needed for exposure monitoring plan developments and exposure data collection efforts. The specific aims of this study focused on the following three objectives:

1. To assess the feasibility of community members to employ the selected low-cost air monitoring sensors in local air quality assessment and the low-cost sensor performance in the breathing-zone
2. To assess the performance of the selected low-cost sensors against EPA Federal Reference Method (FRM) and Federal Equivalent Method (FEM) monitors
3. To assess the feasibility of workers to employ the selected low-cost air monitoring sensors for personal occupational air quality monitoring and the low-cost sensor performance in the breathing-zone

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II. BACKGROUND

A. Citizen Science in Air Quality Monitoring Efforts

Citizen science/Community-Based Participatory Research (CBPR) approach has been increasingly implemented in air pollution studies. McKinley and colleagues defined citizen science as the practice of engaging the public, which in most cases are volunteers, in a scientific project that is reliable and applicable for scientists, decision makers, and the public (McKinley et al., 2017). Citizen science approach incorporates a wide range of methodology retrieved from both citizens and scientists to achieve a variety of goals. Citizens collaboratively engage in the entire scientific process starting with investigation and exploration to address community-defined questions (Woodall et al., 2017). Citizen science has been implemented in several fields including pollution detection and enforcement, for example, Bucket Brigade; Clean Air Coalition of Western New York; and Alabama Water Watch Program (McKinley et al., 2017). According to Commodore and colleagues, community participants partook in air pollution studies attributable to their concerns for air pollution health risks, proximity to contaminated sources, urban sprawl, shortage of air monitoring systems, and knowledge improvement. Most community air monitoring systems are fixed-site stations. Therefore, more personal, school-based, and occupational samplings are needed (Commodor et al., 2017). Emerging sensor technologies empower citizens to create air monitoring networks and collect air quality data to better understand their community environment. Several collaborative air quality research/projects have been the main focus in many countries around the globe.

1. Global Efforts in Citizen Science Air Quality Monitoring

The CITI-SENCE is one of the most notable projects engaging multiple metropolitan countries. The CITI-SENSE's observatories Toolbox provided the public with handy information to monitor and understand their neighborhood air quality (CITI-SENSE, 2015). Another project in Amsterdam, the Netherlands, utilizing a bottom-up approach for urban environmental monitoring was the Wagg Society Amsterdam Smart Citizen Lab project. Participating citizens provided input about their concerns and interests, then developed their test sensor systems to tackle those issues (Jiang et al., 2016). CleanAir@School is a joint initiative of the European Network of the Heads of Environmental Protection Agencies and the European Environment Agency launched in April 2018 and ran until the end of 2019. Across several schools in Europe, students and their parents monitored air pollution around schools in their neighborhood to better understand children's exposure to nitrogen dioxide (NO_2) (Citizen science initiative CleanAir@School — European Environment Agency, 2020). The Clean Air Asia consortium is a partnership of multiple cities in Asia. As an example, several of the projects provided the public with the knowledge to improve air quality in India (Clean Air Asia, n.d.).

2. USEPA Efforts in Citizen Science Air Quality Monitoring

United States Environmental Protection Agency (USEPA) efforts in collaboration and facilitation of citizen scientists in air monitoring include: 1) the Village Green project, a pilot new real-time air monitoring station for O_3, PM, and weather condition measurements located in Durham, North Carolina using solar and wind power with little or no technical support. The project demonstrated the citizen scientists' ability to operate the mid-tier technology (~$6000/each) sensors for long-term air monitoring sessions with continuously streaming data to the publicly available web-based data portal; 2) AirMapper, a portable air sensor developed by EPA researchers that allow citizen scientists to map their environment; 3) REal TIme Geospatial Data Viewer (RETIGO), a free web-based tool that reduces burden to visualize collected air quality data, gears the public to explore air quality and meteorological data from their nearby stations; 4) Air Sensor Loan Programs for Communities, programs providing the public with new technology air sensors for education; 5) Air Sensor Toolbox for Citizen Scientists, an online resource providing information and guidance on new, low-cost sensors and how to understand results from monitoring activities (USEPA, 2014; USEPA, 2016a; USEPA, 2016c; USEPA, 2020). The Air Sensor Toolbox was implemented in Ironbound Community, New Jersey, as a prototype. This pilot study offered opportunities to improve future citizen science in air quality monitoring efforts (Kaufman et al., 2017).

3. Other U.S. Agencies' and Organizations' Efforts in Citizen Science Air Quality Monitoring

In 2016, Clean Air Carolina launched the "AirKeepers" program in Charlotte with volunteers performing both fixed and mobile air monitoring in their environment. The collected data is available for the public and is used by scientists (Clean Air Carolina, n.d.). California Air Resource Board (CARB) which is one of the most active and progressive organizations for community air monitoring networks across the U.S. has implemented several projects including San Ysidro Community Air Study (CARB, 2020). San Ysidro Community Air Study, in San Diego, is an example of a collaborative work among the community, state and local government, and academia. The neighborhood air quality data has been collected by low-cost sensors with the full community participation (OEHHA, 2017).

B. Emerging Technologies in Air Quality Monitoring and Their Challenges

The new paradigm for air quality monitoring is shifting to more miniaturized, low-cost, easy-to-use, and portable air sensors. The collected air quality data will be useful for air quality management activities, such as: 1) supplementing regular ambient air monitoring networks; 2) providing the public with information and education; 3) identifying and characterizing hotspots/local sources; and 4) advancing personal exposure assessment studies. Each activity requires different levels of sensor performance indicated by several characters i.e., bias, precision, data averaging time, and data completeness. For example, sensors employed for the public's education/information purpose require less stringent performance goals than those employed for hotspot identification and characterization purpose (Snyder et al., 2013; Williams et al., 2014). Morawska and colleagues conducted an intensive review of low-cost air sensor applications. Their findings provided evidence that exposure monitoring has had little progress; in addition, more air monitoring studies at a finer scale are needed. This could be explained by the fact that personal exposures require resources including electric power and community engagement (Morawska et al., 2018). Emerging tools facilitating the citizen science approach are new technologies including mobile phone applications, wireless sensor networks, online computers, and video games. These technologies advance the citizen science in terms of disseminating knowledge to a broader audience, improving data collection and control, and increasing data availability and accessibility for decision making (Newman et al., 2012). Several challenges of employing low-cost air sensors in air monitoring networks, such as the quality of collected data, have been encountered as currently, there are no standardized means of addressing a low-cost sensor performance (Williams et al., 2019; Woodall et al., 2017). Nowadays, most commercially available low-cost sensors are predominantly optical (e.g., AirBeam, PurpleAir, MetOne neighborhood PM sensors), electrochemical, or metal oxide semiconductor (e.g., AeroQual S500 NO_2 and O_3 sensors). These technologies do not generally meet the requirements/standards as the Federal Reference Method (FRM) or Federal Equivalent Method (FEM) instruments. The low-cost sensor measurements may be influenced by several factors such as interfering compounds, environmental conditions, and sensor mal-operation. Therefore, it is crucial to validate low-cost sensor performances through collocation field tests against FRM and FEM instruments before employing them to support the communication of potential hazards and public health risk management, as well as regulatory compliance. More traditional instrumentation manufacturers have recently invested research capital into low-cost sensor areas. However, manufacturers may not have enough technical knowledge to test or calibrate their products prior to the market launch, in addition to minimizing intra-variability between each unit of sensor associated with production quality control (Woodall et al., 2017). Another big challenge is the interpretation of sensor readings. Generally, data obtained from these low-cost sensors indicates short-term measurements and cannot be compared to the NAAQS to draw conclusion on health effects associated with exposure concentrations. However, USEPA has piloted a color-coded Sensor Scale for 1-minute PM2.5 and O_3 readings (not for regulatory purposes) as a high-medium-low tier for better understanding the obtained sensor data and the ability to informatively make behavioral decisions for any outdoor activities (USEPA, 2016d).

C. <u>Low-Cost Sensor Applications</u>

Low-cost sensors have been employed for several purposes, particularly for education and raising public awareness; and for supplementing the regulatory air monitoring network. Low-cost sensor networks could provide air quality data for more spatial and temporal variations. In conjunction with air quality modeling, low- cost sensor networks would afford a better understanding of local air quality. Miskell and colleagues employed AeroQual S500 for O_3/NO_2 sensors for personal exposure assessment. While wearing the sensor, participants visited different locations. The collected data supported land use regression models to investigate the finer-scale air quality (Miskell, Salmond, & Williams, 2018; Weissert et al., 2020). Castell et al. conducted a comparison study among low-cost sensor data, air quality modeling data, and fusion data derived from the first two methods. The results suggested that the low-cost sensor data and fusion data highly correlated with reference monitor data ($r \geq 0.9$), while modeling data suggested a lower correlation with reference monitor data ($r=0.8$) because the modeling was not able to capture the local events (Castell et al., 2018). This emphasized an important need for air monitoring in small-scale areas. Low-cost sensor networks are also beneficial for occupational exposure assessments. Low-cost sensor networks have shown a good agreement with the sensors commonly used for occupational personal exposure assessment (e.g., pDR and POM) for PM2.5 and CO

(Zuidema et al., 2019). Low-cost sensor applications may also facilitate the intervention program evaluation. Klepeis and colleagues utilized low-cost sensors i.e., Dylos DC11000 to monitor particulate matters generated from smoking at home, before and after implementing Smoke-Free Home intervention programs (Klepeis et al., 2013). Semple et al. employed a low-cost sensor, Dylos 1700, alongside with Sidepak reference sensor, commonly used for indoor aerosol measurement. The results suggested good agreement between low-cost and reference sensors. They concluded that low-cost sensors may be useful for air quality-based interventions and behavioral changes to smoke-free house motivations (Semple et al., 2015).

D. Performance Assessment of Low-Cost Air Monitoring Sensors

Reliable air monitoring devices are one of the essential elements in air monitoring. At present, there are no existing sensor performance evaluations or certification programs for the low-cost air monitoring sensors (Williams et al., 2019). However, groups of researchers have conducted studies evaluating low-cost air sensors in different conditions i.e., environmental and laboratory settings. Three prominent programs/institutes such as the USEPA Office of Research and Development (ORD); the Air Quality Sensor Performance Evaluation Center (AQ-SPEC), operated by the South Coast Air Quality Management District (SCAQMD); and the Joint Research Center (JRC), operated by the European Commission's Science and Knowledge Service have also been involved in these studies (Clements et al., 2017). The low-cost air sensors utilized in the present study including mobile air sensors i.e., Air Beam, AirBeam2 (Habitatmap, Brooklyn, NY, USA), Terrier (Qsense Inc., Boulder, CO, USA), and Ultrasonic Personal Air Sampler (UPAS) (Access Sensor

Technologies, CO, USA); and stationary air sensors i.e. AeroQual S500 (AeroQual Limited, Auckland, New Zealand), MetOne Neighborhood Monitor (Met One Instruments, Inc., Grants Pass, OR, USA), and PurpleAir (Purple Air, Draper, UT, USA) have been tested and reviewed in previous studies.

1. USEPA's Research on Sensor Evaluation

Williams and colleagues conducted an extensive review on low-cost air sensor performance studies, and suggested the need for additional information and research to determine low-cost sensor operations and their performance for a given purpose (Williams et al., 2018). United States Environmental Protection Agency (USEPA) performed collocated field evaluations of PM and gaseous pollutant monitoring sensors and compared the findings of low-cost sensors with those of reference monitors (USEPA, 2016b). Among all tested PM sensors, RTI MicroPEM had the highest degree of correlation with the reference monitor (i.e., GRIMM) with R^2=0.72 (Williams, Kaufman et al., 2014). AirBeam had a moderate correlation and MetOne had a low correlation with the reference monitor (i.e., BAM) with R=0.65-0.66 and R=0.32-0.41, respectively (Jiao et al., 2016). Across all the tested gas phase sensors, several low-cost air sensors highly correlated with reference analyzers. When comparing ozone monitoring with reference analyzers, CairClip NO_2/O_3 USB version had the highest correlation (R^2=1) (Williams, Long et al., 2014). AeroQual SM50 had a high correlation with R=0.91-0.97 (Jiao et al., 2016). When comparing NO_2 monitoring with reference analyzers, CitiSense and AirCasting sensors demonstrated the highest correlation (R^2=0.98) (Williams, Kilaru et al., 2014). Recently, a 7-month field study conducted in Denver, Colorado evaluating the long-term sensor performance suggested that AeroQual had a high percentage of data recovery (80%) while AirBeam had a lower percentage of data recovery (30-60%). AeroQual and AirBeam highly and moderately correlated with their respective reference monitors with R^2=0.85-0.92 and R^2=0.53-0.74, respectively. The low-cost sensor measurements were found to be more impacted by relative humidity than by wind directions (Feinberg et al., 2018).

2. South Coast Air Quality Management District Research on Sensor Evaluation

South Coast Air Quality Management District (SCAQMD) established the Air Quality Sensor Performance Evaluation Center (AQ-SPEC) program aiming to evaluate and create performance standards for tested sensors. Sensors are evaluated against FRM/FEM instruments in laboratory and field settings. Across all tested PM2.5 sensors, PurpleAir had the highest degree of correlation with reference monitors (i.e., BAM and GRIMM) with R^2=0.93-0.97 (SCAQMD, 2016). AirBeam and AirBeam2 moderately correlated with reference monitors i.e., BAM (R^2=0.65-0.77) and GRIMM (R^2=0.65-0.75). AirBeam mass data was largely overestimated while the particle count showed a good agreement (SCAQMD, 2015a; SCAQMD, 2018). MetOne Neighborhood Monitor moderately correlated with both FEM BAM (R^2=0.65-0.66) and GRIMM (R^2=0.66-0.67) (SCAQMD, 2015b). Mean Absolute Error (MAE) between PurpleAir and the FEM BAM was 6.7-7.0 μg/m^3. MAE between Airbeam and the FEM BAM was 4.4-7.5 μg/m^3. Moreover, the results suggested that the predominant error associated with AirBean and PurpleAir sensors is systematic in nature rather than random (Feenstra et al., 2019). For gas phase sensor evaluations, CairPol demonstrated the highest correlation with the CO reference monitor (R^2=0.94). For ozone measurements, AeroQual sensor highly correlated with the reference monitor with R^2=0.85 (SCAQMD, n.d.). Another study conducted by Collier-Oxandale and colleagues suggested that Personal Ozone Monitoring (POM), a UV-based sensor, showed high accuracy across all tested temperatures and relative humidity ranges, while AeroQual, a MOS-based sensor, were impacted by ambient temperature and humidity since extreme humidity and temperature may reduce the sensitivity of the sensor, in addition to degrading the sensor's hardware (Collier-Oxandale et al., 2020; Wang et al., 2010).

3. Other Sources of Research on Sensor Evaluation

AirBeam and PurpleAir are two of the most popular low-cost PM2.5 sensors utilized in several projects including the present study. The performance of AirBeam has been evaluated in several studies and found to be satisfactory. Sousan and colleagues found that AirBeam, in the exposure chamber tests measuring particulate matter generated from salt, welding and Arizona road dust, moderately correlated with a reference instrument i.e., Scanning Mobility Particle Sizer and Aerodynamic Particle Sizer tandem (SMPS-APS) with R^2=0.70-0.96 (Sousan et al., 2017). Another recent study performed by Mukherjee et al. reported that AirBeam demonstrated a high degree of precision with R^2=0.95-0.99 and a moderate degree accuracy against the FRM GRIMM11-R with R^2=0.6-0.76 (Mukherjee et al., 2017). AirBeam2 was launched in 2018 and employed in the present study. AirBeam2 highly correlated with the TSI DustTrack tested in the concentrated air pollutant chamber (R^2=0.88-0.89) (Heimbinder & Lim, 2018). Kelly and colleagues observed that PurpleAir PMS highly correlated with research-grade instruments (i.e., TSI DustTrack II and GRIMM) tested in the laboratory wind tunnel, as well as with FEM i.e., TEOM tested in ambient conditions (R^2=0.82-

0.87) (Kelly et al., 2017). Recently, DeWitt et al. conducted a 10-month collocated air monitoring study in Houston, TX. The results suggested low intra-variability between AirBeam units (R^2= 0.79-0.98) and low degrees of correlation with FEM (R^2= 0.36-0.42). They also observed the temporal variability of AirBeam performance in addition to a better agreement with FEM with temperatures above 80 degrees Fahrenheit. However, AirBeam readings were impacted by relative humidity (DeWitt, Crow, & Flowers, 2020). Another PM2.5 sensor employed in the present study was the Ultrasonic Personal Aerosol Sensor (UPAS), which has a different operating system compared to the rest of PM2.5 sensor counterparts. UPAS, which is developed by Volckens et al., is designed for personal PM exposure measurements capturing PM2.5 using time-integrated impaction. It does not require calibration, but runs on battery power (battery life is greater than 35 hours at the operating flow rate of 1 lpm). The UPAS performance was conducted against FEM, i.e., URG cyclone and a Personal Environmental Monitor (PEM) widely used in occupational exposure assessment. The findings showed stronger correlations between UPAS and FEM (R^2=0.99) compared to the correlation between PEM and FRM (R^2=0.96). The average mass measured by UPAS was in agreement with the FEM (7% difference) (Volckens et al., 2017). UPAS is very new and has been utilized in very few studies. A previous pilot study conducted by Arku and colleagues characterized exposure to household air pollution in multiple urban and rural communities by using UPAS and Harvard Impactor. An inter-comparison between these two sensors was performed suggesting a high correlation with R^2=0.83 (Arku et al., 2018). Another recent study among rural Honduran women conducted by Pillarisetti et al. observed a strong correlation between UPAS and a commonly used gravimetric pump, cyclone, and filter sampling system with R^2= 0.91 in PM2.5 personal exposure measurement (Pillarisetti et al., 2019).

AeroQual S500 sensor, the fixed/mobile gaseous pollutant sensor used in the study, was employed to measure ozone or nitrogen dioxide. According to Lin et al., AeroQual S500 O_3 measurements highly correlated with the UV-absorption reference analyzer measurements (R^2=0.88-0.96). Whereas, AeroQual S500 NO_2 measurements poorly correlated with those of the reference chemiluminescence analyzer (R^2=0.02) in the testing chamber and in environmental settings. Moderate correlation between AeroQual S500 NO_2 sensor and the reference monitor (R^2=0.47-0.89) was observed. The findings suggested that the AeroQual S500 NO_2 sensor was sensitive to O_3 in the environmental settings (Lin et al., 2015; Lin et al., 2017). The recent study by DeWitt et al. suggested moderate to low intra-variability between AeroQual S500 O_3 units (R^2=0.76-0.81) and moderate to low inter-variability against FEM (R^2=0.72-0.85) (DeWitt et al., 2020).

Particulate matter and gaseous pollutant sensing devices, including the AirBeam, AirBeam2, Terrier, AeroQual S500, MetOne Neighborhood Monitor, PurpleAir, and UPAS, have shown great promise for measuring personal and regional exposures, but little is known about the feasibility of employing them in the field. In addition, occupational exposure assessment has not utilized these mobile air sensors to date. In the present study, these low-cost sensors were employed to characterize the real-time personal exposure of community residents (i.e., community members of four communities in the Chicago area) and workers (i.e., parking and grounds-keeping employees on UIC campus). This work demonstrated the feasibility of utilizing low-cost air monitoring sensors into environmental and occupational settings. Furthermore, the utility and reliability of these sensors for environmental and occupational exposure assessments were determined.

E. Significance of Citizen Science in Public Health and Community Empowerment

Citizen science projects have been accepted in three approaches based on the participants' level of involvement including: 1) the Contributory approach, in which the community engages in only collecting data; 2) the Collaborative approach, in which the community engages in refining research questions, collecting, analyzing, and interpreting data; 3) the Co-created approach, in which the community fully works with the professional scientists and experts in most of all science research steps ranging from gathering information to forming research questions, to concluding and disseminating the findings (Bonney et al., 2009; Rowbotham et al., 2019). The main goals of citizen science projects include providing scientifically rigorous data, effectively communicating with the relevant administrative services, and raising awareness and attention from broader audiences and expanding the opportunities to collaborate with multi-levels of stakeholders (Van & Huyse, 2019). Citizen science/Community-Based Participatory Research (CBPR) is a powerful tool for addressing public health issues and empowering the underserved communities to seek environmental justice and health equity. One of the successful CBPR projects, the West Oakland Environmental Indicators Project (WOEIP), which aimed to reduce diesel exposure in west Oakland, California, demonstrated that the community-based research findings could provide supported information to further define the problems and increase the number of buy-in stakeholders, in addition to pushing the findings to actions including policy implementation. The WOEIP partnerships achieved the goal in persuading the City Council to pass the truck route ordinance that lessened the burden on community air quality. Furthermore, this case study proved that the community works could initiate comprehensive scientific researches conducted by highly reliable government agencies to further examine the public health concerns in the communities (Gonzalez et al., 2011). Another project, THE (Trade, Health, Environment) Impact Project, a collaborative work between community partners and the University of Southern California and Occidental College addressing the impact of air pollution on community health in the massive Los Angeles and Long Beach Ports complex, had a victory on the passage of the Clean Air Action Plan (CAAP) of 2006. In addition, the THE Impact Project helped incorporate the health-related conversations in the policy making decision (Garcia et al., 2013). One of the CBPR projects that recruited the massive number of participants on air quality in Antwerp, Belgium, the CurieuzeNeuzen project, demonstrated the influences of the CBPR on the policy implementation for improving air quality and the increase of the public awareness on the community air quality, as well as, motivated their positive attitudes in supporting the environment-friendly activities in their communities (Van & Huyse, 2019). Another case study in Tonawanda, NY, proved the significance of citizen science in public health. The community residents established the Clean Air Coalition and performed air sampling utilizing a DIY sampler to collect benzene as they considered the association between the community adverse health outcomes and the Tonawanda Coke plant’s release. The citizen science campaign, in addition to collaboratively working with the Department of Environmental Conservation resulted in a 92% decrease of benzene levels in the community, and finally the complete shutdown of the plant (James-Creedon, 2018; Jerving, 2019). One of the major challenges of the community-based project is sustainability. The citizen science/CBPR is a robust measure to build the community capacity and empower the community ensuring the long-term sustainability of the existing projects and the generation of future projects. Furthermore, citizen science has been increasingly implemented in public health research as it is an effective means to practically address health disparities. This can expand the grant opportunities and promote the community-based project continuation (Garcia et al., 2013; Gonzalez et al., 2011; Minkler et al., 2003; Rickenbacker, Brown, & Bilec, 2019).

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III. FEASIBILITY OF COMMUNITY MEMBERS TO EMPLOY LOW-COST SENSORS IN LOCAL AIR QUALITY ASSESSMENT AND LOW-COST SENSOR PERFORMANCE ASSESSMENT IN BREATHING-ZONE

A. Introduction

Citizen science and/or Community-Based Participatory Research (CBPR) approaches have been increasingly implemented in air pollution studies. Citizens collaboratively engage in the entire scientific process starting with investigation and exploration to address community-defined questions (Woodall et al., 2017). According to Commodore and colleagues, community participants partook in air pollution studies and communicated their concerns pertaining to air pollution health risks, proximity to contaminated sources, urban sprawl, shortage of air monitoring systems, and their lack of knowledge and the need for improvement. Most community air monitoring systems are fixed-site stations; therefore, more personal, school-based, and occupational samplings are needed to assess exposures at community or micro-environment level. The citizen science approach incorporates a wide range of methodology retrieved from both citizens and scientists to achieve a variety of goals (Commodore, Wilson, Muhammad, Svendsen, & Pearce, 2017). Emerging tools that facilitate the citizen science approach include new technologies such as mobile phone applications, wireless sensor networks, internet, and video gaming. These technologies have advanced citizen science in terms of disseminating knowledge to broader audiences, improving data collection and control, and increasing data availability and accessibility for decision making (Newman et al., 2012). Air monitoring at a finer scale is necessary to determine spatial variations of outdoor air concentrations and personal exposures.

Reliable air monitoring devices (or sensors) are essential in air monitoring. In addition, personal exposure assessment requires logistical resources including electric power and community engagement. The quality of collected data might be questionable due to the mal-operation of air monitoring sensors, as well as, not having well-established air monitoring procedures in place (Morawska et al., 2018).

The low-cost mobile air monitoring devices or sensors employed in the present study include AirBeam/AirBeam2 and Terrier. AirBeam and AirBeam2 use a light scattering method to measure PM; while, Terrier measures multiple gaseous pollutants using different technologies, i.e., electrochemical (EC) techniques to measure nitric oxide (NO) and carbon monoxide (CO) and nondispersive infrared (NDIR) to measure carbon dioxide (CO_2). These sensors communicate with the AirCasting application every one second (for AirBeam/AirBeam2) or every ten seconds (for Terrier) via Bluetooth application and the collected air quality data (e.g., PM2.5 concentration data) in a single data file are uploaded to the AirCasting website via Wi-Fi for each sampling event.

Several studies have suggested that AirBeam has shown great promise for measuring personal and regional exposures. AirBeam performance has been evaluated in a number of previous studies. AirBeam sensor has a low degree of intra-variability (R^2>0.8) and has demonstrated poor to moderate correlations (R^2) with the reference instruments i.e., Beta Attenuation Method (BAM) and Well Impactor Ninety-Six (WINS) monitors with R^2=0.21-0.83 in various spatial and temporal conditions (Borghi et al., 2018; DeWitt, Crow, & Flowers, 2020; Feenstra, Papapostolou, Der Boghossian, Cocker, & Polidori, 2019; Feinberg et al., 2018; Jiao et al., 2016; Mukherjee, Stanton, Graham, & Roberts, 2017).

Terrier sensor used in this study combines the following three sensors: Alphasense CO-B4, Alphasense NO-B4, and ELT S300-CO_2. In spite of a lack of evaluation of Terrier performance in the scientific literature, several studies have evaluated the performance of one of its three sensors. Alphasense CO-B4 showed low intra-variability (R^2>0.9) and moderate to high degree of correlation with the reference instruments i.e., FRM and FEM (R^2>0.6) (Borrego et al., 2018; Jiao et al., 2016; Smith et al., 2017; Sun et al., 2016). Alphasense NO-B4 demonstrated a moderate to high correlation with the reference instruments i.e., FRM and FEM (R^2>0.7) (Borrego et al., 2018; Jiao et al., 2016; Lewis et al., 2016). Based on the findings of these studies, there is currently little known about the feasibility of employing AirBeam/AirBeam2 and Terrier in community settings and their performance for the real-world community-based personal exposure assessment studies. The present study aims to fill this critical data gap and it consists of two components. The first component, i.e., evaluation of feasibility of air quality sensor use by community residents for outdoor air quality investigations and personal exposure assessment studies, is an integral component of the Quality Assurance and Quality Control (QA/QC) protocol of the Shared Air/Shared Action (SASA) project. Another component of the SASA project was the collocation study, which was conducted at the Northbrook Illinois Environmental Protection Agency (IEPA) air monitoring site from October 6 to December 8, 2017 (see Chapter IV).

In this study, the feasibility of employing two low-cost air monitoring sensors (AirBeam sensor for PM2.5 measurements; and Terrier sensor for NO/CO/CO_2 sensor measurements) under field conditions by community residents was assessed using two approaches. The first approach was based on the assessment of compliance of the sampling protocol by the community participants using a feasibility assessment tool and the second method involved intra-sampler performance evaluation of the two sensors to gain insight into their reliability for air quality and exposure assessment studies in support of health effects research and policy advocacy and outreach efforts.

B. Methods

1. Air Monitoring Sensors

The selection of the air monitoring sensors utilized in the SASA project was based on an extensive literature review, consultation with the EPA staff, and the performance review of the commercially available sensors tested by the EPA and the South Coast Air Quality Management District (SCAQMD) in their respective laboratories and/or in field settings. This comprehensive review led to selection of the following five low-cost air sensors to measure PM and gaseous air pollutants with three operating (MetOne, PurpleAir, Aeroqual) at stationary-mode and the remaining two (AirBeam and Terrier) enabling personal exposure monitoring and operating at mobile mode.

- MetOne Neighborhood Monitor (Met One Instruments Inc., Grants Pass, OR, USA) measures PM2.5 or PM10
- PurpleAir (PurpleAir, Draper, UT, USA) measures PM2.5 and PM10
- AeroQual S500 (AeroQual Limited, Auckland, New Zealand) measures NO_2 or O_3
- AirBeam (HabitatMap, Brooklyn, NY, USA) measures PM2.5
- Terrier (Qsense Inc., Boulder, CO. USA) measured NO, CO, and CO_2

The two low-cost personal exposure/mobile air monitoring sensors, AirBeam measuring PM2.5 and Terrier measuring NO/CO/CO_2, are the sensors utilized by the residents in four distinct communities in the Chicago metropolitan area to measure their personal exposures to air pollutants during two seasonal sampling (i.e., Summer, 2017 and Winter, 2018) sessions with partnership with four community organizations serving each of the four neighborhoods (i.e., Little Village Environmental Justice Organization (LVEJO), Southeast Environmental Task Force (SETF), People with Community Recovery (PCR), and Alliance for a Greener South Loop (AGSL)). During the Winter air monitoring sessions, AirBeam2, which was launched in Spring 2018, was employed instead of the earlier version of the sensor, AirBeam (which was used by all four community organizations in the Summer, 2017 sampling sessions), by the two out of four community participants except for those participants within the geographic domain of the Little Village Environmental Justice Organization (LVEJO) and the Southeast Environmental Task Force (SETF). In addition, Terrier sensor was not employed during the Winter, 2018 sampling sessions. AirBeam/AirBeam2 and Terrier mobile air monitors were operated on the same platform, i.e., AirCasting application, and the recorded data for all sampling sessions were downloaded from the AirCasting website.

2. <u>Participant Recruitment and Training of the Community Organizers</u>

As aforementioned above, the participants from the four Chicago area communities served by AGSL, LVEJO, PCR, and SETF, which are denoted as SL, LV, PC, and SE, respectively, in the remaining of this report, participated in the SASA study and performed personal exposure monitoring using the AirBeam and Terrier sensors in the mobile mode. The geographic locations of these community areas in the Chicago metropolitan area are shown in Figure 1. Prior to initiation of the personal exposure monitoring activities, community organizers were trained by the research team to operate the sensors in a step-by-step fashion in two half-day consecutive training sessions. To facilitate this, the research team prepared user guides enclosed in Appendix A that documented operation of each sensor in step-by-step sequence. These user guides were made available to the community organizers. The SASA study used the train-the-trainer approach and community organizers in each of four community organizations trained their respective residents who took part in the personal exposure monitoring sessions on how to use and operate each sensor appropriately using the user manuals developed by the research team. All the training sessions were scheduled before assigning the equipment to the communities and before initiation of air monitoring activities.

3. Shadowing the Participants During Mobile Air Monitoring Sessions

The SASA study QA/QC protocol called for shadowing of the participants (i.e., (community residents trained on how to operate the sensors and conduct air sampling by their community organizers) in 20% of all total mobile air monitoring events in each community during each sampling season (i.e., Summer, 2017 and Winter, 2018). The participants were shadowed by the research team up to one-hour sampling sessions in each season. These shadowing sampling events were initially randomly selected based on the master mobile monitoring sampling plan for each community during summer (June-September 2017) and winter (January-April 2018). However, due to a host of impediments (raining on the day of scheduled shadowing event, a participant not being present for a scheduled shadowing event, etc.), a random master plan could not be implemented from the beginning to the end of monitoring activities in each season. Instead, shadowing sampling events were scheduled based on availability and convenience of participants for many of the shadowing sampling events. During each sampling event, as instructed in the sampling protocol, the trained participants were expected to wear two of each sensor in the breathing-zone i.e., two AirBeam sensors were placed on the right shoulder and two Terrier sensors were placed on the left shoulder, as shown in Figure 2. In addition, the participants were trained to record time-activity data to document air pollution sources they encountered during the mobile monitoring session chronologically. The participants collected time-activity data using either a manual or a digital method, i.e., either they manually entered the time-activity data in a mobile monitoring observation log (shown in Appendix B) or they took a picture of an air pollution source and note on their sampling route using their cell phone that, then, became an electronic record in the AirCasting application and could be downloaded along with the air monitoring data from the AirCasting website. These methods allowed the participants to capture environmental conditions/characteristics, particularly PM generating activities, encountered during each sampling event. During the shadowing mobile air monitoring sessions, the investigators recorded the time-activity data and shadowed the participants throughout the entire sampling event and observed to assess the feasibility of utilizing the low-cost air sensors in community-based studies using a number of metrics/indicators and to assess the effectiveness of the train-the-trainer approach followed in this study to train the participants who performed the personal exposure monitoring. The feasibility of utilizing the low-cost air sensors in community-based studies was assessed using the tool shown in Appendix C, that captures information pertaining to participant's compliance with the sampling protocol using the following metrics/indicators: correctly placing the sensors in their breathing-zone; correctly following the sampling route specified in the master air monitoring plan; level of comfortable in using the sensors; periodically checking the sensors during the sampling session; utilizing any of measures provided for recording air pollution sources; level of compliance for recording of time-activity data which access by the calculating the percent agreement between the time-activity data recorded by the investigators and those recorded by the participants; and level of compliance with the general air sampling procedures.

4. Data Management and Analyses

Air quality data for each second and every ten seconds of each sampling event collected by AirBeam/AirBeam2 and Terrier sensors, respectively, were saved at the end of each sampling session with a specific file naming nomenclature (e.g., LV1_0116AM) and these files containing the data for each sampling session were stored on Cloud, AirCasting website. The recorded air monitoring data for each sampling session were, then, downloaded in a csv format and further managed on MS Excel spreadsheets. The collected data from the time-activity recording effort (i.e., manual mobile monitoring observation log record or the digital record documented by both investigators and participants) and the feasibility assessment tool explained above were entered into Excel spreadsheets for data cleaning and analysis. We observed missing 1-second data points only in the AirBeam data files. Consequently, AirBeam data were treated and imputed for the missing 1-second data following the criteria delineated in Appendix H. One-minute mean concentration for each pollutant was computed and utilized for statistical data analysis including descriptive statistics and intra-sampler comparisons. The descriptive statistics of air pollutant concentrations were determined for each community and for each season. Furthermore, the spatial and temporal variabilities of air pollutant concentrations across communities were analyzed. Time-activity pattern/environmental characteristics including the traffic conditions and number of Heavy-Duty Vehicles (HDVs) of each sampling event were documented. HDV density (counts/minute) was calculated as the total number of HDVs counted divided by the sampling duration of each sampling event. The calculated HDV density were classified into three categories, i.e., class 1: <0.4 (25^{th}percentile); class 2: 0.4-1.2 (between 25^{th} and 75^{th} percentiles); and class 3: >1.2 (75^{th} percentile). The correlation between measured 1-minute PM2.5 mean concentration and HDV density was investigated utilizing the correlation plot. Traffic conditions were observed and classified, based on the justification of the trained investigators, into the following five categories, i.e., class 1: light; class 2: light to medium; class 3: medium; class 4: medium to heavy; and class 5: heavy. During the sampling sessions, the investigators tracked the traffic conditions, including intensity of vehicle lineups at the traffic intersections and Light Duty Vehicles (LDVs) congestion. However, the exact number of LDVs were not counted due to infeasibility of documenting an accurate manual count of LDVs during the entire sampling event in busy urban environment. Due to less frequent occurrence of HDVs and their prominent role in air pollution, an effort was expanded into counting HDVs during each sampling period.

The data collected during each sampling event in response to questions in the feasibility assessment tool shown in Appendix C were analyzed to gain insight into compliance of sampling protocol by the community participants who partook in the sampling effort. We calculated percent of community residents that complied with each measure documented in Appendix C.

In addition, the correlation between the measured concentrations by two units of AirBeam sensor on the right shoulder and by two units of Terrier sensor on the left shoulder in the participants' breathing-zone during shadowing sampling events was determined to evaluate sensor intra-variability as an indicator of sensor reliability under field conditions. In this evaluation, the following evaluation metrics were used based on the coefficient of determination (R^2) (i.e., a very strong correlation ($R^2 \geq 0.9$), a strong correlation (R^2=0.7-0.89), a moderate correlation (R^2=0.5-0.69), a weak correlation (R^2=0.3-0.49), a very weak correlation (R^2=0.1-0.29), and a no correlation (R^2=0.0-0.09)) and the slope and the intercept of the regression line (Collier-Oxandale et al., 2020).

C. Results

1. Summary of the QA/QC Shadowing Mobile Air Monitoring Efforts with Communities

We shadowed participants during 33 sampling events, i.e., 16 sampling events during Summer 2017 and 17 sampling events during Winter 2018. Tables XXXV-XXXVII in Appendix D summarize the attributes of the shadowing data collected with AirBeam and Terrier sensors during Summer 2017 and Winter 2018 sampling sessions. As noted above, both AirBeam and Terrier sensors were employed during summer sampling events; however, only AirBeam/AirBeam2 sensor was employed during winter sampling events. For AirBeam/AirBeam2 sensors, the percentage of complete sampling sessions, which are sessions in which data were acquired from two units operating in tandem next to each other on the right side of the shoulder in the breathing-zone of a participant , was 42 (33% during summer, 9% during winter). For Terrier sensors, the percentage of complete sampling sessions in Summer 2017, which are sessions in which data were acquired from two units operating in tandem next to each other on the left side of the shoulder in the breathing zone of a participant, was 25 (i.e., 4 sessions out of 16 total sessions) (see Appendix D). The rationale for incomplete events included: 1) at least one of the AirBeam/Terrier sensors failed to record data during a sampling event; 2) the recorded data was missing or not saved; 3) at least one of the Terrier sensors had all zero readings for CO/NO measurements; and 4) only one AirBeam/Terrier sensor could be operated during air monitoring events due to technical or logistical reasons. During winter sessions, the percentage of missing data was higher in the collected data of the communities (PC and SL) employing AirBeam2 as compared to those of communities (LV and SE) employing AirBeam (see Table III). Among all the shadowing sessions (N=33), 58% of the total sessions had only one participant (community resident) performing the air monitoring, while 39% and 3% had two and three participating community residents performing the air monitoring as a team, respectively. During any session in which more than one community resident performed the air monitoring, one participant wore the sensors (and/or kept track of the timestamp), the other took notes (and/or kept track of the timestamp), and all participants collectively counted the PM generating sources encountered along the sampling route, e.g., buses and trucks. In addition, 26% of the total sessions had one and 23% had two community organizers accompanying/assisting during the summer and winter air sampling efforts.

2. Descriptive Statistics of PM2.5 and Gaseous Pollutant Concentrations in the Communities

A summary of the 1-minute mean concentration of each pollutant measured during each sampling event during the summer air monitoring effort is shown in Table I. The 1-minute PM2.5 concentrations observed in Little Village (LV) were the lowest (5.5-7.8 µg/m^3) and not significantly different among time periods and locations, while those of South Loop (SL) and Altgeld Gardens (PC) had more variation with concentration range of 6.1-19.6 µg/m^3 and 5.6-16.1 µg/m^3, respectively. Similar to LV, the Southeast side of Chicago (SE) had a low variability with consistent measurements for PM2.5 concentrations across different sampling locations and time periods ranging from 10.0 µg/m^3 to 15.2 µg/m^3. The 1-minute CO mean concentrations were not substantially different among the locations and time periods in LV and SL communities. On the other hand, CO_2 and NO mean concentrations varied among the locations in each community. For CO_2 measurements, the range of mean concentrations were 440-875 ppm for LV, and 463-923 ppm for SL. For NO measurements, the range of mean concentrations were 0.4-1.2 ppb for LV, and 0.5-1.6 ppb for SL.

Time-activity data for the HDV density, traffic condition, and other PM generating sources counted during each sampling session in Summer 2017 are summarized in Table II. Across all study times and locations, LV and SL had a medium to heavy traffic, while SE and PC had light to heavy traffic. The box plots demonstrated that, at sampling times and locations in SE and SL communities with higher HDV density (>1.2 counts/minute), higher PM2.5 concentrations were observed, as compared to those communities with lower HDV density (≤1.2 counts/minute). The PM2.5 concentrations were not significantly different among sampling events with different levels of HDV density in the LV community as shown in Figure 3. The 1-minute mean CO measured concentrations were not significantly different among different levels of HDV density in LV, SE, and SL communities. The CO data were not available for any of the four sampling events in PC and two sampling events in SE communities (Figure 4). The 1-minute NO concentrations were higher at the sampling events with higher HDV density as shown in Figure 5, while the 1-minute mean CO_2 concentrations varied across the sampling events independent of the HDV density (Figure 6). The box plots that explore the relationship between the 1-minute air pollutant concentrations and the traffic condition were also generated (see Appendix E). These demonstrated similar trend to those observed with the HDV density. During the winter sampling efforts, the 1-minute PM2.5 mean concentrations in the LV community ranged from 3.3 to 13.7 µg/m^3 across four sampling sessions, while narrower ranges were observed in other communities. The box plots suggested that during sampling events with higher HDV density (>1.2 counts/minute), higher PM2.5 concentrations were measured as shown in Figure 7. However, one sampling event with low HDV density (<0.4 counts/minutes) in the LV community was observed to have the highest PM2.5 measured concentration (13.7 µg/m^3) (see Table III, Appendix E). Based on the correlation plot analysis, we observed no correlation between 1-minute measured pollutant (i.e., PM2.5, CO, CO_2, NO) concentrations and HDV density (the plots are not shown in this report).

3. Feasibility of Employing the Sensors by Community Residents

The feasibility of employing the low-cost sensors in community-based air monitoring studies was assessed by utilizing the feasibility assessment tool questions. The results of the feasibility assessment survey data collected during the shadowing sampling events are summarized in Table IV in Appendix F. Most of the participating community residents had properly placed the sensors in the breathing-zone (61%), had followed the sampling route specified (97%), were highly comfortable in using the sensors (80%), had recorded the time-activity pattern during sampling sessions (90%), and were in high compliance with the general sampling procedures (90%). Among the participants following the sampling route, some followed the route reversely from the master sampling plan; some did not follow the exact route but covered all areas indicated in the master sampling plan. Furthermore, some routes needed to be adjusted during the sampling sessions due to safety. Eighty percent of the time-activity records were at the low level of compliance (<50% agreement between the investigators' records vs. community participants' records). The investigator observed some deficiencies pertaining to the time-activity recording of community participants, which included one participant not documenting the timestamp of each recorded PM generating sources observed during the sampling event; one participant recording only PM2.5 readings at specific timestamps but not the time-activity data during sampling; and one participant recording only the sampling start time but no other information, in addition to inserting the wrong date for the sampling event. The feasibility assessment results suggested a significant drop in the percentage of participants who had correctly placed the sensors in the breathing-zone complying with the study protocol from 15 (summer air sampling events) to 5 (winter air sampling events), mostly participants not complying with the study protocol placed one unit of AirBeam sensors on their left shoulder and the other on their right shoulder as opposed to place two units tandemly on their right shoulder in the breathing-zone as instructed in the study protocol. Moreover, the winter time-activity pattern records were missing, with an exception of two sessions in LV. These records were retrieved from the AirCasting website.

4. Performance of Low-Cost Sensors in Community Air Monitoring

The intra-sampler performance of AirBeam and Terrier sensors was investigated by examining the correlation between two of the same sensors operating in the breathing-zone of the participant in the same side of the shoulder (AirBeam sensor on the right and Terrier sensor on the left shoulder) as shown in Figure 8-11 and Appendix G. As instructed in the study protocol, each type of sensor was placed consistently on the same side of the shoulder across all sampling events not to add additional variability to the data collected. However, logistically, among 39% (n=13) of participants not complying with the study protocol in correctly placing the sensors in the breathing-zone, 15% (n=2) operated only one unit of AirBeam sensor placing on their left shoulder in their breathing-zone during the sample sessions, while 77% (n=10) placed one AirBeam on their left shoulder and the other on their right shoulder in the breathing-zone. The collected PM2.5 concentrations from all sampling sessions with two units of AirBeam operated was included in the intra-sampler performance assessment. The intra-sampler comparisons suggested, overall, a moderate correlation between the two units of AirBeam measuring PM2.5 (R^2=0.51), two units of Terrier measuring CO_2 (R^2=0.51), and two units of Terrier measuring NO (R^2=0.67). However, a weak correlation between two units of Terrier measuring CO (R^2=0.19) was obtained. R^2 values had variability across the sampling events in each community ranging from 0.12 for PC to 0.57 for SE (AirBeam), 0.12 for SE to 0.97 for PC (Terrier-CO_2), 0.17 for SE to 0.98 for PC (Terrier-NO), and 0.06 for LV, 0.93 for SL (Terrier-CO) (see Figure 8 to 11, Appendix G).

D. Discussion

The uniqueness of this study included the full engagement of communities in planning and performing air monitoring. The community organizers, who were trained by the investigators on how to properly operate the sensors and conduct air monitoring, trained their community residents on study protocols, how to perform air monitoring, how to record the time-activity data manually and electronically, how to save collected data in a file using the AirCasting application on their phone, and how to upload the file containing data to cloud for retrieval from the online Aircasting platform. The feasibility assessment tool was deployed to obtain an understanding of the practicality of employing the sensors among community residents in the Chicago area communities, in addition to evaluating the effectiveness of the train-the-trainer approach. The findings suggested that, overall, participants were highly comfortable in using sensors and complied with the general air sampling procedures. However, some concerns, which were observed during the shadowed air monitoring sessions, were noted and these included the improper placement of the sensors as instructed in the sampling protocol and the low level of participant compliance with recording the time-activity data during sampling events. This might be due to having to multi-task during air monitoring that may have distracted the participants from observing and recording the air pollution sources. Team sampling may be one of the approaches that can remedy this deficiency and improve the compliance with sampling protocol. Approximately 80% of the participants preferred documenting time-activity data manually by utilizing the observation log sheet rather than taking pictures and notes of the PM generating sources along the sampling route and saving this information as an electronic record in the AirCasting application. The findings highlight an important need for training of citizen scientists to collect representative data for the time-activity pattern recording. We observed no correlation between measured PM2.5 personal exposures and the heavy-duty vehicle density based on the methods utilized. This may be an artifact of: 1) the manual heavy duty vehicle counts data collection method used in the study instead of digital radar meter, or pneumatic road tube methods that provide more precision and accuracy; and 2) the small sample size since the manual traffic count occurred only in 20% of the total sampling events.

A study conducted by Matkovic and colleagues observed technical issues during sampling events including connecting AirBeam sensors with the AirCasting application and data synchronization. In addition, data recording was very demanding as it required the participants to start, stop, and properly save the session, as well as to check whether the recording had occurred or was disrupted (Matkovic et al., 2017). These issues emphasized the critical need for training on how to operate the sensors in a step-by-step fashion with hands-on experiences and making user-friendly sensor operating manuals available to participants. Our results indicate that the thorough step-by-step training provided to the community organizers by the research team facilitated a high level of comfort in using the sensors by the participants, which also provide evidence for the effectiveness of the train-the-trainer approach followed in the current study. The previous study conducted by Duvall et al. reinforced the necessity of training and observed the challenges in remembering how to operate sensors due to the lag between training and sampling events (Duvall et al., 2016). In the present study, the investigators held refreshing training sessions to community organizers prior to the second phase (Winter 2018) of sampling efforts to remedy this potential problem. During the winter sampling, two out of four communities utilized AirBeam2, the new generation of AirBeam; however, the community organizers were not trained by the investigators on how to operate the AirBeam2 as they were trained for AirBeam. Even though the concept of the sensor operation was not significantly different, apart from the update of the AirCasting application display, a high level of comfort was observed among the participants using the new generation of AirBeam sensors in the winter sampling efforts. Another improvement of the updated version of the AirCasting application for the AirBeam sensor was the process of saving the sampling session prior to the start of the sampling session as opposed to the end of the sampling session employed in the earlier and original model of AirBeam. This would lessen the burden of remembering to save the session at the end and preventing losing data unnecessarily. However, during the winter sampling, the updated AirCasting application had just been launched with some level of instability. The investigators observed the several application crashes and disconnections between the sensors and the application. This could be one of the main causes of the incomplete events in the winter sampling sessions, which was witnessed in the two communities (PC and SL). The present study highlighted and confirmed the value of the train-the-trainer approach which is in agreement with the ongoing air quality citizen science programs including the “Los Angeles Public Library Air Sensor Loan Program” and the “Engaging youth and fostering leadership through the Imperial Air Project youth program” (USEPA, 2018).

Several studies have attempted to assess the low-cost sensor performance; however, only a few of them focused on sensor evaluations for personal exposure monitoring, particularly with citizen scientist participation. The current study is the first study that evaluated the intra-sampler performance of low-cost sensors in the field settings and provided valuable information on the performance of two mobile low-cost sensors, one for PM2.5 monitoring (AirBeam) and the other for gaseous air pollutant monitoring (Terrier) for personal air monitoring by citizens. Across all sampling events, AirBeam had a moderate to high intra-sampler variability, Terrier measuring NO/CO/CO_2 had a low to high intra-sampler variability. Several previous studies, in addition to the SASA collocation study performed as part of this dissertation (see Chapter IV), observed a high correlation among units of the AirBeam sensor (R^2>0.8) (Borghi et al., 2018; DeWitt et al., 2020; Feinberg et al., 2018; Jiao et al., 2016; Mukherjee et al., 2017; Mukherjee et al., 2019; SCAQMD, 2015). The findings from the 84-hour collocated testing for Terrier sensor performances in the SASA study suggested Terrier sensor had a low to high intra-sampler variability depending on the gaseous pollutant measured. Terrier sensor measuring CO_2 had the lowest intra-variability (R^2=0.65-0.92), followed by NO (R^2=0.52-0.91) and CO (R^2=0.29). The intra-sampler variability of AirBeam and Terrier sensors observed in this study were greater than those of the previous studies. This might be due to the additional variability introduced by operating the sensors in a mobile platform as opposed to a stationary air monitoring platform employed in the previous studies. Another cause could be the different sampling orientation with respect to the incoming air flow for the two sensor units, which operated simultaneously, as the participant recorded concentration data along a pre-determined sampling route. The participants' movement while conducting the air monitoring along the sampling route could slightly shift the sampling orientation of each unit of the sensors resulting in measurement discrepancies between the two units (Mukherjee et al., 2017). No studies have yet reported intra-sampler performance data for AirBeam and Terrier sensors operating in the breathing-zone in mobile air monitoring. The previous studies assessed AirBeam performance at the stationary sampling locations. Terrier sensor has not been evaluated its performance in the field conditions prior the SASA collocation study. Thus, there might be a limitation to compare our results to those published in the literatures.

Citizen science is a very powerful tool for addressing public health issues including air quality concerns. Citizen science air monitoring provides reliable exposure information corresponding to the individuals' behaviors and activities (Mahajan et al., 2020). The unequal distribution of exposures across different groups of population, which might be due to one's socioeconomic status, travel behaviors, and living and health conditions, emphasizes the need for personal exposure monitoring (Liang et al., 2019). Engaging in air monitoring sensors can raise awareness and the belief in the risk and severity of air pollution (Oltra, Sala, Boso, & Asensio, 2017). This study provides an improved understanding on the feasibility of using the low-cost sensors by community members and the reliability of the low-cost sensors (AirBeam and Terrier) for the personal exposure assessments in support of exposure and health risk assessment studies, environmental equity and justice analysis, community empowerment, and public health protection. Moreover, while our study offers information pertaining to approaches implemented for assessing the feasibility of employing two low-cost air sensors for personal exposure assessment, it could also be used as a prototype for the assessment of the feasibility of employing other low-cost air sensors by community organizations in support of citizen science projects focused on community-level air quality investigations and exposure assessment studies.

E. Conclusion

Our findings demonstrated that the community residents in four communities across the Chicago Metropolitan area successfully used the low-cost sensors for personal air quality monitoring. We further demonstrated that it is feasible to employ the sensors for local air quality assessment in support of citizen science projects with careful planning, training, rigorous implementation of QA/QC protocols while working in unison with community organizations and resident participants. The two low-cost sensors (AirBeam sensor for PM2.5 monitoring; and Terrier sensor for $CO/NO/CO_2$ monitoring) demonstrated low to high precision in collecting air quality data across different spatial and temporal conditions. The low-cost sensors were useful in assessing the personal exposures corresponding to time-activity data and addressing public health issues pertaining to air quality that warrant the comprehensive evaluation of air pollution relevant to certain locations and activities. However, further studies are needed to address the knowledge gap and the uncertainties impacting the low-cost sensor performance in mobile air monitoring applications for local air quality assessment and policy advocacy and outreach by the citizens and the community organizations.

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TABLE I. 1-MINUTE MEAN CONCENTRATIONS OF PM2.5/CO/CO_2/NO MEASURED BY AIRBEAM/TERRIER, SUMMER 2017[a]

Sampling sessions	Sampling start time	Sampling stop time	Obs time (min)	PM2.5 (μg/m³)			
				N	%Missing	Mean (sd)	Min-Max
LV1	6/21/2017 9:13	6/21/2017 10:33	80	71	11.2	6.4 (8.2)	1.6-54.9
				71	11.2	7.8 (7.5)	1.8-47.9
LV2	6/22/2017 18:09	6/22/2017 19:13	64	64	0.0	5.6 (1.1)	3.1-9.1
				64	0.0	5.9 (1.5)	3.4-11.3
LV3	6/15/17 18:04	6/15/17 19:04	60	60	0.0	7.5 (2.0)	3.4-14.9
				60	0.0	6.8 (2.1)	3.1-14.7
LV4	6/16/2017 19:06	6/16/2017 19:38	32	31	3.1	5.5 (1.8)	3.2-11.2
				NA	NA	NA	NA
SE1	7/21/17 9:53	7/21/17 10:41	48	48	0.0	12.39 (3.7)	6.5-20.9
				48	0.0	10.0 (2.6)	5.8-15.7
SE2	7/19/17 9:03	7/19/17 10:03	60	60	0.0	15.17 (3.0)	11.8-33.4
				60	0.0	13.5 (2.8)	8.9-29.2
SE3	7/21/17 8:43	7/21/17 9:32	49	23	53.1	12.7 (3.9)	8.2-27.1
				23	53.1	13.6 (3.8)	8.0-26.9
SE4	7/19/17 7:35	7/19/17 8:37	62	62	0.0	12.1 (1.7)	9.7-17.4
				NA	NA	NA	NA
PC1	8/28/17 12:26	8/28/17 13:17	51	51	0.0	16.1 (1.8)	12.8-20.9
				NA	NA	NA	NA
PC2	8/16/17 13:49	8/16/17 14:49	60	17	71.7	11.3 (0.6)	10.0-12.6
				17	71.7	13.7 (0.6)	12.7-14.4
PC3	8/18/17 12:34	8/18/17 13:34	60	60	0.0	5.6 (1.0)	3.8-7.8
				NA	NA	NA	NA
PC4	8/18/17 16:05	8/18/17 16:31	26	26	0.0	8.3 (2.1)	5.8-18.1
				NA	NA	NA	NA
SL1	9/25/17 17:03	9/25/17 17:59	56	48	14.3	8.4 (1.6)	6.4-15.7
				48	14.3	6.3 (1.2)	3.8-9.0
SL2	9/25/17 17:13	9/25/17 18:19	66	30	54.5	6.1 (0.8)	4.7-8.5
				30	54.5	6.2 (1.1)	4.6-8.9
SL3	9/22/17 9:00	9/22/17 9:53	53	53	0.0	11.2 (4.7)	1.3-20.1
				53	0.0	19.6 (2.4)	10.0-25.2
SL4	9/22/17 8:51	9/22/17 9:49	58	58	0.0	17.1 (3.7)	6.7-31.8
				58	0.0	14.4 (3.4)	5.9-31.9

TABLE I. 1-MINUTE MEAN CONCENTRATIONS OF PM2.5/CO/CO_2/NO MEASURED BY AIRBEAM/TERRIER, SUMMER 2017 [a] **(continued)**

Sampling sessions	**CO (ppm)**				**CO_2 (ppm)**			
	N	%missing	mean (sd)	Min-Max	N	%missing	mean (sd)	Min-Max
LV1	26	67.5	0.4 (0.1)	0.3-0.7	32	60.0	778.4 (304.7)	445.7-1601.0
	26	67.5	0.3 (0.1)	0.2-0.5	32	60.0	726.2 (239.3)	507.1-1467.0
LV2	64	0.0	0.3 (0.1)	0.1-0.6	64	0.0	471.7 (123.4)	346.4-901.8
	64	0.0	0.3 (0.1)	0.2-0.6	64	0.0	571.2 (123.5)	440.7-950.6
LV3	60	0.0	0.3 (0.1)	0.2-0.6	60	0.0	821.7 (225.5)	539.6-1633.0
	60	0.0	0.6 (0.1)	0.3-1.0	60	0.0	875.2 (183.9)	575.8-1335.0
LV4	28	12.5	0.4 (0.1)	0.3-0.6	NA	NA	NA	NA
	28	12.5	0.3 (0.1)	0.1-0.5	NA	NA	NA	NA
SE1	48	0.0	1.1 (-0.6)	0.4-2.1	39	18.7	644.6 (168.8)	500.9-1130.0
	NA	NA	NA	NA	39	18,7	499.3 (183.8)	363.7-1314.0
SE2	NA	NA	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA	NA	NA
SE3	NA	NA	NA	NA	25	49.0	648.7 (128.3)	494.8-953.4
	23	53.1	0.5 (0.7)	0.2-3.3	31	36.7	632.1 (212.3)	398.4-1121.0
SE4	NA	NA	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA	NA	NA
PC1	NA	NA	NA	NA	51	0.0	557.0 (314.3)	444.3-2413.0
	NA	NA	NA	NA	51	0.0	640.1 (503.2)	479.2-522.5
PC2	NA	NA	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA	NA	NA
PC3	NA	NA	NA	NA	56	6.7	494.2 (9.3)	479.2-522.5
	NA	NA	NA	NA	NA	NA	NA	NA
PC4	NA	NA	NA	NA	NA	NA	NA	NA
	NA	NA	NA	NA	NA	NA	NA	NA
SL1	NA	NA	NA	NA	43	23.2	495.1 (132.2)	354.1-936.6
	48	14.3	0.3 (0.1)	0.2-0.5	43	23.2	601.5 (138.7)	480.7-1039.0
SL2	30	54.5	0.3 (0.0)	0.3-0.4	30	54.5	618.3 (76.6)	498.9-822.7
	NA		NA	NA	17	74.2	923.1 (404.8)	541.9-1969.0
SL3	53	0.0	0.6 (0.2)	0.3-1.3	53	0.0	635.1 (368.3)	502.9-2656.0
	53		0.4 (0.2)	0.3-0.9	53	0.0	463.0 (340.9)	317.5-2242.0
SL4	58	0.0	0.2 (0.1)	0.2-0.5	58	0.0	739.4 (400.7)	491.7-2435.0
	58	0.0	0.4 (0.2)	0.2-1.5	58	0.0	729.4 (254.0)	520.1-1875.0

TABLE I. 1-MINUTE MEAN CONCENTRATIONS OF PM2.5/CO/CO_2/NO MEASURED BY AIRBEAM/TERRIER, SUMMER 2017[a] **(continued)**

Sampling sessions	NO (ppb)			
	N	%missing	mean (sd)	Min-Max
LV1	26	67.5	0.9 (0.1)	0.8-1.3
	26	67.5	1.2 (0.3)	0.9-2.5
LV2	64	0.0	0.9 (0.2)	0.4-1.3
	64	0.0	0.6 (0.1)	0.3-0.8
LV3	60	0.0	0.4 (0.4)	0.2-2.6
	60	0.0	1.0 (1.1)	0.4-7.9
LV4	NA	NA	NA	NA
	NA	NA	NA	NA
SE1	48	0.0	0.4 (0.4)	0.2-2.5
	48	0.0	0.1 (0.1)	0.1-0.6
SE2	NA	NA	NA	NA
	NA	NA	NA	NA
SE3	31	36.7	0.3 (0.05)	0.2-0.5
	31	36.7	0.3 (0.03)	0.3-0.4
SE4	60	3.2	1.4 (1.7)	0.4-10.3
	NA	NA	NA	NA
PC1	51	0.0	0.8 (1.0)	0.3-5.2
	51	0.0	2.0 (2.4)	0.6-13.7
PC2	NA	NA	NA	NA
	NA	NA	NA	NA
PC3	56	6.7	1.4 (0.6)	0.8-3.3
	NA	NA	NA	NA
PC4	NA	NA	NA	NA
	NA	NA	NA	NA
SL1	44	21.4	0.8 (0.1)	0.6-1.7
	44	21.4	1.6 (0.3)	1.2-2.5
SL2	30	54.5	0.6 (0.1)	0.5-0.8
	NA	NA	NA	NA
SL3	53	0.0	1.0 (1.4)	0.2-7.6
	53	0.0	1.5 (1.4)	0.7-7.1
SL4	58	0.0	1.6 (1.7)	0.7-8.4
	58	0.0	0.6 (0.5)	0.3-2.7

[a] NA: not applicable/no records

TABLE II. HEAVY-DUTY VEHICLES AND OTHER PM SOURCES COUNTED DURING SAMPLING SESSIONS, SUMMER 2017

Sampling sessions	Observation time (min)	# of HDVs	# of other PM generating sources	Traffic Conditions	HDV density (counts/min)
LV1	80	90	0	heavy	1.1
LV2	64	39	0	medium to heavy	0.6
LV3	60	18	0	medium	0.3
LV4	32	27	0	heavy	0.8
SE1	48	6	0	light	0.1
SE2	60	76	0	medium to heavy	1.3
SE3	49	121	0	heavy	2.5
SE4	62	39	0	medium	0.6
PC1	51	35	1	light to medium	0.7
PC2	60	39	0	light to medium	0.7
PC3	60	869	0	heavy	14.5
PC4	26	4	0	light	0.2
SL1	56	31	5	medium	0.6
SL2	66	22	5	medium to heavy	0.3
SL3	53	23	1	medium to heavy	0.4
SL4	58	27	7	medium to heavy	0.5

TABLE III. 1-MINUTE MEAN PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM AND HEAVY-DUTY VEHICLES AND PM SOURCES, WINTER 2018

Sampling sessions	Start time	Stop time	Obs time (min)	PM2.5 (μg/m^3)				# of HDVs	# of other PM generating sources	Traffic Conditions	HDV density (counts/min)
				N	%missing	Mean (sd)	Min-Max				
LV1w	3/23/2018 6:29	7:06	37	31	16.2	7.1 (2.1)	3.5-11.6	31	0	medium to heavy	0.8
LV2w	3/23/2018 18:00	19:00	60	59	1.7	3.3 (3.3)	1.0-21.2	26	1	medium to heavy	0.4
LV3w	3/26/2018 7:00	7:38	38	37	2.6	10.0 (1.9)	6.3-14.2	101	0	heavy	2.7
LV4w	3/26/2018 17:00	18:00	60	60	0.0	13.7 (2.1)	10.9-21.3	18	0	light to medium	0.3
SE1w[a]	3/23/2018 11:15	11:45	30	28	6.7	1.9 (1.0)	0.7-4.2	53	0	medium to heavy	1.8
				28	6.7	2.1 (1.9)	0.9-4.9				
SE2w[a]	3/23/2018 12:55	13:30	35	35	0.0	3.7 (2.3)	1.2-10.8	84	0	heavy	2.4
				35	0.0	3.8 (2.6)	1.0-13.7				
SE3w[a]	3/23/2018 9:55	10:36	41	39	4.9	1.2 (0.3)	0.7-2.1	32	1	medium	0.8
				39	4.9	1.0 (0.2)	0.7-1.7				
PC1w	5/4/2018 11:10	11:56	46	35	23.9	2.2 (0.6)	1.7-3.6	289	0	heavy	6.3
PC2w	5/4/2018 12:26	13:10	44	44	0.0	4.1 (1.0)	2.1-7.2	9	0	light to medium	0.2
PC3w	5/4/2018 13:46	14:31	45	41	8.9	4.5 (1.0)	3.0-8.9	54	0	medium	1.2
SL1w	4/25/2018 8:35	9:35	60	32	46.7	2.3 (0.7)	1.0-4.1	37	0	medium	0.6
SL2w	4/25/2018 9:55	10:42	47	15	68.1	2.3 (0.5)	1.6-3.3	22	0	medium	0.5
SL3w	4/25/2018 11:03	12:10	67	22	67.2	2.2 (0.6)	1.2-3.6	20	0	medium	0.3
SL4w	4/27/2018 8:49	9:55	66	42	36.4	3.5 (1.1)	2.0-8.6	36	0	medium	0.5

[a]Only SE community operated two units of AirBeam sensor and successfully retrieved the data from both units. More detail of the successful air sampling event was described in the Appendix F.

TABLE IV. PERCENTAGE OF PARTICIPANTS OBSERVED UNDER EACH FEASIBILITY ASSESSMENT METRIC[a]

Feasibility Assessment Parameters		**Overall (N=33)**	**Summer (N=16)**	**Winter (N=17)**
		n (%)	**n (%)**	**n (%)**
Correctly Placement of Sensors	Yes	20 (61)	15 (94)	5 (29)
	No	13 (39)	1 (6)	12 (71)
Correctly Following Sampling Route	Yes	32 (97)	15 (94)	17 (100)
	No	1 (3)	1 (6)	0 (0)
Level of Comfortable in Using Sensors	High	27 (82)	12 (75)	15 (88)
	Medium	4 (12)	3 (19)	1 (6)
	Low	2 (6)	1 (6)	1 (6)
Periodically Checking the Sensors	Yes	28 (85)	13 (81)	15 (88)
	No	5 (15)	3 (19)	2 (12)
Recording During Sampling Period	Mobile application	4 (12)	2 (12)	2 (12)
	Observation log sheet	27 (82)	14 (88)	13 (76)
	Mixed	0 (0)	0 (0)	0 (0)
	Not recording	2 (6)	0 (0)	2 (12)
Compliance for Recording Time-Activity	High	2 (6)	1 (6)	1 (6)
	Medium	2 (6)	2 (12.5)	NA
	Low	11 (33)	11 (69)	NA
	NA	18 (55)	2 (12.5)	16 (94)
Level of Compliance for Sampling Procedure	High	32 (97)	15 (94)	17 (100)
	Medium	1 (3)	1 (6)	0 (0)
	Low	0 (0)	0 (0)	0 (0)

[a]NA: not applicable/no records

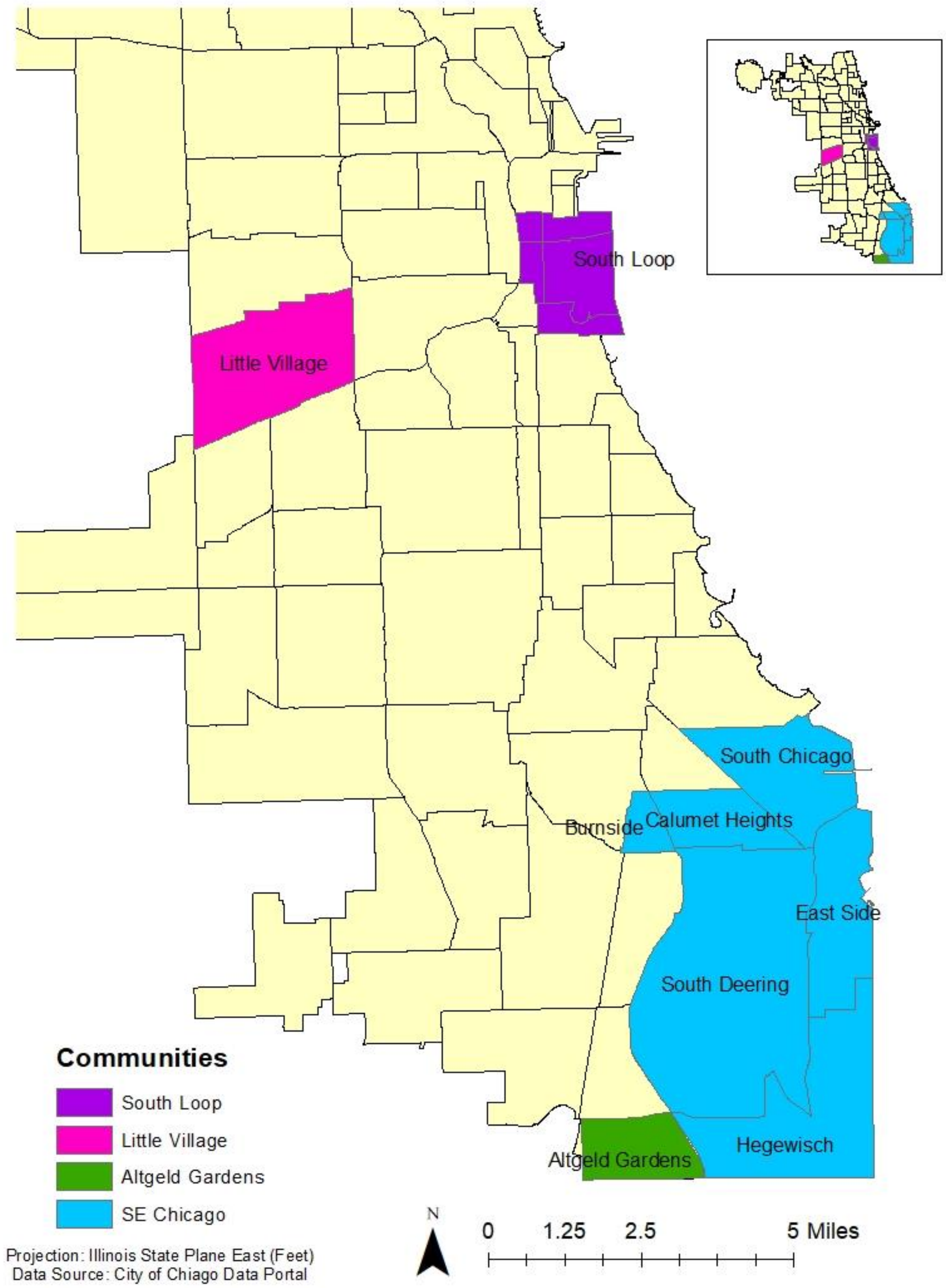

Figure 1. Map of study communities in the Chicago metropolitan area

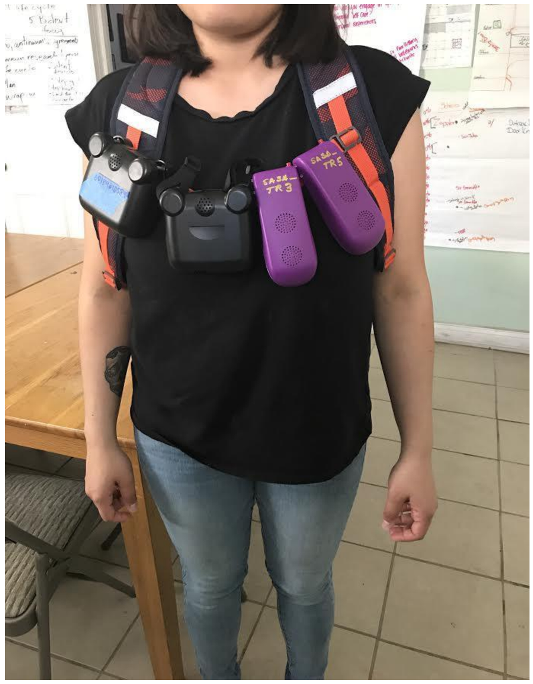

Figure 2. Side-by-side air monitoring sensors (two AirBeam (black) and two Terrier (purple) sensors in the participant's breathing-zone

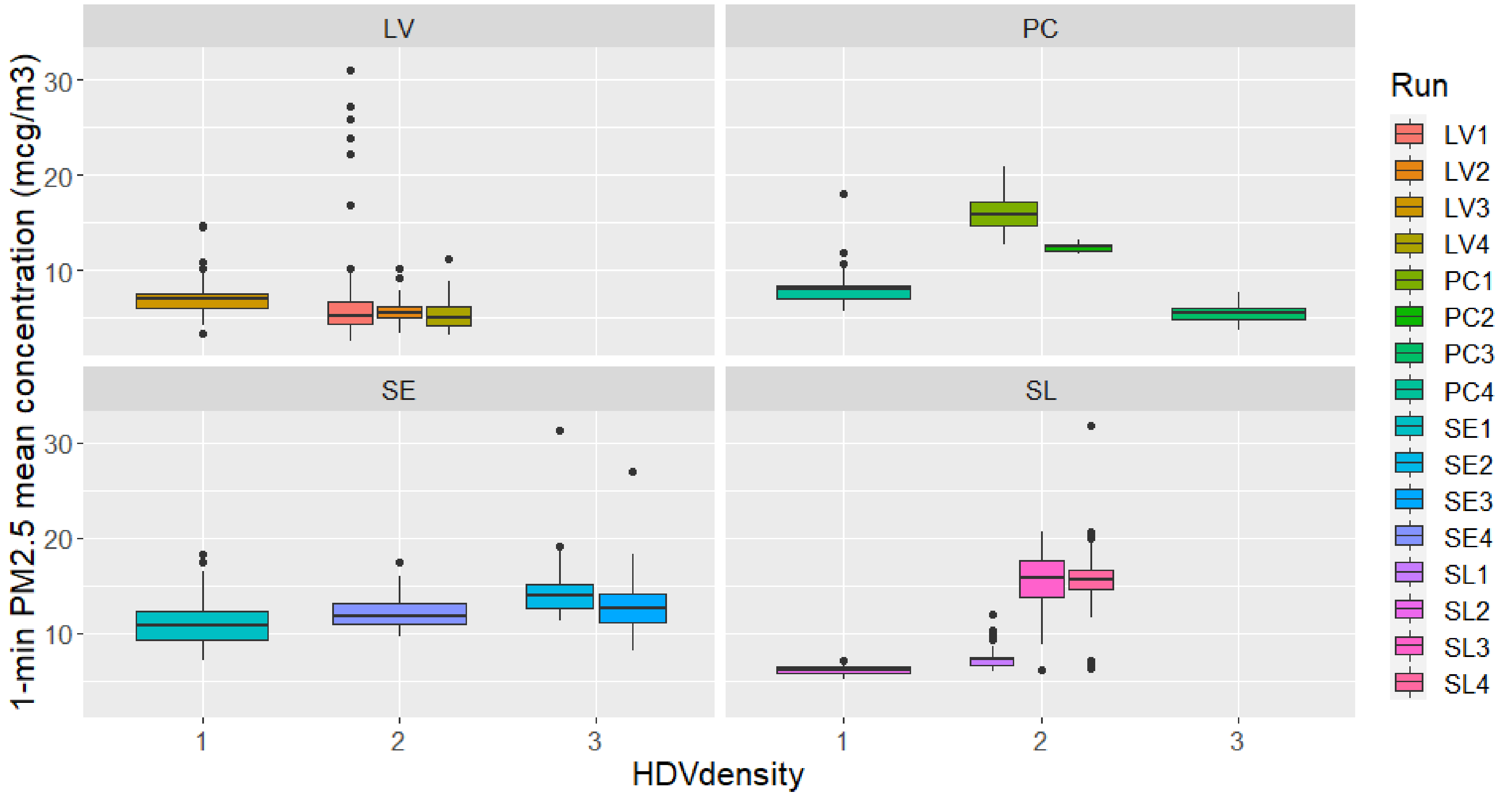

Figure 3. 1-minute PM2.5 mean concentrations (µg/m^3) by HDV density by each sampling session of each community during summer, 2017. Three classes of HDV density i.e., class 1: <0.4 (25th percentile), class 2: 0.4-1.2, and class 3: >1.2 (75th percentile) counts/minute.

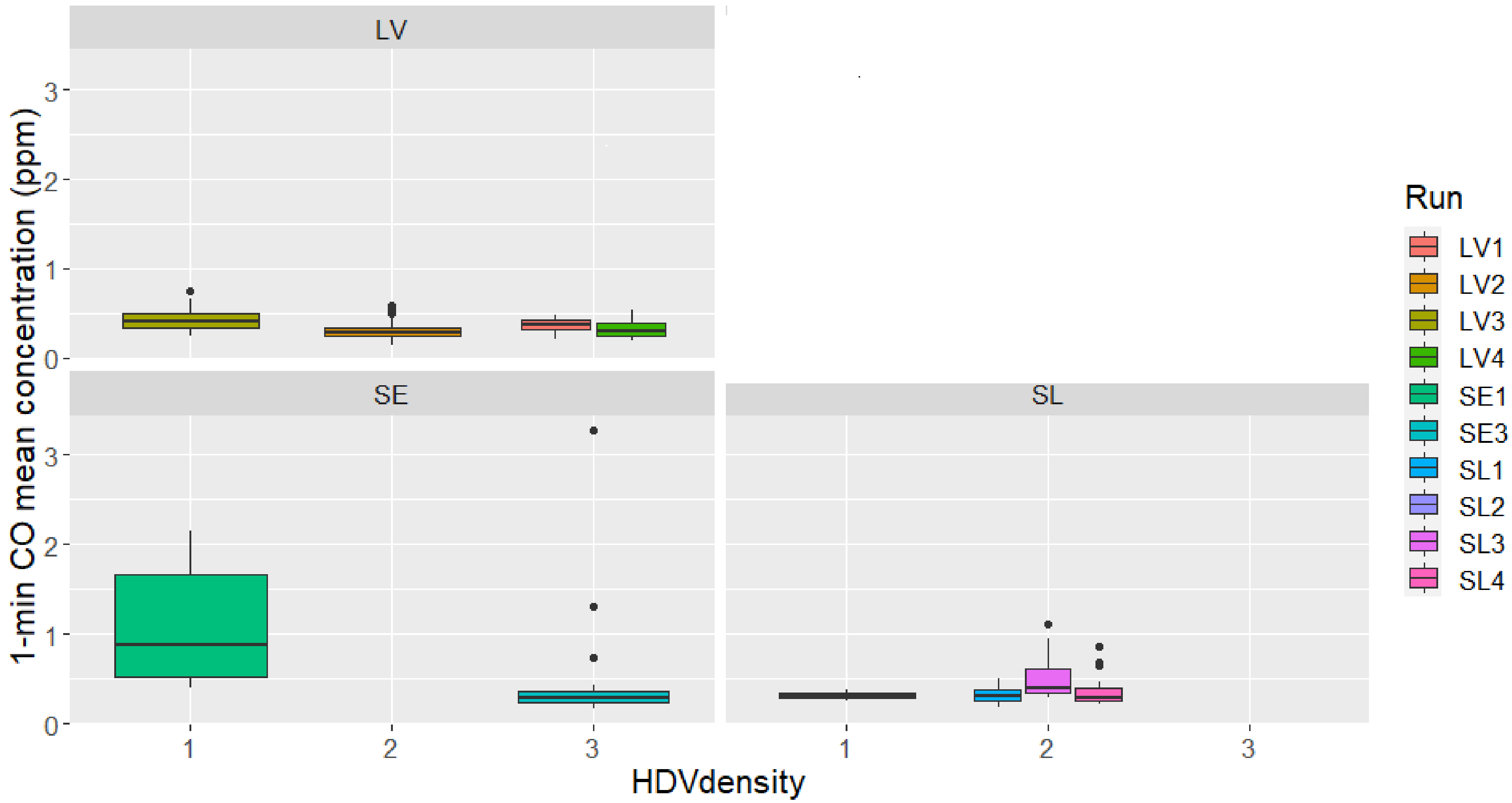

Figure 4. 1-minute CO mean concentrations (ppm) by HDV density by each sampling session of each community during summer, 2017. Three classes of HDV density i.e., class 1: <0.4 (25th percentile), class 2: 0.4-1.2, and class 3: >1.2 (75th percentile) counts/minute.

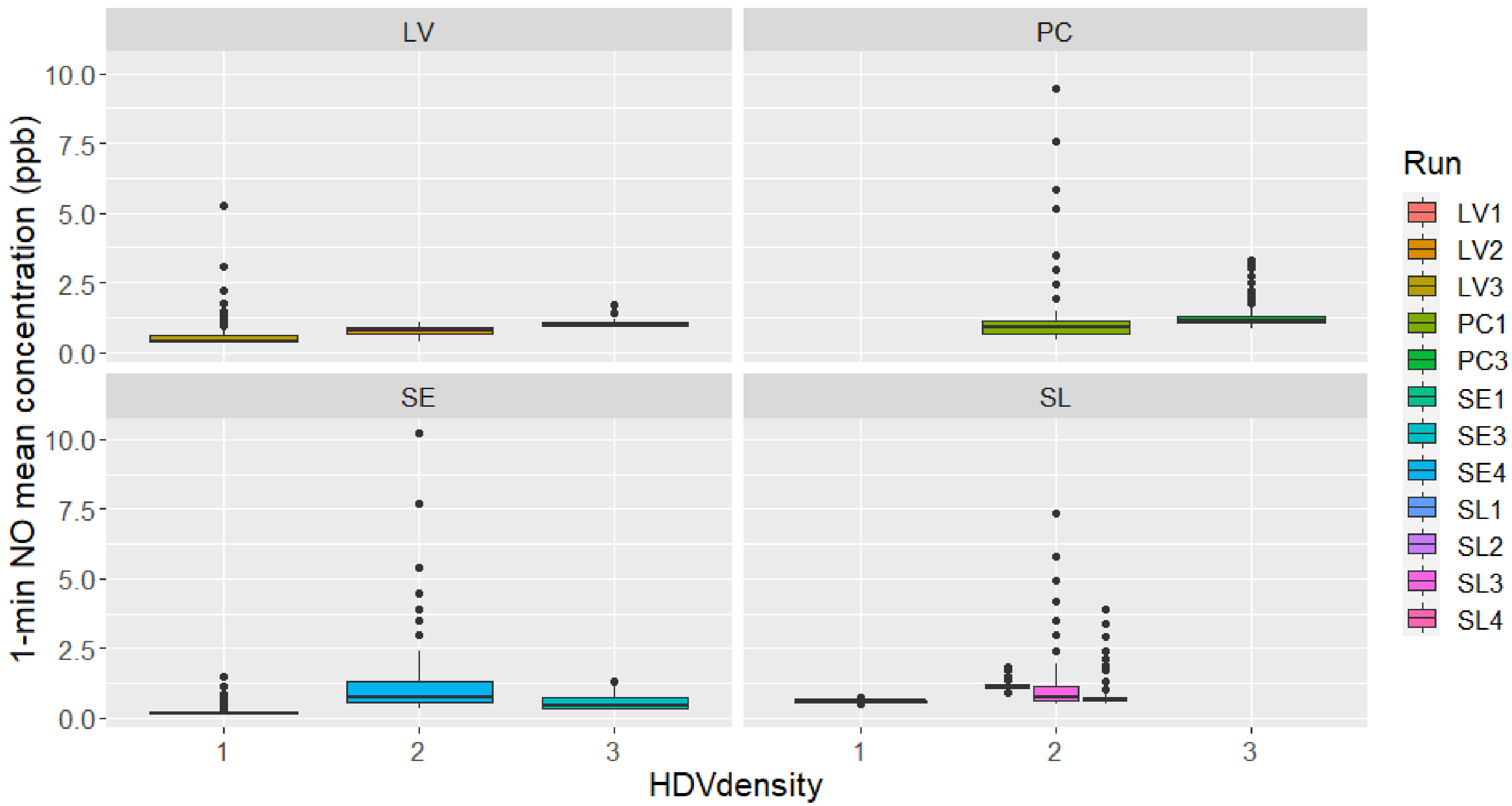

Figure 5. 1-minute NO mean concentrations (ppb) by HDV density by each sampling session of each community during summer, 2017. Three classes of HDV density i.e., class 1: <0.4 (25th percentile), class 2: 0.4-1.2, and class 3: >1.2 (75th percentile) counts/minute.

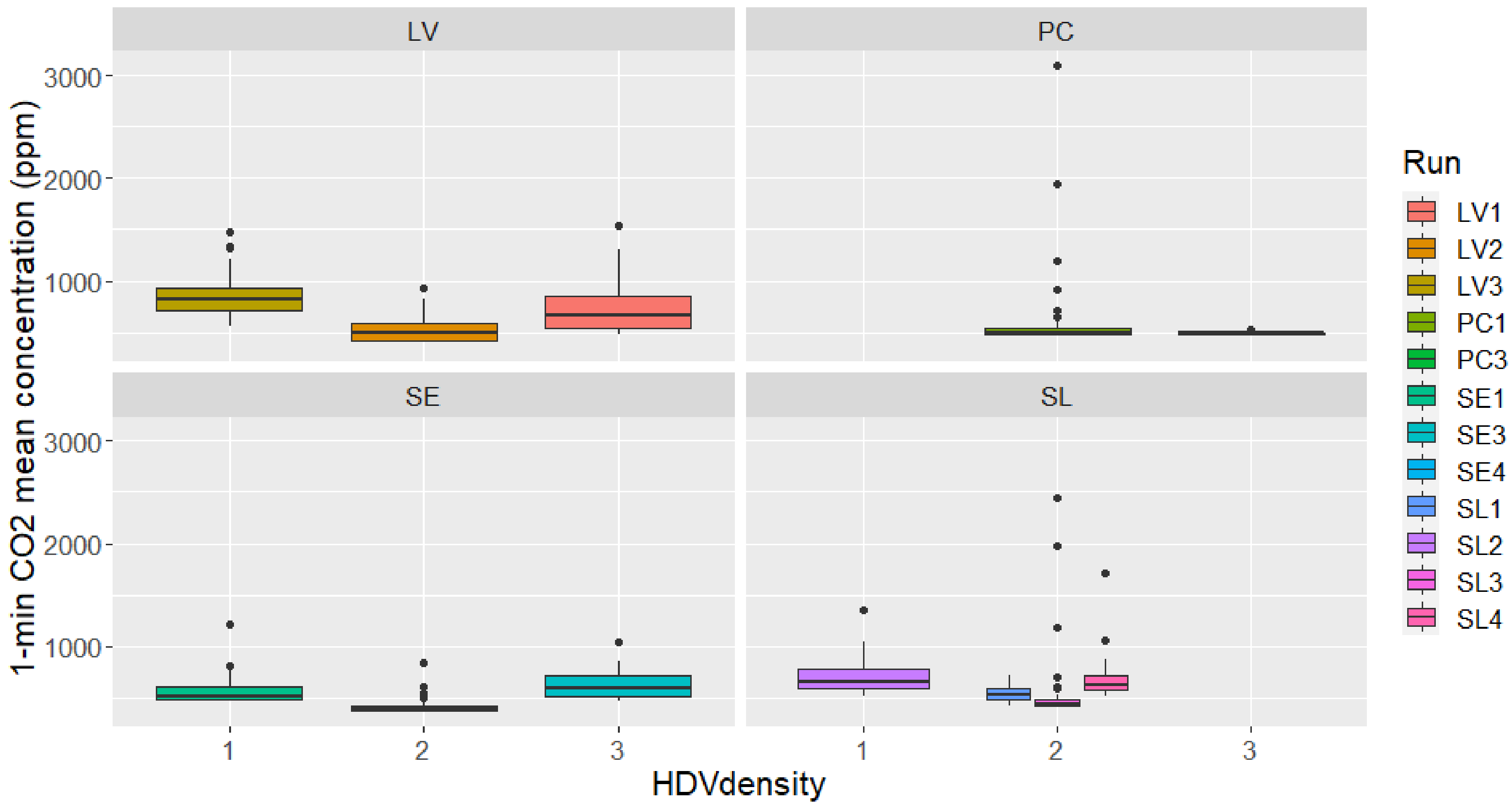

Figure 6. 1-minute CO_2 mean concentrations (ppm) by HDV density by each sampling session of each community during summer, 2017. Three classes of HDV density i.e., class 1: <0.4 (25th percentile), class 2: 0.4-1.2, and class 3: >1.2 (75th percentile) counts/minute.

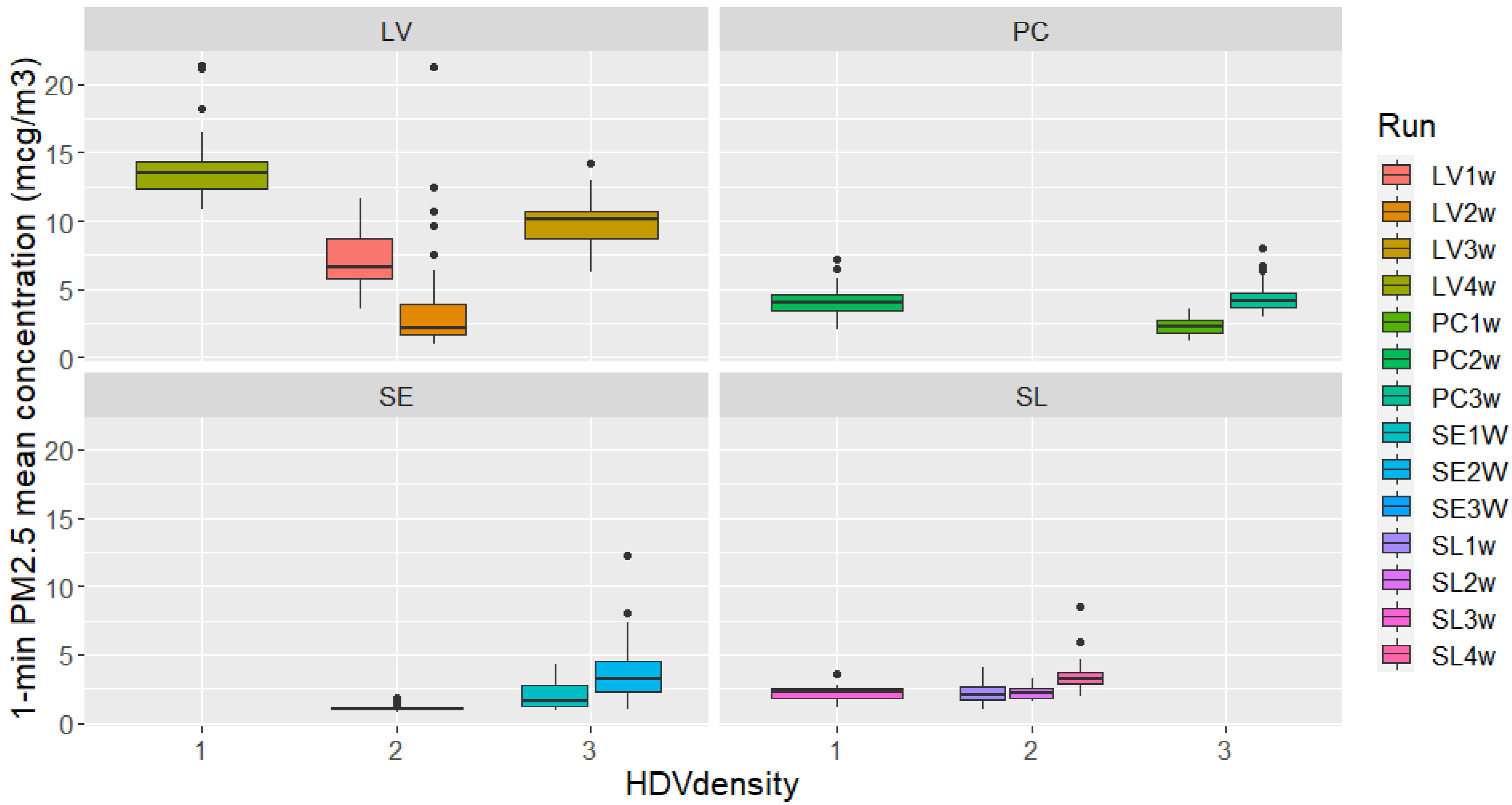

Figure 7. 1-minute PM2.5 mean concentrations (µg/m^3) by HDV density by each sampling session of each community during winter, 2018. Three classes of HDV density i.e., class 1: <0.4 (25th percentile), class 2: 0.4-1.2, and class 3: >1.2 (75th percentile) counts/minute.

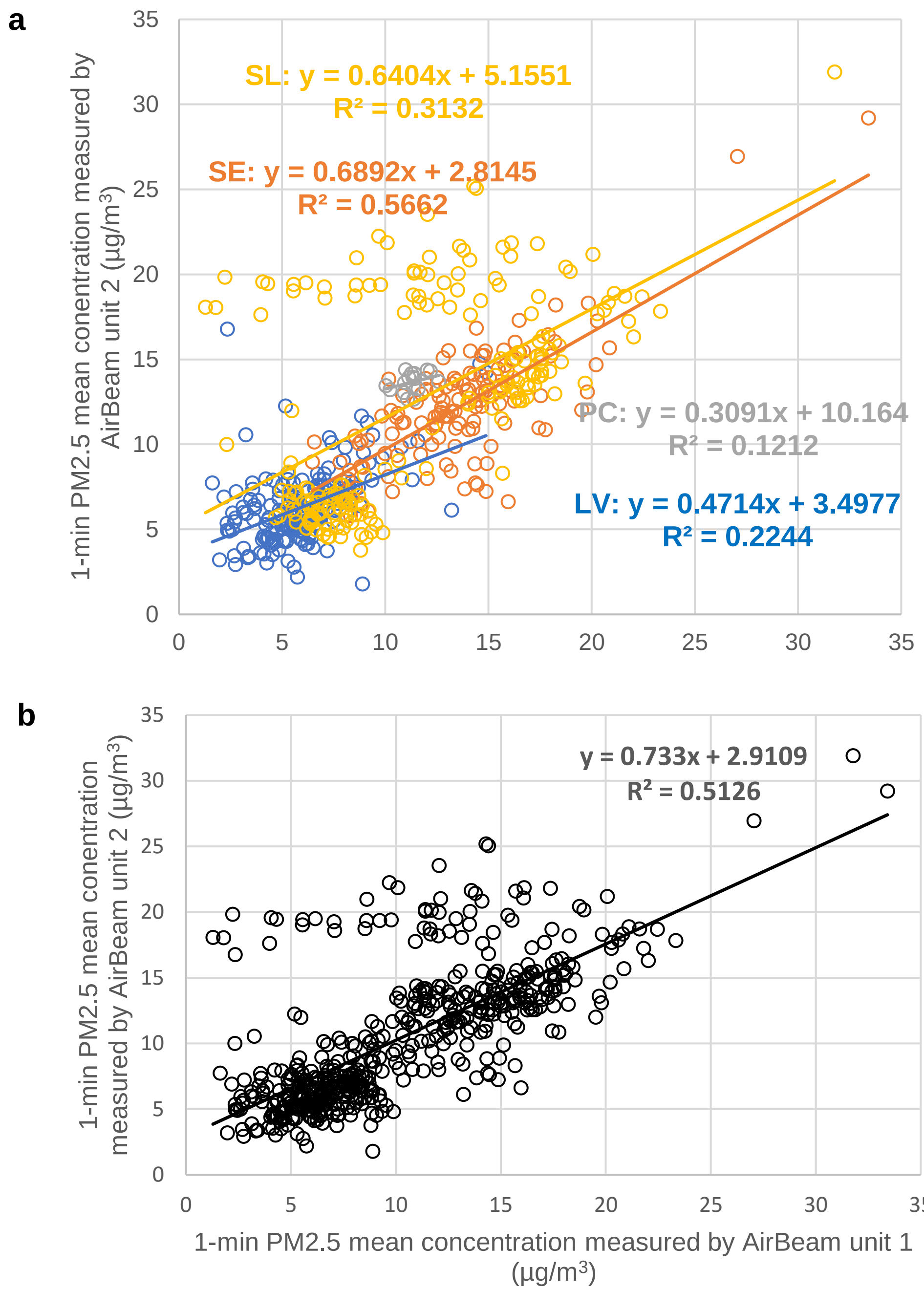

Figure 8. The correlation plots between 1-minute PM2.5 mean concentrations measured by two units of AirBeam during summer air monitoring efforts by each community (a) and across all communities (b). Number of observations: 179 (LV), 131 (SE), 17 (PC), and 189 (SL).

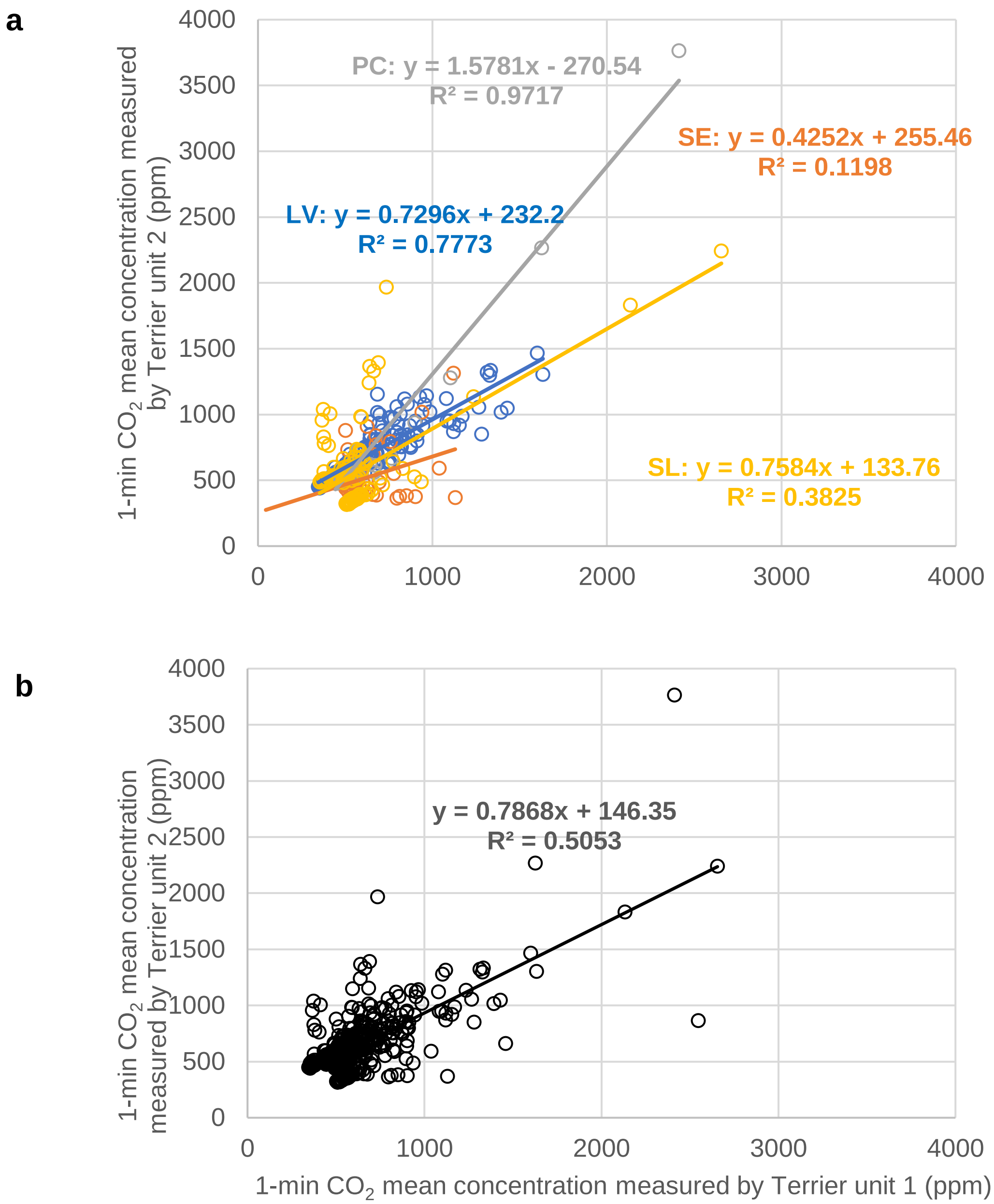

Figure 9. The correlation plots between 1-minute CO_2 mean concentrations measured by two units of Terrier during summer air monitoring efforts by each community (a) and across all communities (b). Number of observations: 158 (LV), 45 (SE), 51 (PC), and 114 (SL).

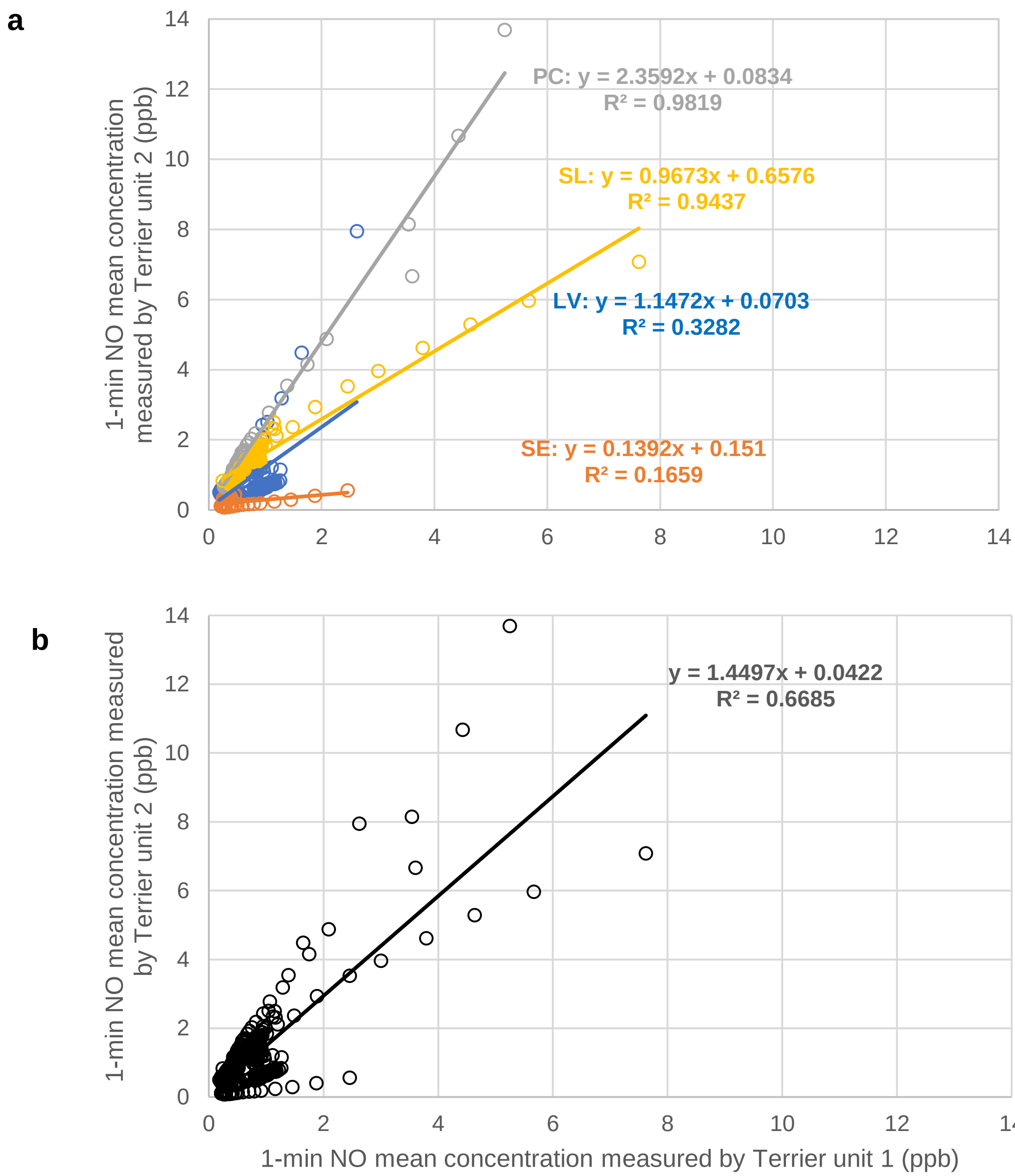

Figure 10. The correlation plots between 1-minute NO mean concentrations measured by two units of Terrier during summer air monitoring efforts by each community (a) and across all communities (b). Number of observations: 151 (LV), 80 (SE), 55 (PC), and 98 (SL).

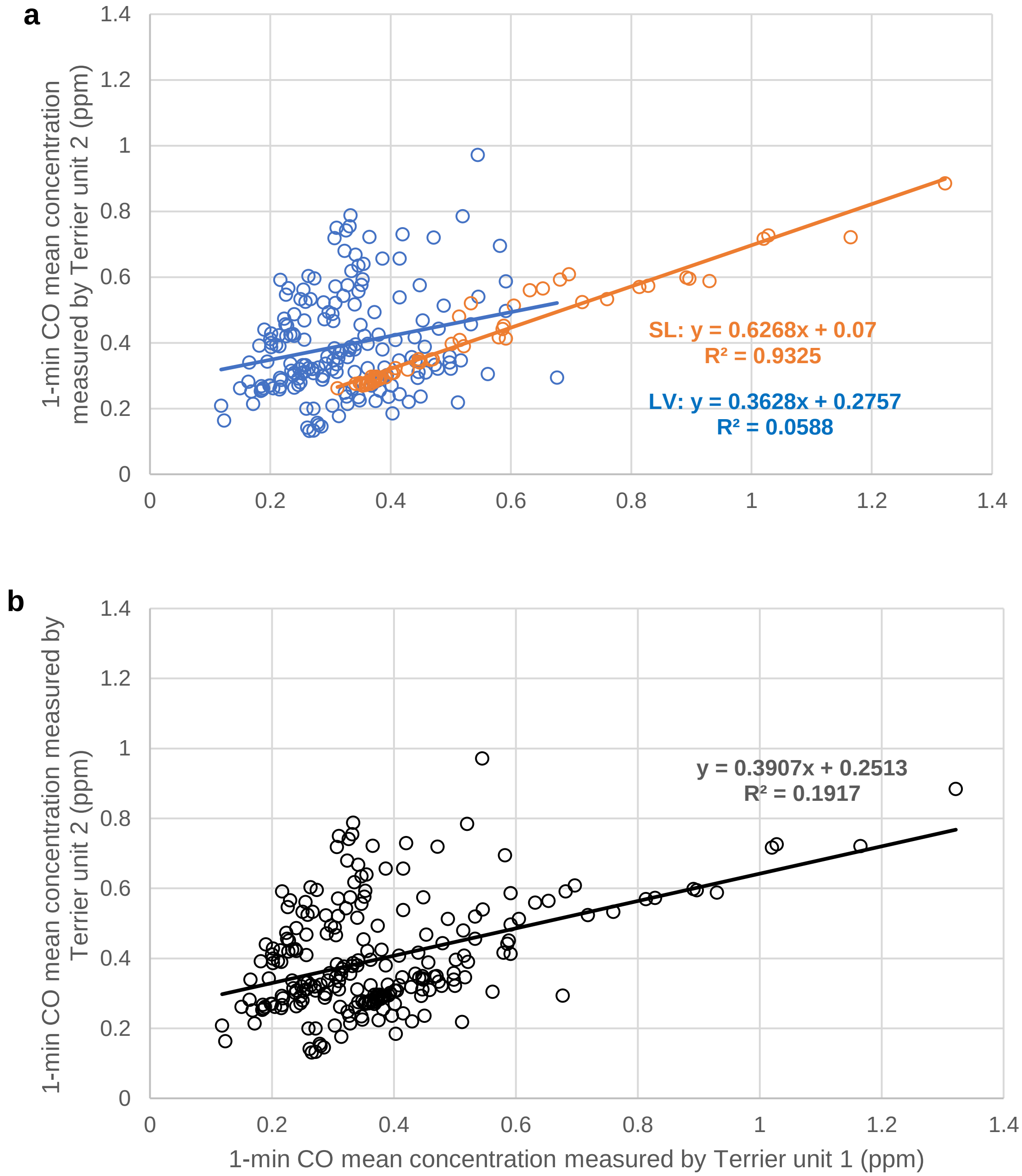

Figure 11. The correlation plots between 1-minute CO mean concentrations measured by two units of Terrier during summer air monitoring efforts by each community (a) and across two communities (b). Number of observations: 180 (LV), and 54 (SE).

IV. LOW-COST AIR SENSOR PERFORMANCE ASSESSMENT IN FIELD CONDITIONS AT ILLINOIS ENVIRONMENTAL PROTECTION AGENCY AIR MONITORING SITE

A. Introduction

Air pollution has been considered as a public health concern since several epidemiologic studies demonstrated the association between short-term and long-term air pollution exposures, even at low concentrations, and ranges of adverse health outcomes such as cardiovascular diseases, respiratory issues, lung cancer, adverse birth outcomes, and overall quality of life (Bentayeb et al., 2015; Cohen et al., 2017; Lin, H. et al., 2018; Pope et al., 2011; Wu et al., 2016). Overall, air quality has been improved across the U.S. However, in many areas, pollution levels still exceed the National Ambient Air Quality Standards (NAAQS) of at least one of the six criteria air pollutants (USEPA, 2019).

Air quality monitoring has been shifted to more miniaturized and low-cost sensors due to an inadequate number of traditional fixed-site air monitoring stations conducted by government agencies. Low-cost sensors enhance the ability to understand air quality in a wide range of spatial and temporal conditions; in addition to advancing personal exposure assessment studies. These sensors will increase accessibility of air quality data among communities and laypeople (Clements et al., 2017; Kumar et al., 2015; Snyder et al., 2013; Steinle, Reis, & Sabel, 2013). However, there are several challenges in employing low-cost sensors including the development of sensors producing high quality data and the evaluation of sensor performances in environmental and occupational settings, in addition, no standards and certifications of addressing a low-cost sensor performance exist (Snyder et al., 2013; Williams et al., 2019; Woodall et al., 2017).

Several studies have attempted to assess the low-cost air sensor performance against their respective Federal Reference Method (FRM) and Federal Equivalent Method (FEM) monitors. AirBeam sensor has demonstrated poor to high correlations (R^2) with the reference instruments i.e., Beta Attenuation Method (BAM) and Well Impactor Ninety-Six (WINS) monitors with R^2=0.21-0.83 in various spatial and temporal conditions (Borghi et al., 2018; DeWitt, Crow, & Flowers, 2020; Feenstra et al., 2019; Feinberg et al., 2018; Jiao et al., 2016; Mukherjee et al,, 2017; SCAQMD, 2015a). PurpleAir sensor has demonstrated poor to high correlations with FEM BAM, GRIMM, and Tapered Element Oscillating Microbalance (TEOM) monitors with R^2=0.32-0.95 (Feenstra et al., 2019; Kelly et al., 2017; Magi et al., 2020; Malings et al., 2020; SCAQMD, 2016). MetOne Neighborhood has demonstrated poor to moderate correlations with FEM BAM and GRIMM with R^2=0.41-0.67 (Malings et al., 2020; SCAQMD, 2015b). AerQual S500 has shown a high correlation with FEM with R^2=0.72-0.96 (DeWitt et al., 2020; Lin et al., 2015; Lin et al., 2017). Terrier sensor used in this study combines the following three sensors: Alphasense CO-B4, Alphasense NO-B4, and ELT S300-CO_2. In spite of a lack of evaluation of Terrier performance in the scientific literature, several studies have evaluated the performance of one of its three sensors. Alphasense CO-B4 showed low intra-variability (R^2>0.9) and moderate to high degree of correlation with the reference instruments i.e., FRM and FEM (R^2>0.6) (Borrego et al., 2018; Jiao et al., 2016; Sun et al., 2016). Alphasense NO-B4 demonstrated a moderate to high correlation with the FRM and FEM (R^2>0.7) (Borrego et al., 2018; Jiao et al., 2016; Lewis et al., 2016).

Previous studies emphasized the importance of the collocation studies to address how low-cost sensors perform compared to the reference instruments operating in the fields. This knowledge is essential for establishing field calibration parameters to minimize the inter-variability between the measurements of low-cost sensors and reference instruments. In addition, the calibration parameters might change among different times and locations (Castell et al., 2018; Clements et al., 2019; Malings et al., 2020; Mukherjee et al., 2017). Several collocation studies have been done in many areas across the U.S. and worldwide; however, three low-cost PM (AirBeam, MetOne Neighborhood, PurpleAir) and two low-cost gaseous pollutant (Terrier and AeroQual S500) sensors utilized in the present study have not been tested side-by-side against the FRM and FEM monitors in the Midwest area. The present study aims to fill this critical data gap and it consists of two components. One component was the collocation study, which was conducted at the Northbrook Illinois Environmental Protection Agency (IEPA) air monitoring site from October 6 to December 8, 2017. Another component was evaluation of feasibility of air quality sensor use by community residents for outdoor air quality investigations and personal exposure assessment studies, is an integral component of the Quality Assurance and Quality Control (QA/QC) protocol of the Shared Air/Shared Action (SASA) project (see Chapter III).

This collocation study provided valuable information pertaining to low-cost PM and gaseous pollutant sensor performance against EPA FRM/FEM monitors. The inter- and intra-sampler variabilities of these low-cost sensors were assessed in order to gain an understanding of their reliability in support of future exposure assessment studies. These results will facilitate future efforts in the calibration and use of low-cost sensor systems in different spatial and temporal conditions.

B. Methods

1. Collocated Air Monitoring Efforts at the Illinois Environmental Protection Agency (IEPA) Monitoring Site

All low-cost air monitoring sensors included both mobile and stationary air sensors for PM (i.e., PM10 and PM2.5) and gaseous pollutants (CO, CO_2, NO, NO_2, and O_3) utilized in the SASA project were selected based on an extensive literature review, consultation with the EPA staff, and the performance review of the commercially available sensors tested by the EPA and the South Coast Air Quality Management District (SCAQMD) in their respective laboratories and/or in field settings. All applied low-cost sensors were listed in Table V. The collocation study was conducted at a fixed air monitoring site operated by the IEPA located at Northbrook Water Plant, Northbrook, IL from October 6 to December 8, 2017. This air monitoring site was selected due to being highly equipped with monitors measuring CO, NO/NOy, O_3, PM10, PM2.5, PM2.5 speciation, SO_2, VOC, Toxics, and Meteorological conditions in the study region i.e., Cook County, IL. At the IEPA air monitoring site, two or three of each study low-cost sensors were placed next to their respective EPA FRM/FEM monitors (see Table VI and Figure 12) to assess the inter- and intra-variability of low-cost air sensors. The air monitoring effort at the IEPA site had to be scheduled based on the availability of the study sensors as they were not needed in support of the community air monitoring efforts. AeroQual S500 measured ozone during October 6 to 27, 2017 before the sensor was changed to measure NO_2 from October 27 to December 8, 2017. In addition, the intra-variability performance assessment of MetOne Neighborhood Monitor was limited to PM2.5 concentration measurement due to only one unit of MetOne sampler was available for PM10 monitoring. AirBeam and Terrier sensors (three units of each) were operated for a short period of time denoted as “Sub-Experiment”, which is approximately 84 hours during the beginning of the sampling period (October 12 to 20 2017) alongside with other low-cost sensors and the FRM/FEM instruments. The completed two-month sampling period was denoted as “Overall-Experiment”.

2. Air Quality Data Retrieval and Management

Air quality data collected by each low-cost sensor were retrieved from different platforms. AirBeam and Terrier sensor collected data were transferred from the sensors to cloud using manufacturer developed algorithms and were downloaded from the AirCasting website. AeroQual S500 collected data was manually downloaded from the sensors using the manufacturers’ program. The MetOne Neighborhood collected data was transferred to cloud using Comet software developed by MetOne Instruments, INC. and downloaded from the manufacturer’s platform, and PurpleAir collected data was retrieved from the PurpleAir website. Among the several parameters collected by PurpleAir sensor, PM2.5_ATM and PM10_ATM, the average particle density for outdoor particulate matter (PM2.5 and PM10, respectively) according to the manufacturer’s user guide, were utilized in the analysis since the air monitoring efforts in the present study were performed outdoors. The air quality data collected by IEPA FRM/FEM monitors were retrieved from the EPA website for specific air pollutants and air monitoring timeframes. All retrieved data were cleaned and managed in Microsoft Excel and R version 3.6.3. The missing data of each dataset obtained from each unit of sensor were identified. Each sensor measurement, with the exception of AirBeam and Terrier sensors, was missing in approximately no greater than 5% of total collected data points. To maximize data points included in the data analysis, AirBeam recorded data was properly treated and imputed for the missing 1-second data following the criteria delineated in Appendix H. PurpleAir sensor records the measurements with two channels (A and B) simultaneously. The correlation plots of measurements of each PurpleAir channel operated at IEPA Northbrook air monitoring site demonstrated a very high degree of correlation for both PM2.5 (R^2>0.91) and PM10 (R^2>0.94) (see Appendix I). Therefore, the average measurement of these two channels was utilized for the data analyses.

3. Air Quality Data Analyses

The collected air quality data retrieved from each sensor with different recording interval time were computed for 1-hour and 24-hour average concentrations by each unit and across all units of each type of sensor, which were designated as ABaver (for AirBeam), PAaver (for PurpleAir), MOaver (for MetOne Neighborhood), AQaver (for AeroQual), and TRaver (for Terrier), were used for descriptive statistical, intra- and inter-sampler performance, and regression model analyses. The flow chart summarizing data management procedure is shown in Figure 13. The collocated air quality data from different sensors was matched for the same timestamps throughout the air monitoring duration. Descriptive statistics of pollutant concentrations were calculated and documented. The precision of low-cost sensors (intra-sampler performance) was evaluated by means of pair-wise correlation plots between the measurements of the different units of each type of sensor e.g., PM2.5 measured concentration of AirBeam-1 vs. AirBeam-2 vs AirBeam-3. Linear regression parameters including the correlation of determination (R^2), slope, and intercept of the regression line were employed to determine the agreement between the units of each type of sensor. Two main approaches were carried out to determine the accuracy of low-cost sensors (inter-sampler performance) i.e., the conventional approach, which is commonly used by other researchers and published in the literatures in the air monitoring and exposure assessment/characterization studies, and the alternative approach, which is unique to the present study employing statistical parameters and modeling analyses.

a) <u>Conventional Approach</u>

The inter-sampler comparisons between low-cost sensors and their respective instruments (e.g., PM2.5 measured concentration of MetOne vs. EPA FEM and PM2.5 measured concentration of PurpleAir vs. EPA FEM) were analyzed using linear regression statistics (slope, intercept, and correlation of determination) and measurement errors (Mean Absolute Error (MAE), Mean Bias Error (MBE), and Root Mean Square Error (RMSE)). The coefficient of determination (R^2), which is accepted as a very strong correlation ($R^2 \geq 0.9$), a strong correlation (R^2=0.7-0.89), a moderate correlation (R^2=0.5-0.69), a weak correlation (R^2=0.3-0.49), a very weak correlation (R^2=0.1-0.29), and a no correlation (R^2=0.0-0.09), in addition to the slope and intercept of the best-fit line were investigated (Collier-Oxandale et al., 2020). The slope being one and the intercept being zero indicate the perfect agreement between the low-cost sensor and the reference monitor measurements. Mean Absolute Error (Equation IV-1) is an average of absolute errors which are differences, in the absolute value, between the measurements of the FRM/FEM monitors and the low-cost sensors indicating the magnitude of error. Mean Bias Error (Equation IV-2) is an average of bias errors, which are differences between the measurements of the FRM/FEM monitors and the low-cost sensors indicating whether low-cost sensors overestimate or underestimate the pollutant concentrations as compared to the FRM/FEM monitors. Root Mean Square Error (Equation IV-3) is a total square error indicating how each error influences the total in proportion to its square and how concentrated the data around the best-fit line. RMSE is more impacted by larger errors and sensitive to outliers. The ratio of the MBE and MAE indicates the proportion of the error due to the systematic error as opposed to the random error (Collier-Oxandale et al., 2020).

Equation IV-1: $$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_t - x_i|$$

Equation IV-2: $$MBE = \frac{1}{n}\sum_{i=1}^{n} (x_t - x_i)$$

Equation IV-3: $$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n} (x_t - x_i)^2\right]^{1/2}$$

x_t is the measurement of the FRM/FEM monitor, x_i is the measurement of the low-cost sensor, and n is the number of the time-matched data pairs.

b) <u>Alternative Approach</u>

The alternative approach for evaluating the agreement between the low-cost sensors and their respective reference instruments (i.e., FRM and FEM monitors) included the Bland-Altman plots (B-A plots) and Lin’s Concordance Correlation Coefficient (CCC). Based on B-A plots, the mean of differences between measurements of low-cost sensors and the FRM/FEM monitors closing to zero, in addition to having a narrow limit of agreement (95% confidence interval), suggest a good agreement between the low-cost sensor and FRM/FEM monitor (Bland & Altman, 1999; Bland &

Altman, 2010; Giavarina, 2015). CCC consists of two components i.e., Pearson Correlation assessing the precision of measurements, and Bias Correction Factor (C_b) assessing the accuracy of measurements. CCC indicates an agreement between low-cost sensors and the FRM/FEM monitors based on the similar criteria as other correlation coefficients including Pearson Correlation Coefficient (Akoglu, 2018): a high degree of agreement (CCC≥0.8); a moderate degree of agreement (CCC=0.6-0.8); and a low degree of agreement (CCC<0.6). C_b closer to one indicates a high degree of agreement between the best-fit-linear regression line and the line of equality between the measurements of FRM/FEM instruments and low-cost sensors (Lin Lawrence I-Kuei, 1989). CCC and C_b were computed using the R version 3.6.3 package DescTools.

Furthermore, impacts of weather conditions i.e., temperature and % relative humidity (%RH) on low-cost sensor performance were investigated employing the plots between bias error, which is the difference between the measurements of the FRM/FEM monitors and the low-cost sensors, and %RH or temperature. The slope of the linear regression line is expected to be zero and located on y=0 axis indicating no impacts of temperature or humidity on the sensor performances (Feenstra et al., 2019). The Multiple Linear Regression (MLR) coefficient parameters were computed and used to develop the correction equations employed to calculate estimated PM and gaseous pollutant concentrations based on low-cost sensor measurements adjusted for temperature and/or humidity. The inter-sampler comparisons were evaluated between the estimated concentrations and the concentration measured by FRM/FEM monitors.

C. Results

1. Summary of Collected Air Quality Data

The data recovery for 1- and 24-hour mean measured concentrations were >90% (for AeroQual) and ≥80% (for MetOne, PurpleAir, and AirBeam), while Terrier sensors had approximately 70% data recovery (see Table VII to IX). The AirBeam recording time interval is 1 second, while that of other sensors are 10 seconds or more; therefore, only AirBeam 1-second missing collected measurements were imputed, if required, following a stringent protocol delineated in Appendix H. This protocol minimized an inappropriate assumption making for those missing data points preventing the artificial under or over estimating of the mean PM concentrations. Less than 2% of the total data points (1-second PM2.5 measured concentrations) were imputed. The descriptive statistics of imputed and non-imputed datasets of AirBeam measurements were performed and no discrepancies between the two datasets were observed (see Appendix J).

2. Descriptive Analysis of PM and Gaseous Pollutant Measurements

The descriptive statistics of PM and gaseous pollutant concentrations, temperature, and %relative humidity (%RH) are shown in Table X to XII. Across all low-cost PM sensors, measurements obtained from each unit of sensor were aligned with one another suggesting that study PM low-cost sensors had a low intra-sampler variability. The PM2.5 mean concentrations measured by MetOne Neighborhood ranged from 1.5 μg/m^3 to 36.8 μg/m^3 with a mean of 7.7 μg/m^3 (1-hour mean), and from 2.2 μg/m^3 to 28.7 μg/m^3 with a mean of 7.6 μg/m^3 (24-hour mean), which were similar to those measured by FEM and FRM. PM2.5 mean concentrations measured by PurpleAir ranged from 0.2 µg/m^3 to 58.5 µg/m^3 with a mean of 13.0 µg/m^3 (1-hour mean), and from 1.2 µg/m^3 to 49.0 µg/m^3 with a mean of 13.2 µg/m^3 (24-hour mean), which were higher than those of FEM and FRM. The PM10 mean concentrations measured by PurpleAir were closer to FRM than those of MetOne Neighborhood. During the Sub-Experiment sampling effort, AirBeam measurements ranged from 1.4 µg/m^3 to 30.9 µg/m^3 with a mean of 6.2 µg/m^3 (1-hour mean).

Across all low-cost gaseous pollutant sensors, for AeroQual measuring NO_2, and Terrier measuring CO, the readings obtained from each unit of sensor were similar. CO concentrations measured by one unit of Terrier were excluded from the analyses since all measured concentrations were zero. The NO_2 mean concentration measured by AeroQual ranged from 0.4 ppm to 48.9 ppm with a mean of 21.5 ppm (1-hour mean), and from 7.3 ppm to 36.8 ppm with a mean of 21.7 ppm (24-hour mean). The O_3 concentrations measured by AeroQual ranging from 0.00 ppm to 0.05 ppm with a mean of 0.03 ppm were very similar to those of FEM.

3. Low-Cost Sensors Performance

a) Low-Cost PM Sensors Performance

(1) PM Sensor Performance Evaluations by the Conventional Approach

The correlation plots were generated between the measurements of different units of low-cost PM2.5 sensors for the intra-sampler comparison analysis. The low intra-variability was observed between the units of each type of PM2.5 sensor (R^2=0.96-1.00) (see Table XIII). The PM2.5 concentration time series plots demonstrated similar trends of the measured concentrations among study PM2.5 sensors and FEM (see Figure 14). MetOne sensors were in agreement with the FEM, while PurpleAir sensors, in general, overestimated the FEM measurements. The pair-wise correlation plots were generated between measurements of low-cost sensors and FRM/FEM instruments for the inter-comparison analysis. MetOne and PurpleAir sensors had a moderate to strong correlation with FRM (R^2=0.66-0.73) and a weak to moderate correlation with FEM (R^2=0.42-0.59), while AirBeam had a no to very weak correlation with FEM (R^2=0.03-0.12) (see Table XIV). The slope and intercept values demonstrated a high agreement between MetOne and FRM with the slope values within -0.25 of the 1.0 perfect value and the intercept values within <2 of the 0.0 perfect value. Measurement errors (MAE and MBE) indicate the differences between low-cost sensors and FRM/FEM. MetOne had the smallest MAE among all study low-cost PM2.5 sensors (MAE=2-4 μg/m^3), while the MAE of PurpleAir ranged from 4.1 μg/m^3 to 7.5 μg/m^3 and that of AirBeam was approximately 6 μg/m^3. The differences between the measurements of AirBeam and FRM were not analyzed due to a shortage of collected data since AirBeam sensors were operated for a short duration (84 hours). The MBE values suggested that all study PM2.5 low-cost sensors, in exception of AirBeam unit 3, were found to overestimate the PM2.5 concentrations as compared to the FRM/FEM monitors with MBE values ranging from 0.1 μg/m^3 to 6.5 μg/m^3 (Table XIV). The higher ratios of MBE and MAE of PurpleAir (0.8-0.9) compared to those of other PM2.5 low-cost sensors (≤0.3) suggested that systematic errors had a lower proportion contributing to MetOne measurement error as compared to that of PurpleAir. The RMSE values of MetOne were the smallest (RMSE=3.0-5.3 μg/m^3), AirBeam and PurpleAir had greater RMSE values, 6.9 µg/m^3 to 10.7 µg/m^3 (see Table XIV). Overall, among all study PM2.5 low-cost sensors, MetOne had the best performance.

Among PM10 low-cost sensors, PurpleAir measuring had a high consistency among different units (R^2=0.99-1.00) (see Table XIII). The PM10 concentration time series plots in Figure 15 demonstrated similar trends of measured concentrations among tested PM10 sensors and FRM. Both PurpleAir and MetOne, in general, recorded lower PM10 concentrations as compared to those of the FRM. PurpleAir had a better agreement with FRM than MetOne. PurpleAir had a high correlation and agreement with FRM with R^2=0.75-0.76, in addition to, the slope values within -0.05 of the 1.0 perfect value and the intercept values within <3 of the 0.0 perfect value. PurpleAir had MAE values ranging from 6.5 µg/m^3 to 7.0 µg/m^3. Both MetOne and PurpleAir were found to underestimate the PM10 concentrations as compared to the FRM measurements with MBE values, 2.9-3.6 µg/m^3 (for PurpleAir) and 9.3 µg/m^3 (for MetOne). The MBE and MAE ratios of PurpleAir (0.4-0.6) were lower than that of MetOne (1.0) (see Table XIV), which suggested that systematic errors had a lower proportion contributing to the PurpleAir measurement error as compared to that of MetOne. Overall, PurpleAir measuring PM10 had a better performance as compared to MetOne; however, this interpretation was based on the limited data retrieved from only one unit of MetOne measuring PM10 available during the collocation air monitoring effort.

(2) PM Sensor Performance Evaluations by the Alternative Approach

The B-A plot parameters, including the mean of differences between measurements of FEM or FRM and the low-cost sensor and the limit of agreement, in addition to Lin's Concordance Correlation Coefficient (CCC) were employed to determine an agreement between low-cost sensors and FRM/FEM instruments.

Bland-Altman mean of differences and CCC of measurements between PM2.5 low-cost sensors and reference monitors are shown in Table XV. MetOne measuring PM2.5 was observed to have a small mean of differences (≤0.4 μg/m^3). CCC and C_b values were aligned with the B-A plot findings. MetOne had a high degree of agreement with FRM (CCC=0.81-0.82 and C_b=0.99-1.00) and a moderate agreement with FEM (CCC=0.64-0.65 and C_b=0.97-1.00). AirBeam had a mean of differences ranging from 0.11 μg/m^3 to 1.6 μg/m^3. PurpleAir had a relatively greater mean of differences compared to other tested low-cost PM2.5 sensors, which were approximately 4 μg/m^3 and 6 μg/m^3, as compared to FRM and FEM measurements, respectively. CCC suggested that AirBeam and PurpleAir sensors had a poor agreement with FEM and FRM.

PurpleAir measuring PM10 had a high agreement with FRM (mean of differences <4 μg/m^3, CCC=0.82-0.84 and C_b=0.95-0.96), in contrast MetOne had a poor agreement with FRM (mean of differences 9.3 μg/m3, CCC=0.38 and C_b=0.0.47).

b) Impacts of Weather Conditions on PM Low-Cost Sensor Performance

The plots between bias error and %RH or temperature were generated and are shown in Figure 16 to 19. For MetOne measuring PM2.5 sensors, the slope of the linear regression line is close to zero and aligned with y=0 axis suggesting MetOne measuring PM2.5 sensors were not strongly impacted by humidity and/or temperature (see Figure 16). The plots demonstrated that PurpleAir and AirBeam overestimated the PM2.5 concentration as the %RH increased without any correlation with the temperature (see Figure 17 and 18). The plots shown in Figure 19 illustrated that Metone and PurpleAir measuring PM10 sensors were impacted by temperature and humidity. The MLR statistics of each corrected model were computed (see Table XVI). After applying corrections to low-cost sensor measurements, in case of PM2.5 sensors, the measurement errors (MAE, MBE, and RMSE) of the PurpleAir sensor estimated/adjusted measurements significantly decreased as compared to those unadjusted measurements. On the other hand, for the measurements of MetOne and AirBeam, no differences of measurement errors were observed between the unadjusted and adjusted measurements. For PM10 measurements, the best improvement of the correlation between adjusted low-cost sensor measurements and those of their respective reference monitors was observed after applying corrections adjusted for both temperature and humidity. The agreements between low-cost PM sensors and FRM were significantly improved. R^2 increased from 0.65 to 0.91 (for MetOne) and from 0.75 to 0.89 (for PurpleAir). Moreover, The MAE, MBE and RMSE of the adjusted low-cost measurements decreased more than 50% (see Table XVII and XVIII).

c) Low-Cost Gaseous Pollutant Sensor Performance

(1) Gaseous Pollutant Sensor Performance Evaluations by the Conventional Approach

The intra-comparison analysis suggested various intra-variabilities among low-cost sensors measuring different gaseous pollutants. AeroQual measuring NO_2 showed low intra-sampler variability with R^2=0.78, while, Terrier measuring CO demonstrated the highest intra-sampler variability with R^2=0.29 followed by NO with R^2=0.52-0.91 and CO_2 with R^2=0.69-0.92 (see Table XIX). The gas pollutant concentration time series plots shown in Figure 20 demonstrated that the O_3 concentrations measured by AeroQual were very similar to those measured by FEM. The time series plots for Terrier sensors measuring CO/NO shown in Figure 21 and 22 demonstrated that Terrier sensors measuring both CO and NO were seem to have better agreement with the reference monitors in conditions with low %RH than those of high %RH, regardless of the temperature conditions. The inter-sampler comparison analysis between low-cost sensors and EPA monitors suggested a moderate degree of correlation between AeroQual measuring O_3 and FEM with R^2=0.68. In addition, the slope value was within -0.25 of the 1.0 perfect value and the intercept was very close to the 0.0 perfect value. Terrier showed a very weak to moderate correlation with FRM for CO measurements (R^2=0.18-0.64); and a no to very weak correlation with the reference monitor (Non-Federal Reference Method) for NO measurements (R^2=0.03-0.12). The slope and intercept values demonstrated a low agreement between Terrier measuring CO/NO and EPA monitors with the slope values being within the range of 0.5-0.7 of the 1.0 perfect value and the intercept values within the range of 0.1-10 of the 0.0 perfect value. The MAE (0.006 ppm), MBE(-0.002 ppm), and RMSE (0.007 ppm) of AeroQual measuring O_3 were relatively small, suggesting a small difference between measurements of AeroQual and FEM, while the measurement error parameters greatly varied among the units of Terrier sensor measuring CO/NO (see Table XX).

(2) <u>Gaseous Pollutant Sensor Performance Evaluations by the Alternative Approach</u>

The Bland-Altman means of differences suggested that the measurements of AeroQual-O_3 almost perfectly in agreement with those of O_3 FEM with the mean of difference being very close to zero (-0.0023 ppm) and the limit of agreement being narrow (-0.016,0.001 ppm). Moreover, CCC and C_b suggested a high degree of agreement between AeroQual measuring O_3 and FEM with CCC=0.81 and C_b=0.98. The mean of differences between measurements of Terrier measuring CO and FRM ranged from -0.002 ppm to 0.078 ppm. Terrier measuring CO had a poor to moderate agreement with FRM (CCC=0.30-0.54 and $C_b \geq 0.2$ of the 1.0 perfect value), while Terrier measuring NO had a poor agreement with the reference monitor (CCC=0.08-0.27 and $C_b \geq 0.3$ of the 1.0 perfect value) (see Table XXI).

d) <u>Impacts of Weather Conditions on Low-Cost Gaseous Pollutant Sensor Performance</u>

The plots between bias error and %RH or temperature shown in Figure 23 demonstrated that AeroQual measuring O_3 was not significantly impacted by temperature and humidity. Terrier measuring CO sensors were impacted by humidity and temperature. The bias errors slightly increased as %RH increased, while the bias errors decreased as temperature increased (see Figure 24). Terrier measuring NO sensors were also observed to be impacted by temperature and humidity. As humidity increased, bias errors were more deviated from y=0 indicating Terrier sensors overestimated the NO concentrations (see Figure 25). The MLR statistics of each corrected model were computed and documented in Table XXII. After applying corrections to AeroQual-O_3 measurements, the improvement of R^2 between the measurements of FEM and AeroQual-O_3 was observed in the AeroQual-O_3 measurements adjusted for the temperature, R^2 increased from 0.68 (unadjusted measurements) to 0.76 (adjusted measurements), in addition, MAE and RMSE decreased for approximately 30%. For Terrier sensor, the R^2 between CO measurements of the low-cost sensor and FRM increased from 0.46 (unadjusted measurements) to 0.58 (adjusted measurements) when applying the correction adjusted for humidity. On the other hand, no improvement of R^2 between NO measurements of the low-cost sensor and the reference monitor after applying corrections was observed. Measurement error parameters were not significantly different between unadjusted and adjusted CO measurements, while the measurement errors of Terrier measuring NO were decreased suggesting that correction of low-cost measurements with humidity and temperature was needed (see Table XXIII).

D. Discussion

The present study was a collocated testing of several low-cost PM and gaseous pollutant sensors at Northbrook Water Plant, Northbrook, IL, a suburb ambient environment. The low-cost PM (AirBeam, MetOne Neighborhood, and PurpleAir) and gaseous pollutant (AeroQual and Terrier) sensors were operated alongside with the EPA FRM/FEM monitors. The precision and accuracy of each sensor were investigated during a two-month sampling period in early October to early December 2017. Due to the approximate duration of the sampling period being two months, the long-term drifting of the low-cost sensor performance was not addressed in the present study. However, a previous study conducted by Dewitt and colleagues observed no significant decline in AirBeam and AeroQual accuracy during a 10-month air monitoring session (Dewitt et al.,2020). Several factors and uncertainties can influence sensor performances, however, in the present study, only temperature and humidity were captured. Other factors that can impact sensor measurements including wind speed, wind direction, and other pollutants or chemical compounds that are not a target, in addition to factors that can specifically impact PM measurements i.e., particle size distribution and sampling orientation (Mukherjee et al., 2017) were not investigated in this study. The challenges of employing low-cost sensors in the field are not only limited to the sensor performances but also include the misinterpretation between the measure quantity and mass of PM. Furthermore, managing the large datasets of collected air quality data is very demanding (Williams et al., 2019).

Overall, the low-cost sensors tested in the current study had a high percentage of data recovery (≥ 70%). Due to a power shutdown during the Sub-Experiment sampling period, the 10-hour data was lost and excluded from the data recovery percentage calculation. AirBeam and Terrier sensors had a lower percentage of data recovery compared to other low-cost sensors. This might be due to the sensors being operated in a mobile mode, instead of a stationary mode since the stationary mode could not be set up due to logistical and technical problems including Wi-Fi connection which is essential for setting up a communication between sensors and AirCasting platform. A number of metrics have been employed in previous studies for evaluating precision and accuracy of sensors including linear regression statistics (intercept, slope, and R^2), measurement errors (MAE, MBE, RMSE), and coefficient of variation (Sousan et al., 2017; Zheng et al., 2018). These metrics were utilized in the current study, in addition to other alternative metrics, to determine the agreement between low-cost sensors and the reference instruments. The alternative approach includes Bland-Altman plots (mean of differences and limit of agreement) and Lin's Concordance Correlation Coefficient which are useful for understanding different aspects of air quality data analysis for assessing low-cost sensor performance.

Among PM low-cost sensors evaluated in the present study, AirBeam was observed to have low intra-sampler variability, which bolstered the findings from previous studies showing a high degree of correlation among units of the AirBeam sensor (R^2>0.8). In addition, the investigators observed that AirBeam had a very weak correlation with FEM BAM, while other studies reported AirBeam to have a low to high degree of correlation with FEM and WINS (R^2=0.21-0.83). The summary of comparisons between the AirBeam sensor evaluation findings from our and from previous published literatures are shown in Table XXIV (Borghi et al., 2018; DeWitt et al., 2020; Jiao et al., 2016; Mukherjee et al., 2017; SCAQMD, 2015a). AirBeam measurements were impacted by meteorological conditions including temperature and humidity since, in general, low-cost sensors do not have the heating system to treat sampling air in order to minimize the hygroscopic aerosols, which can increase detecting light scatters and measurements (Mukherjee et al., 2019). Feinberg and colleagues observed a greater particle count response in higher humidity conditions.

The PM2.5 concentration peaks were noticed under conditions with %RH around 90 (Feinberg et al., 2018). One limitation of the present study is that AirBeam sensors were operated for a short period (approximately 84 hours) which could limit the observation of temperature and humidity variations impacting AirBeam sensor performance. The present study captured the conditions with relatively low temperature (a mean of 7.6 ^{o}C) and high %RH (a mean of 70%). Previous studies that operated AirBeam for longer sampling durations suggested that Airbeam sensor had a better performance in environments with lower %RH and higher temperature depending on the different times of the day and months of the year. AirBeam sensor performance was observed to be better during summer sampling events than that of during winter sampling events (Borghi et al., 2018; Feinberg et al., 2018; Mukherjee et al., 2019). In addition, particle counts showed a better agreement with reference monitors than mass concentrations, which suggested that the count-mass conversion algorithms should be revised (Mukherjee et al., 2017; SCAQMD, 2015a). As in the present study, the available data was particle mass (µg/m^3), this could be one explanation of the observed low correlation between AirBeam sensor and the reference monitor measurements.

Fine particulate matter (PM2.5) concentrations measured by both MetOne Neighborhood and PurpleAir weakly to moderately correlated with those of FEM and moderately to strongly correlated with those of FRM. Furthermore, MetOne Neighborhood had a good agreement with FEM and FRM. The findings from the present study were in agreement with the previous study conducted by SCAQMD and Malings and colleagues. The summary of comparisons between the MetOne and PurpleAir sensor evaluation findings from our and from previous published literatures are shown in Table XIV and XXVI, respectively (Malings et al., 2020; SCAQMD, 2015b). Previous studies observed a high degree of correlation between PurpleAir and FEM monitors (Feenstra et al., 2019; Magi et al., 2020; Malings et al., 2020). In the current study, as compared to MetOne Neighborhood sensor, PurpleAir sensor demonstrated a lower degree of agreement with the FRM/FEM monitors. As compared to the measurements of FRM/FEM monitors, PurpleAir sensor overestimated PM2.5 concentrations, while MetOne Neighborhood sensor slightly underestimated PM2.5 concentrations. Malings et al. suggested that the corrected MetOne measurements utilizing multiple linear regression models adjusted for temperature and %RH improved the correlation (R^2) between MetOne sensor and FEM monitor from 0.41 (uncorrected measurements) to 0.58 (corrected measurements), and decreased the error and bias by more than 50%. In addition, an overestimation of PM2.5 concentrations was observed at conditions with %RH being >80 (for PurpleAir) and >85 (for MetOne Neighborhood) (Malings et al., 2020), which were also observed in the present study. MetOne was not significantly impacted by humidity and temperature. PurpleAir and AirBeam overestimated the PM2.5 concentration as the %RH increased without any correlation with the temperature. After applying corrections to low-cost measurements, the measurement errors of PurpleAir significantly decreased, while no improvement was observed in the agreement between the measurements of MetOne and the FRM/FEM monitor. These findings suggested that temperature and humidity had less impact on MetOne Neighborhood as compared to PurpleAir. One of the potential reasons might be due to a 12-Watt, 4-s resident time heating element in the MetOne inlet, which is activated when %RH reaches 40. This heating system minimizes the humidity in the sampling air before particulate matters are detected. PurpleAir does not have a heating system; however, the Wi-Fi chip in the sensor could slightly elevate the temperature and decrease the humidity inside the sensor housing.

Among gaseous pollutant low-cost sensors investigated in the present study, both AeroQual S500 measuring NO_2 or O_3 and Terrier measuring NO/CO/CO_2 had very low intra-sampler variability. AeroQual measuring NO_2 demonstrated low intra-sampler variability (R^2=0.78). One limitation of this study was that an inter-sampler comparison analysis between AeroQual measuring NO_2 and reference monitor could not be performed due to the shortage of reference NO_2 concentration data at the Northbrook air monitoring site since only NO/NOy concentrations were collected (USEPA, 2015). The NO_2 reference concentration, in addition to O_3 concentrations measured by AeroQual operated simultaneously adjacent to the AeroQual measuring NO_2, are vital for correcting the AeroQual-NO_2 measured concentrations according to the manufacturer's correction algorithm. The estimation of NO_2 concentrations was not validated due to missing concentration information on several components of oxides of nitrogen including NO_z and NO_x. AeroQual measuring O_3 demonstrated a moderate degree of correlation with the IEPA FEM monitor (R^2=0.68), which was slightly lower than those of previous studies (R^2>0.72) (see Table XXVII) (Lin et al., 2015; Lin et al., 2017). A high degree of agreement between AeroQual measuring O_3 and the FEM monitor was observed suggesting the reliability of the sensor. AeroQual measuring O_3 was not significantly impacted by temperature and humidity which supported by the findings in previous studies conducting the field calibration of AeroQual-O_3 measurements. Their results suggested that no sensor performance differences between uncorrected and corrected (i.e., adjusted for temperature and humidity) measurements, while corrected AeroQual-NO_2 measurements significantly improved the correlation with FEM monitors (Lin et al., 2015; Lin et al., 2017; Masey et al., 2018). Terrier sensor measures multiple pollutants i.e., NO, CO, and CO_2, simultaneously. Our study is the first study that evaluated the Terrier sensor performance in the field conditions. Similar to AirBeam, Terrier sensors were operated for a short period (approximately 84 hours) which could limit the observation of temperature and humidity variations impacting Terrier performance. Terrier sensors demonstrated a wide range of precision depending on the measured gaseous pollutants (R^2=0.29-0.92) and, in general, performed poorly as compared to other sensors that were tested. Terrier measuring CO showed highest intra-sampler variability, followed by CO_2 and NO. Another issue with Terrier was that one out of three units of Terrier sensor recorded zero for all CO measurements; thus, data from this specific unit was excluded from all analyses. Despite a lack of evaluation of the Terrier performance, a number of studies have evaluated the performance of one of its three sensors i.e., Alphasense CO-B4, Alphasense NO-B4, and ELT S300-CO2. Alphasense CO-B4 showed a moderate to high correlation with FRM instruments (R^2>0.6) (Borrego et al., 2018; Jiao et al., 2016; Sun et al., 2016). Similarly, Alphasense NO-B4 demonstrated a moderate to high correlation with FRM instruments (R^2=0.7-0.8) (Borrego et al., 2018; Lewis et al., 2016). The findings from previous studies are not aligned with the observations from the present study summarized in Table XXVII. This might be due to Terrier sensor measuring several pollutants at the same time, its performance for each pollutant may not have been calibrated for optimum performance, in addition to the impacts of humidity and temperature. Temperature, humidity, and gas cross-sensitivity are common factors that could impact the gaseous sensor performances. Metal Oxide Semiconductor (MOS) gaseous pollutant sensors e.g., AeroQual measuring O_3, in general, are impacted by humidity and temperature. Humidity decreases the sensor sensitivity via the intervention of sensor surface-gas interaction and the inhibition of electron transmission to sensor sensing layers. Ambient temperature can impact the operating temperature to be lower or higher than the optimal operating system, which may decrease the response of MOS sensors (Wang, Yin, Zhang, Xiang, & Gao, 2010). The performance of electrochemical (EC) gas sensors including Alphasense NO-B4 and Alphasense CO-B4, the components of Terrier sensor, could be impacted by temperature and humidity. Previous studies reported that EC sensor performance could be impacted by temperature and less impacted by humidity, at %RH >75 (Masson, Piedrahita, & Hannigan, 2015; Wei et al., 2018). Moreover, the correlation between this sensor and FRM monitors decreased in the environment with a temperature higher than 25ºC (Cross et al., 2017).

E. Conclusion

All tested low-cost sensors showed very high precision and sufficient accuracy in obtaining air pollutant concentrations at various locations to assess the relative air quality. The low-cost sensors had varying degree of correlation and agreement with their respective IEPA FRM/FEM monitors; therefore, the low-cost sensors should not be used for compliance assessment. However, they are very useful tools in determining the locations with higher concentrations that warrant further evaluation using regulatory monitoring tools and methods, and for public education, outreach, and advocacy efforts.

In addition, the low-cost sensor measurements were impacted by temperature and humidity; therefore, an additional correction of sensor measurements for these meteorological conditions should be applied. This suggested more collocated studies in diverse temporal and spatial conditions to fill the knowledge gap of the sensor performance in different geographic locations and develop more appropriate and representative correction algorithms for specific locations that take the impact of weather conditions on sampler performance into account.

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TABLE V. LIST OF STUDY LOW-COST SENSORS[a]

Instruments Sensor	Air Pollutants Measured	Air Monitoring Mode	Sensor Technologies/Recording Time Interval	Web Link for the Sensor
AeroQual S500 (AeroQual Limited, Auckland, New Zealand)	NO_2 or O_3	stationary	electrochemical (NO_2) or sensitive metal oxide semiconductor (O_3)/ 1 minute	http://www.aeroqual.com/product/series-500-portable-air-pollution-monitor
AirBeam (HabitatMap, Brooklyn, NY, USA)	PM2.5	mobile	light scattering/ 1 second	http://www.takingspace.org/aircasting/airbeam/
MetOne Neighborhood Monitor (Met One Instruments Inc., Grants Pass, OR, USA)	PM2.5 or PM10	stationary	light scattering/ 15 minutes	http://www.metone.com/?wpfb_dl=591
PurpleAir (PurpleAir, Draper, UT, USA)	PM2.5 and PM10	stationary	light scattering/ 1 minute	http://www.purpleair.org/
Terrier (Qsense Inc., Boulder, CO, USA)	NO, CO, and CO_2	mobile	electrochemical (NO, CO) and NDIR (CO_2)/ 10 seconds	NA (This product was discontinued.)

[a] NA: not applicable

TABLE VI. LIST OF EPA INSTRUMENTS RESPECTIVE TO THE STUDY LOW-COST SENSORS AT THE NORTHBROOK WATER PLANT, NORTHBROOK, ILLINOIS

Instruments	**Method**	**Air Pollutants Measured**
R & P Model 2000 PM-2.5 Air Sampler w/VSCC-Gravimetric	Reference	PM2.5
Thermo Scientific 5014i or FH62C14-DHS w/VSCC-Beta Attenuation	Equivalent	PM2.5
HI-VOL SA/GMW-1200-GRAVIMETRIC	Reference	PM10 (Total Suspended Particles)
Gas Filter Correlation Thermo Electron 48i-TLE	Reference	CO
ULTRAVIOLET ABSORPTION	Equivalent	O_3
Chemiluminescence Thermo Electron 42C-Y, 42i-Y	Non-Federal Reference	NO, NO_y (Reactive Nitrogen)

TABLE VII. DATA SUMMARY OF PM2.5 CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS

Experiment	PM2.5 Sensors	# of missing datapoints	# of data available	total expected data points	% of missing data points
Overall-Experiment					
24-hr mean concentration	FRM	0	20	20	0.0
	FEM	1	62	63	1.6
	MO1	0	63	63	0.0
	MO3	0	63	63	0.0
	MOaver	0	63	63	0.0
	PA1	1	62	63	1.6
	PA2	1	62	63	1.6
	PA3	1	62	63	1.6
	PAaver	1	62	63	1.6
1-hr mean concentration	FEM	116	1385	1501	1.6
	MO1	1	1500	1501	0.1
	MO3	24	1477	1501	1.6
	MOaver	1	1500	1501	0.1
	PA1	76	1425	1501	5.1
	PA2	55	1446	1501	3.7
	PA3	56	1445	1501	3.7
	PAaver	53	1448	1501	3.5
Sub-Experiment					
1-hr mean concentration	MO1	0	71	71	0.0
	MO3	11	60	71	15.5
	MOaver	0	71	71	0.0
	PA1	13	58	71	18.3
	PA2	0	71	71	0.0
	PA3	0	71	71	0.0
	PAaver	0	71	71	0.0
	AB1	16	55	71	22.5
	AB2	12	59	71	16.9
	AB3	9	62	71	12.7
	ABaver	4	67	81	5.6

TABLE VIII. DATA SUMMARY OF PM10 CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS

Data	**PM10 Sensors**	**# of missing data**	**# of data available**	**# of total expected data points**	**% of missing data**
1-hr mean concentration	PA1	76	1425	1501	5.1
	PA2	55	1446	1501	3.7
	PA3	56	1445	1501	3.7
	PAaver	53	1448	1501	3.5
	MO2	24	1477	1501	1.6
24-hr mean concentration	FRM	0	10	10	0.0
	PA1	1	62	63	1.6
	PA2	1	62	63	1.6
	PA3	1	62	63	1.6
	PAaver	1	62	63	1.6
	MO2	1	62	63	1.6

TABLE IX. DATA SUMMARY OF GASEOUS POLLUTANT CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS

	Gaseous Pollutant	Air monitoring sensors	# of missing data	# of data available	# of total expected data points	% of missing data
Overall-Experiment						
1-hr mean concentration	NO_2	AQ1	80	925	1005	8.0
		AQ2	89	916	1005	8.9
		AQaver	0	1005	1005	0.0
	NO_y	EPA non-federal ref. monitor	5	1000	1005	0.5
	NO	EPA non-federal ref. monitor	4	1001	1005	0.4
	O_3	AQ2	16	490	506	3.2
		EPA-UV absorption	4	502	506	0.8
Sub-Experiment						
1-hr mean concentration	NO	TR1	0	70	70	0.0
		TR2	7	63	70	10.0
		TR3	11	59	70	15.7
		EPA non-federal ref. monitor	0	70	70	0.0
	CO	TR2	19	65	84	22.6
		TR3	23	61	84	27.4
		EPA-FRM	2	82	84	2.4
	CO_2	TR1	12	72	84	14.3
		TR2	19	65	84	22.6
		TR3	23	61	84	27.4

TABLE X. DESCRIPTIVE STATISTICS OF PM CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS, TEMPERATURE, %RELATIVE HUMIDITY, OVERALL-EXPERIMENT, OCTOBER 6 TO DECEMBER 8, 2017, NORTHBROOK, ILLINOIS[a]

Parameters	**Air Monitoring Devices**	**Number of obs (1-hour mean)**	**1-hr mean range (min-max)**	**1-hr mean (sd)**	**Number of observations (24-hour mean)**	**24-hr mean range (min-max)**	**24-hr mean (sd)**
Temperature (°C)		1501	-8.0-24.8	7.6 (6.7)	64	-5.1-20.1	7.5 (6.3)
%RH		1501	16.0-87.0	69.9 (18.7)	64	46.3-99.0	69.9 (14.3)
PM2.5 mean concentration (µg/m³)	PA1	1425	0.2-57.9	13.8 (12.1)	62	1.3-49.9	13.7 (10.5)
	PA2	1446	0.1-63.4	12.8 (12.3)	62	1.1-50.5	13.0 (10.7)
	PA3	1445	0.1-56.1	12.6 (11.6)	62	1.1-46.7	12.8 (10.0)
	PAaver	1448	0.2-58.5	13.0 (11.9)	62	1.2-49.0	13.2 (10.4)
	MO1	1500	1.0-40.8	7.8 (6.0)	63	1.3-30.9	7.9 (5.2)
	MO3	1477	2.0-33.5	7.7 (5.0)	63	3.0-26.5	7.7 (4.3)
	MOaver	1500	1.5-36.75	7.7 (5.5)	63	2.2-28.7	7.8 (4.7)
	PM2.5 FEM	1385	-8.5-43.4	7.7 (6.4)	62	1.2-23.6	7.6 (4.5)
	PM2.5 FRM	NA	NA	NA	20	1.5-21.4	7.2 (5.1)
PM10 mean concentration (µg/m³)	PA1	1425	0.2-72.6	15.5 (14.6)	62	1.5-63.1	15.5 (12.6)
	PA2	1446	0.1-70.8	14.3 (14.2)	62	1.2-61.0	14.5 (12.4)
	PA3	1445	0.1-70.4	14.4 (13.9)	62	1.2-59.1	14.6 (12.0)
	PAaver	1448	0.2-71.0	14.7 (14.2)	62	1.3-61.0	14.9 (12.3)
	MO2	1477	1.5-35.8	9.3 (5.6)	64	2.3-28.9	9.2 (4.9)
	EPA PM10-TSP	NA	NA	NA	11	5.0-42.0	17.6 (12.1)

[a] NA: not applicable

TABLE XI. DESCRIPTIVE STATISTICS OF PM CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS, TEMPERATURE, %RELATIVE HUMIDITY, SUB-EXPERIMENT, NORTHBROOK, ILLINOIS

Parameters	**Air Monitoring Devices**	**Number of Observations**	**1-hr mean range (min-max)**	**1-hr mean (sd)**
Temperature (ºC)		81	9.4-22.5	14.5 (3.2)
%RH		81	16.0-96.0	60.9 (21.2)
1-hour PM2.5 mean concentration (µg/m^3)	AB1	55	1.4-36.0	7.1 (6.7)
	AB2	59	1.2-30.7	6.7 (5.5)
	AB3	62	1.4-25.9	6.1 (4.7)
	ABaver	67	1.4-30.9	6.2 (5.4)
	PA1	58	0.2-37.0	10.3 (7.9)
	PA2	71	0.2-38.4	8.7 (7.1)
	PA3	71	0.2-37.0	8.9 (7.1)
	PAaver	71	0.2-37.4	8.9 (7.1)
	MO1	71	2.0-14.0	5.6 (3.0)
	MO3	60	2.8-13.0	6.7 (3.0)
	MOaver	1	2.0-13.4	5.7 (3.0)
	PM2.5 FEM	30	-1.6-27.9	9.0 (6.8)

TABLE XII. DESCRIPTIVE STATISTICS OF GASEOUS POLLUTANT CONCENTRATIONS MEASURED BY LOW-COST SENSORS AND REFERENCE INSTRUMENTS, TEMPERATUREM, %RELATIVE HUMIDITY, OVERALL-EXPERIMENT, OCTOBER 6 TO DECEMBER 8, 2017, NORTHBROOK, ILLINOIS[a]

Gaseous Pollutants	Air Monitoring Devices	Number of Observations	1-hr mean range (min-max)	1-hr mean (sd)	24-hr mean range (min-max)	24-hr mean (sd)
NO_2 (ppm)	AQ1	925	3.8-53.4	22.9 (7.8)	8.2-33.6	22.8 (5.5)
	AQ2	916	0.4-57.8	21.1 (10.7)	6.3-42.8	21.1 (8.3)
	AQaver	1005	0.4-48.9	21.5 (9.1)	7.3-36.8	21.7 (6.7)
O_3 (ppm)	AQ2	490	0.00-0.05	0.03 (0.01)	0.01-0.04	0.03 (0.01)
	FEM	502	0.00-0.06	0.02 (0.01)	0.02-0.04	0.02 (0.01)
NO (ppb)*	TR1	70	0.3-47.2	9.2(9.9)		
	TR2	63	0.3-36.7	7.9 (8.3)		
	TR3	59	0.4-103.7	12.0 (18.3)		
	NOy/NO-non reference method	70	0.4-59.8	3.4 (5.6)		
CO (ppm)*	TR2	65	0.1-0.5	0.3 (0.06)		
	TR3	61	0.1-0.5	0.2 (0.07)		
	FRM	72	0.1-0.7	0.2 (0.10)		
CO_2 (ppm)*	TR1	72	341.0-461.6	379.7 (30.2)		
	TR2	65	478.6-588.1	514.4 (28.5)		
	TR3	61	422.0-505.8	452.1 (21.2)		

[a] Sub-Experiment: Terrier sensors were operated in the beginning of the sampling period for 84 hours alongside with other low-cost sensors and their respective reference instruments.

TABLE XIII. INTRA-SAMPLER COMPARISONS BETWEEN PM MEASURED CONCENTRATIONS OF LOW-COST SENSOR UNIT-1,-2,-3, OCTOBER 6 TO DECEMBER 8 2017, NORTHBROOK, ILLINOIS[a]

Pairs of Sensors	Number of Observations	Intercept	Slope	R^2
PM2.5				
MO1 vs MO3	1477	1.3805	0.8029	0.96
PA1 vs PA2	1420	-0.9731	1.0133	0.99
PA1 vs PA3	1420	-0.354	0.951	0.99
PA2 vs PA3	1420	0.5905	0.938	1.00
AB1 vs AB2*	46	0.2234	0.8544	1.00
AB1 vs AB3*	46	0.8761	0.7265	0.99
AB2 vs AB3*	46	0.6822	0.8508	1.00
PM10				
PA1 vs PA2	1417	-0.6629	0.9745	0.99
PA1 vs PA3	1417	-0.2777	0.956	0.99
PA2 vs PA3	1417	0.3845	0.9803	1.00

[a]Sub-Experiment: AirBeam sensors were operated in the beginning of the sampling period for 84 hours.

TABLE XIV. LINEAR REGRESSION STATISTICS AND MEASUREMENT ERRORS OF MEASUREMENTS BETWEEN PM LOW-COST SENSORS AND REFERENCE INSTRUMENTS[a,b]

Sensors	Reference monitors	Number of obs.	R^2	Slope	Intercept	MAE (µg/m³)	MBE (µg/m³)	MBE/MAE	RMSE (µg/m³)
PM2.5 Sensors[#]									
FEM	FRM	20	0.89	1.0179	-0.1949	1.0	-0.2	0.2	1.3
MO1	FEM	1375	0.42	0.6265	3.2946	3.7	-0.5	0.1	5.3
MO3	FEM	1375	0.43	0.5159	3.926	3.6	-0.2	0.0	4.9
MOaver	FEM	1375	0.43	0.5712	3.6103	3.6	-0.3	0.1	5.0
PA1	FEM	1319	0.57	1.4382	3.0012	7.5	-6.5	0.9	10.7
PA2	FEM	1319	0.58	1.4813	1.8152	7.0	-5.6	0.8	10.4
PA3	FEM	1319	0.59	1.4071	2.1701	6.7	-5.4	0.8	9.6
PAaver	FEM	1319	0.58	1.4422	2.3288	7.0	-5.8	0.8	10.2
AB1*	FEM	28	0.03	0.219	7.4189	5.8	-1.6	0.3	8.8
AB2*	FEM	28	0.09	0.3096	6.3497	5.9	-0.1	0.0	8.2
AB3*	FEM	28	0.12	0.3052	5.2276	5.8	0.6	0.1	7.6
ABaver*	FEM	28	0.09	0.3053	6.5192	5.9	-0.2	0.0	8.2
MO1	FRM	20	0.68	0.9079	0.6787	2.3	-0.3	0.1	3.2
MO3	FRM	20	0.66	0.7621	1.9772	2.1	-0.3	0.1	3.0
MOaver	FRM	20	0.67	0.835	1.4686	2.2	-0.3	0.1	3.0
PA1	FRM	20	0.69	1.6139	-0.188	4.8	-4.2	0.9	7.5
PA2	FRM	20	0.72	1.6471	-1.2757	4.3	-3.4	0.8	7.0
PA3	FRM	20	0.73	1.5235	-0.5025	4.1	-3.3	0.8	6.2
PAaver	FRM	20	0.71	1.5948	-0.6554	4.3	-3.6	0.8	6.9
PM10 sensors									
MO2	FRM	11	0.65	0.3497	2.1298	9.3	9.3	1.0	12.3
PA1	FRM	11	0.75	0.981	-2.5988	6.7	2.9	0.4	7.2
PA2	FRM	11	0.75	0.9479	-2.9317	7.0	3.8	0.6	7.4
PA3	FRM	11	0.78	0.973	-3.1182	6.5	3.6	0.6	7.0
PAaver	FRM	11	0.76	0.9673	-2.8829	6.7	3.5	0.5	7.2

[a]Sub-Experiment: AirBeam sensors were operated in the beginning of the sampling period for 84 hours.

[b]MOaver, PAaver, ABaver indicate the average concentration across all unit of sensors.

TABLE XV. BLAND-ALTMAN PARAMETERS AND CCC OF MEASUREMENTS BETWEEN PM LOW-COST SENSORS AND REFERENCE MONITORS[a,b]

Sensors	Reference monitors	Number of obs.	B-A plots		Lin's Concordance Correlation Coefficient	
			Mean of differences ($\mu g/m^3$)#	95%CI ($\mu g/m^3$)	CCC	C_b
PM2.5 Sensors						
FEM	FRM	20	-0.24	(-2.78,2.31)	0.97	1.00
MO1	FEM	1375	-0.40	(-10.90,10.09)	0.65	1.00
MO3	FEM	1375	-0.18	(-9.99,9.64)	0.64	0.97
MOaver	FEM	1375	-0.29	(-10.33,9.75)	0.65	0.99
PA1	FEM	1319	-6.46	(-23.64,10.72)	0.51	0.68
PA2	FEM	1319	-5.61	(-23.07,11.85)	0.53	0.70
PA3	FEM	1319	-5.38	(-21.34,10.58)	0.56	0.73
PAaver	FEM	1319	-5.82	(-22.64,11.00)	0.53	0.70
AB1*	FEM	28	-1.60	(-19.16,15.96)	0.30	0.92
AB2*	FEM	28	-0.11	(-16.73,16.50)	0.30	1.00
AB3*	FEM	28	0.58	(-14.9-,16.06)	0.29	0.99
ABaver*	FEM	28	-0.24	(-16.99,16.50)	0.30	1.00
MO1	FRM	20	-0.30	(-6.76,6.16)	0.82	0.99
MO3	FRM	20	-0.26	(-6.35,5.83)	0.81	1.00
MOaver	FRM	20	-0.28	(-6.46,5.90)	0.82	1.00
PA1	FRM	20	-4.24	(-16.99,8.52)	0.59	0.71
PA2	FRM	20	-3.39	(-15.88,9.10)	0.63	0.74
PA3	FRM	20	-3.27	(-14.17,7.62)	0.66	0.77
PAaver	FRM	20	-3.63	(-15.63,8.36)	0.63	0.74
PM10 sensors						
MO2	FRM	11	9.28	(-7.65,26.21)	0.38	0.47
PA1	FRM	11	2.93	(-10.92,16.78)	0.83	0.96
PA2	FRM	11	3.85	(-9.44,17.13)	0.82	0.95
PA3	FRM	11	3.59	(-9.02,16.20)	0.84	0.95
PAaver	FRM	11	3.46	(-9.76,16.67)	0.83	0.96

[a] Sub-Experiment: AirBeam sensors were operated in the beginning of the sampling period (October 1 to 20) for 84 hours.
[b]Mean of differences between measurements of the reference monitor and low-cost sensor ($\mu g/m^3$)

TABLE XVI. MLR STATISTICS OF MODELS FOR ESTIMATING/ADJUSTING LOW-COST MEASURED CONCENTRATIONS

Sensors	Variable included	Number of Obs.	beta0	beta1	beta2	beta3	ANOVA test (compare b/w models)	RMSE	Adjusted R^2
PM2.5 sensors									
MetOne	MOaver	1375	1.70213	0.75221			Reference	4.831	0.43
	MOaver+Temp		1.27865	0.7555	0.5531		p-value=0.001	4.818	0.43
	MOaver+RH		3.368311	0.764872	-0.024907		NS	4.812	0.43
	MOaver+Temp+RH		3.022892	0.769436	0.061019	-0.026728	p-value=0.001	4.796	0.44
PurpleAir	PAaver	1319	2.37954	0.173085			Reference	4.179	0.58
	PAaver+Temp		2.520707	0.403082	-0.022099		NS	4.178	0.58
	PAaver+RH		6.103367	0.425378	-0.057565		NS	4.06	0.60
	PAaver+Temp+RH		6.247148	0.426416	-0.022359	-0.05758	NS	4.058	0.60
AirBeam	ABaver	28	6.3433	0.2899			Reference	6.781	0.05
	ABaver+Temp		7.86392	0.29227	-0.09962		NS	6.91	0.02
	ABaver+RH		3.42892	0.17929	0.06392		NS	6.882	0.03
	ABaver+Temp+RH		4.17817	0.1852	-0.0406	0.06107	NS	7.023	-0.02
PM10 sensors									
MetOne	MO2	11	2.1772	1.8593			Reference	7.55	0.61
	MO2+Temp		-13.8791	2.524	1.1899		p-value=0.001	4.516	0.86
	MO2+RH		-6.445	1.9998	0.1058		NS	7.957	0.57
	MO2+Temp+RH		6.5633	2.2548	1.3786	-0.282	p-value=0.001	4.23	0.88
PurpleAir	PAaver	11	6.4858	0.785			Reference	6.263	0.73
	PAaver+Temp		4.1633	0.7973	0.2421		NS	6.459	0.72
	PAaver+RH		25.1343	0.7173	-0.2508		NS	6.059	0.75
	PAaver+Temp+RH		39.6229	0.6779	0.822	-0.5518	Sig (p-value=0.01)	4.738	0.85

TABLE XVII. LINEAR REGRESSION STATISTICS AND MEASUREMENT ERRORS OF MEASUREMENTS BETWEEN PM2.5 LOW-COST SENSORS AND REFERENCE MONITORS: UNADJUSTED AND ADJUSTED CONCENTRATIONS[a]

PM2.5 Sensors	Reference monitors	Number of obs.	R^2	Slope	Intercept	MAE ($\mu g/m^3$)	MBE ($\mu g/m^3$)	MBE/MAE	RMSE ($\mu g/m^3$)
MOaver	***FEM***	***1375***	***0.43***	***0.5712***	***3.6103***	***3.6***	***-0.3***	***0.08***	***5.0***
MOaver_M1	FEM	1375	0.43	0.4297	4.4178	3.5	0.0	0.00	4.8
MOaver_M2	FEM	1375	0.27	0.4464	7.8612	5.4	-3.6	0.66	6.9
MOaver_M3	FEM	1375	0.43	0.4345	4.3799	3.5	0.0	0.00	4.8
MOaver_M4	FEM	1376	0.44	0.4386	4.3428	3.5	0.0	0.00	4.8
PAaver	***FEM***	***1319***	***0.58***	***1.4422***	***2.3288***	***7.0***	***-5.8***	***0.83***	***10.2***
PAaver_M1	FEM	1320	0.58	0.2496	2.7826	4.3	3.1	0.73	5.9
PAaver_M2	FEM	1321	0.58	0.5804	3.3118	3.1	0.0	0.00	4.2
PAaver_M3	FEM	1322	0.60	0.6038	3.127	3.0	0.0	0.00	4.1
PAaver_M4	FEM	1323	0.60	0.6043	3.1228	3.0	0.0	0.00	4.1
ABaver	***FEM***	***28***	***0.09***	***0.3053***	***6.5192***	***5.9***	***-0.2***	***0.04***	***8.2***
ABaver_M1	FEM	28	0.09	0.0885	8.2332	4.8	0.0	0.00	6.5
ABaver_M2	FEM	28	0.09	0.09	8.2189	4.7	0.0	0.00	6.5
ABaver_M3	FEM	28	0.10	0.0973	8.1532	4.6	0.0	0.00	6.5
ABaver_M4	FEM	28	0.10	0.0976	8.1506	4.6	0.0	0.00	6.5

[a]An italicizing indicates the unadjusted model of each sensor. M1 (Sensor), M2 (Sensor+T), M3 (Sensor+RH), and M4 (Sensor+T+RH) represent the adjusted low-cost measurements employing the MLR statistics (Table 12).

TABLE XVIII. LINEAR REGRESSION STATISTICS AND MEASUREMENT ERRORS OF MEASUREMENTS BETWEEN PM10 LOW-COST SENSORS AND REFERENCE MONITORS: UNADJUSTED AND ADJUSTED CONCENTRATIONS[a]

PM10 Sensors	Reference monitors	Number of obs.	R^2	Slope	Intercept	MAE (μg/m³)	MBE (μg/m³)	MBE/MAE	RMSE (μg/m³)
MO2	***FRM***	***11***	***0.65***	***0.3497***	***2.1298***	***9.3***	***9.3***	***1.00***	***12.3***
MO2_M1	FRM	12	0.65	0.6502	6.1372	6.2	0.0	0.00	6.8
MO2_M2	FRM	13	0.89	0.8887	1.952	3.0	0.0	0.00	3.9
MO2_M3	FRM	14	0.65	0.6547	6.0615	6.0	0.0	0.00	6.8
MO2_M4	FRM	15	0.91	0.9146	1.4966	2.5	0.0	0.00	3.37
PAaver	***FRM***	***11***	***0.76***	***0.9673***	***-2.8829***	***6.7***	***3.5***	***0.51***	***7.2***
PAaver_M1	FRM	12	0.76	0.7593	4.2227	4.2	0.0	0.00	5.7
PAaver_M2	FRM	13	0.77	0.7725	3.992	4.1	0.0	0.00	5.5
PAaver_M3	FRM	14	0.80	0.7997	3.5161	4.2	0.0	0.00	5.2
PAaver_M4	FRM	15	0.89	0.8929	1.8775	2.7	0.0	0.00	3.8

[a]An italicizing indicates the unadjusted model of each sensor. M1 (Sensor), M2 (Sensor+T), M3 (Sensor+RH), and M4 (Sensor+T+RH) represent the adjusted low-cost measurements employing the MLR statistics (Table 12).

TABLE XIX. INTRA-SAMPLER COMPARISONS BETWEEN GASEOUSE POLLUTANT MEASURED CONCENTRATIONS OF LOW-COST SENSOR UNIT-1,-2,-3, OCTOBER 6 TO DECEMBER 8 2017, NORTHBROOK, ILLINOIS[a]

Air Pollutants	**Pairs of sensors**	**Number of Obs.**	**Intercept**	**Slope**	**R^2**
NO_2	AQ1 vs AQ2	836	-5.5722	1.1902	0.78
NO	TR1 vs TR2	52	0.0996	0.8315	0.91
	TR1 vs TR3	52	1.2138	1.2752	0.52
	TR2 vs TR3	52	-0.7455	1.3066	0.72
CO	TR2 vs TR3	52	0.0162	0.6328	0.29
CO_2	TR1 vs TR2	54	189.13	0.8555	0.92
	TR1 vs TR3	54	255.09	0.5239	0.65
	TR2 vs TR3	54	144.21	0.6028	0.69

[a]AeroQual sensors (AQ1 and AQ2) were operated from October 27 to December 8, while Terrier sensors were operated during the beginning of the sampling event (October 12 to 20) for approximately 84 hours.

TABLE XX. LINEAR REGRESSION STATISTICS AND MEASUREMENT ERRORS OF MEASUREMENTS BETWEEN GASEOUS POLLUTANT LOW-COST SENSORS AND REFERENCE INSTRUMENTS[a]

Sensors	Reference monitor	Number of obs.	R^2	Slope	Intercept	MAE (ppm/ppb)	MBE (ppm/ppb)	MBE/MAE	RMSE (ppm/ppb)
O_3 sensor									
AQ2	FEM	486	0.68	0.7496	0.0084	0.006	-0.002	-0.385	0.007
CO sensors									
TR2	FRM	52	0.64	0.4787	0.1369	0.052	-0.002	-0.035	0.070
TR3	FRM	52	0.18	0.3004	0.1036	0.092	0.078	0.849	0.131
TRaver	FRM	52	0.46	0.3895	0.1202	0.055	0.038	0.692	0.091
NO sensors									
TR1	Non-Federal Reference	53	0.08	0.5153	7.7549	6.397	-4.757	-0.744	10.279
TR2	Non-Federal Reference	53	0.12	0.5139	6.3859	6.115	-4.270	-0.698	9.046
TR3	Non-Federal Reference	53	0.03	0.5435	10.591	9.353	-7.928	-0.848	19.144
TRaver	Non-Federal Reference	53	0.06	0.5242	8.2439	6.858	-5.185	-0.756	11.6

[a]The unit of O_3 and CO concentrations are ppm and the unit of NO concentration is ppb.

TABLE XXI. BLAND-ALTMAN PARAMETERS AND CCC OF MEASUREMENTS BETWEEN GASEOUS POLLUTANT LOW-COST SENSORS AND REFERENCE MONITORS[a,b]

Sensors	Reference monitors	Number of obs.	B-A plots		Lin's Concordance Correlation Coefficient	
			Mean of differences	95%CI (Limits of agreement)	CCC	C_b
O_3 sensor						
AQ2	FEM	486	-0.0023	(-0.0163,0.00116)	0.81	0.98
CO sensors						
TR2	FRM	52	-0.0018	(-0.14406,0.14049)	0.70	0.88
TR3	FRM	52	0.0778	(-0.1339,0.2896)	0.30	0.71
TRaver		52	0.0380	(-0.1280,0.2040)	0.54	0.79
NO sensors						
TR1	Non-Federal Reference	53	-4.7574	(-23.1119,13.5971)	0.22	0.71
TR2	Non-Federal Reference	53	-4.2703	(-20.3477,11.8071)	0.27	0.76
TR3	Non-Federal Reference	53	-7.9276	(-43.0781,27.2229)	0.08	0.48
TRaver	Non-Federal Reference	53	-5.1851	(-26.1773,15.8070)	0.18	0.66

[a]Mean of differences between measurements of the reference instrument and the low-cost sensor.
[b]The unit of O_3 and CO is ppm and the unit of NO is ppb.
AeroQual (AQ2) was operated from October 6 to 27, while Terrier sensors were operated during the beginning of the sampling event (October 12 to 20) for approximately 84 hours.

TABLE XXII. MLR STATISTICS OF MODELS FOR ESTIMATING/ADJUSTING GASEOUS POLLUTANT CONCENTRATIONS

Sensors	**Variable included**	**Number of Obs**	**beta0**	**beta1**	**beta2**	**beta3**	**ANOVA test (compare b/w models)**	**RMSE**	**Adjusted R^2**
O_3 sensor									
AeroQual	AQ2	486	0.000170	0.909370			Reference	0.0069	0.68
	AQ2+Temp		-0.006557	0.754700	0.000766		p-value=0	0.0059	0.76
	AQ2+RH		0.001157	0.808900	-0.000116		NS	0.0066	0.71
	AQ2+Temp+RH		0.001563	0.702500	0.000697	-0.000076	p-value=0	0.0058	0.77
CO sensor									
Terrier	TRaver	52	-0.004768	1.193386			Reference	0.0829	0.45
	TRaver+Temp		0.198828	1.137679	-0.012919		p-value=0	0.0744	0.56
	TRaver+RH		-0.0180513	1.1368604	0.0004293		NS	0.0834	0.45
	TRaver+Temp+RH		0.2267619	1.193483	-0.0138023	-0.0004527	p-value=0	0.0748	0.56
NO sensor									
Terrier	TRaver	53	2.15713	0.13396			Reference	5.032	0.06
	TRaver+Temp		7.58715	0.09095	-0.33227		NS	4.969	0.09
	TRaver+RH		0.99028	0.11422	0.02416		NS	5.051	0.05
	TRaver+Temp+RH		6.97654	0.086307	-0.320359	0.007898	NS	5.005	0.07

TABLE XXIII. LINEAR REGRESSION STATISTICS AND MEASUREMENT ERRORS OF MEASUREMENTS BETWEEN GASEOUS POLLUTANT LOW-COST SENSORS AND REFERENCE MONITORS: UNADJUSTED AND ADJUSTED CONCENTRATIONS[a]

Sensors	Reference monitor	Number of obs.	R^2	Slope	Intercept	MAE (ppm/ppb)*	MBE (ppm/ppb)*	MBE/MAE	RMSE (ppm/ppb)*
O_3 sensor									
AQ2	***FEM***	***486***	***0.68***	***0.7496***	***0.0084***	***0.006***	***-0.002***	***0.385***	***0.007***
AQ2_M1	FEM	486	0.68	0.6817	0.0078	0.005	0.000	0.000	0.007
AQ2_M2	FEM	486	0.76	0.7636	0.0058	0.004	0.000	0.001	0.005
AQ2_M3	FEM	486	0.71	0.712	0.0071	0.005	0.000	0.009	0.007
AQ2_M4	FEM	486	0.78	0.7759	0.0055	0.004	0.000	0.003	0.006
CO sensors									
TRaver	***FRM***	***52***	***0.46***	***0.3895***	***0.1202***	***0.055***	***0.038***	***0.692***	***0.091***
TRaver_M1	FRM	52	0.46	0.4649	0.1387	0.055	0.000	0.000	0.081
TRaver_M2	FRM	52	0.58	0.5779	0.1094	0.050	0.000	0.000	0.072
TRaver_M3	FRM	52	0.47	0.4687	0.1377	0.054	0.000	0.000	0.081
TRaver_M4	FRM	52	0.58	0.5816	0.1085	0.049	0.000	0.000	0.072
NO sensors									
TRaver	***Non-Federal Reference***	***70***	***0.08***	***0.5639***	***6.6211***	***6.858***	***-5.185***	***0.756***	***11.640***
TRaver_M1	Non-Federal Reference	70	0.08	0.0755	3.0441	3.352	0.000	0.000	4.959
TRaver_M2	Non-Federal Reference	70	0.11	0.1113	2.9596	3.430	-0.033	0.010	4.861
TRaver_M3	Non-Federal Reference	70	0.08	0.0822	3.0223	3.329	0.000	0.000	4.941
TRaver_M4	Non-Federal Reference	70	0.11	0.1124	2.9228	3.399	0.000	0.000	4.860

[a]An italicizing indicates the unadjusted model of each sensor. M1 (Sensor), M2 (Sensor+T), M3 (Sensor+RH), and M4 (Sensor+T+RH) represent the adjusted low-cost measurements employing the MLR statistics (Table 18).

TABLE XXIV. COMPARISONS BETWEEN PUBLISHED AIRBEAM SENSOR EVALUATION FINDINGS

Studies	Study Location	Sampling Condition	Reference Instruments	Sensor Performances	
				R^2	Bias and Precision
(Sousan et al., 2017)	Iowa	Laboratory exposure chamber	SMPS-APS (Scanning Mobility Particle Sizer and Aerodynamic Particle Sizer tandem)	0.49-0.92	%bias=-36 (for salt) and -83 (for welding fume) %CV= 2-9
(SCAQMD, 2015a)	California	Collocation, 8 weeks	FEM GRIMM and BAM	0.68-0.70 (vs. GRIMM); 0.66-0.67 (vs BAM)	
(Borghi et al., 2018)	Italy	Collocation, 2-4 weeks	EPA WINS	0.77-0.83	
(Feenstra et al., 2019)	California	Collocation, 8 weeks	FEM	0.57-0.59	MAE=4.4,6.5,7.5µg/m³ MBE: 2.9, 5.7, 6.8 µg/m³ RMSE=6.6, 10.6, 12.4 µg/m³
(DeWitt et al., 2020)	Texas	Collocation, 10 months	FEM BAM	0.36-0.42	
(Mukherjee et al., 2017)	California	Collocation, 12 weeks	FEM BAM and GRIMM	0.21-0.33 (vs. BAM), 0.62-0.71 (GRIMM)	
(Jiao et al., 2016)	Atlanta, GA	Collocation, 4 weeks	FEM BAM	0.42-0.43	
(Feinberg et al., 2018)	Denver	Collocation, 7 months	FEM	0.67-0.71	
This study (SASA)	**Northbrook, IL**	**Collocation, 84 hours[a]**	**FEM/FRM**	**0.03-0.12**	**MAE=5.8-5.9 µg/m³** **MBE=-1.6-0.6 µg/m³** **RMSE=7.6-8.8 µg/m³**

[a]Sub-Experiment: AirBeam sensors were operated in the beginning of the sampling period (October 1 to 20) for 84 hours.

TABLE XXV. COMPARISONS BETWEEN PUBLISHED PURPLEAIR SENSOR EVALUATION FINDINGS

Studies	Study Location	Sampling Condition	Reference Instruments	Sensor Performances	
				R^2	Bias and Precision
(Feenstra et al., 2019)	California	Collocation, 8 weeks	FEM	PM2.5: 0.95	MAE=6.7-7.0 μg/m^3 MBE=4.7-5.0 μg/m^3 RMSE=9.7-10.6 μg/m^3
(Magi et al., 2020)	North Carolina	Collocation, 16 months	FEM BAM	PM2.5: 0.54	MAE=5.8 μg/m^3 RMSE=7.5 μg/m^3
(SCAQMD, 2016)	California	Collocation, 8 weeks	FEM GRIMM and BAM	PM2.5: 0.91-0.93 (vs. GRIMM), 0.70-0.79 (vs. BAM); PM10: 0.43-0.45 (vs. GRIMM), 0.32-0.34 (vs. BAM)	
(Malings et al., 2020)	Pennsylvania	Collocation, 4-5 months	FEM BAM	PM2.5: 0.58	MAE=4.2 μg/m^3 bias=1.9 μg/m^3
(Kelly et al., 2017)	Utah	Collocation, 6 weeks	FEM TEOM	PM2.5: 0.83,0.86	
This study (SASA)	**Northbrook, IL**	**Collocation, 2 months**	**FEM/FRM**	**PM2.5: 0.57-0.59** **PM10: 0.75-0.78**	**PM2.5:** **MAE=6.7-7.5 μg/m^3** **MBE=-6.5to-5.4 μg/m^3** **RMSE=9.6-10.7 μg/m^3** **PM10:** **MAE=6.5-7.0 μg/m^3** **MBE=2.9-3.8 μg/m^3** **RMSE=7.0-7.4μg/m^3**

TABLE XXVI. COMPARISONS BETWEEN PUBLISHED METONE NEIGHBORHOOD SENSOR EVALUATION FINDINGS

Studies	Study Location	Sampling Condition	Reference Instruments	Sensor Performances	
				R^2	Bias and Precision
SCAQMD (2015)	California	Collocation, 8 weeks	FEM GRIMM and BAM	PM2.5: 0.53-0.56 (vs. GRIMM), 0.66-0.67 (vs. BAM)	
Malings et al. (2019)	Pennsylvania	Collocation, 4-5 months	FEM BAM	PM2.5: 0.41	MAE=4.8 µg/m^3 bias=-3.5µg/m^3
This study (SASA)	**Northbrook, IL**	**Collocation, 2 months**	**FEM (PM2.5)/FRM (PM10)**	**PM2.5:0.42,0.43 PM10: 0.65**	**PM2.5: MAE=3.6,3.7 µg/m^3 MBE= -0.2,-0.5µg/m^3 RMSE=4.9,5.3µg/m^3 PM10: MAE=9.3µg/m^3 MBE=9.3 µg/m^3, RMSE=12.3µg/m^3**

TABLE XXVII. COMPARISONS BETWEEN PUBLISHED GASEOUE POLLUTANT SENSOR EVALUATION FINDINGS

Sensors	Studies	Study Location	Sampling Condition	Reference Instruments	Sensor Performances	
					R^2	Bias and Precision
AeroQual S500-O_3	(DeWitt et al., 2020)	Texas	Collocation, 10 months	FEM	0.72-0.85; no impacts of meteorological parameters	
	(Lin, C. et al., 2015)	Edinburgh, UK	Collocation, >2 months	O_3 UV absorption analyzer	0.91	
	(Lin, Chun et al., 2017)	UK	Collocation, 7 months	O_3 UV absorption analyzer	0.88-0.96	
	This study (SASA)	**Northbrook, IL**	**Collocation, 2 months**	**FEM (O_3)**	**0.68**	**MAE=0.006ppm MBE= -0.002ppm RMSE=0.007ppm**
Terrier (i.e., Alphasense CO-B4, Alphsense NO-B4)	(Sun et al., 2016)	Hong Kong, China	Collocation, 3 days	Reference analyzer	CO: 0.97	ME<0.01
	(Lewis et al., 2016)	UK	Collocation, 17 days	Chemiluminescence	NO: 0.73±0.21	
	(Borrego et al., 2016)	Portugal	Collocation, 2 weeks	Infrared photometry (CO)/Chemiluminescence (NO_x)	CO: >0.8 NO: 0.8	
	This study (SASA)	**Northbrook, IL**	**Collocation, 84 hours[a]**	**FEM /FRM**	**CO: 0.18,0.64 NO: 0.03-0.12**	**CO: MAE=0.092,0.052ppm MBE=-0.002,0.078ppm RMSE=0.070,0.131ppm NO: MAE=6-9ppb MBE=-7 to -4 ppb RMSE=9-19ppb**

[a]Sub-Experiment: Terrier sensors were operated in the beginning of the sampling period (October 1 to 20) for 84 hours.

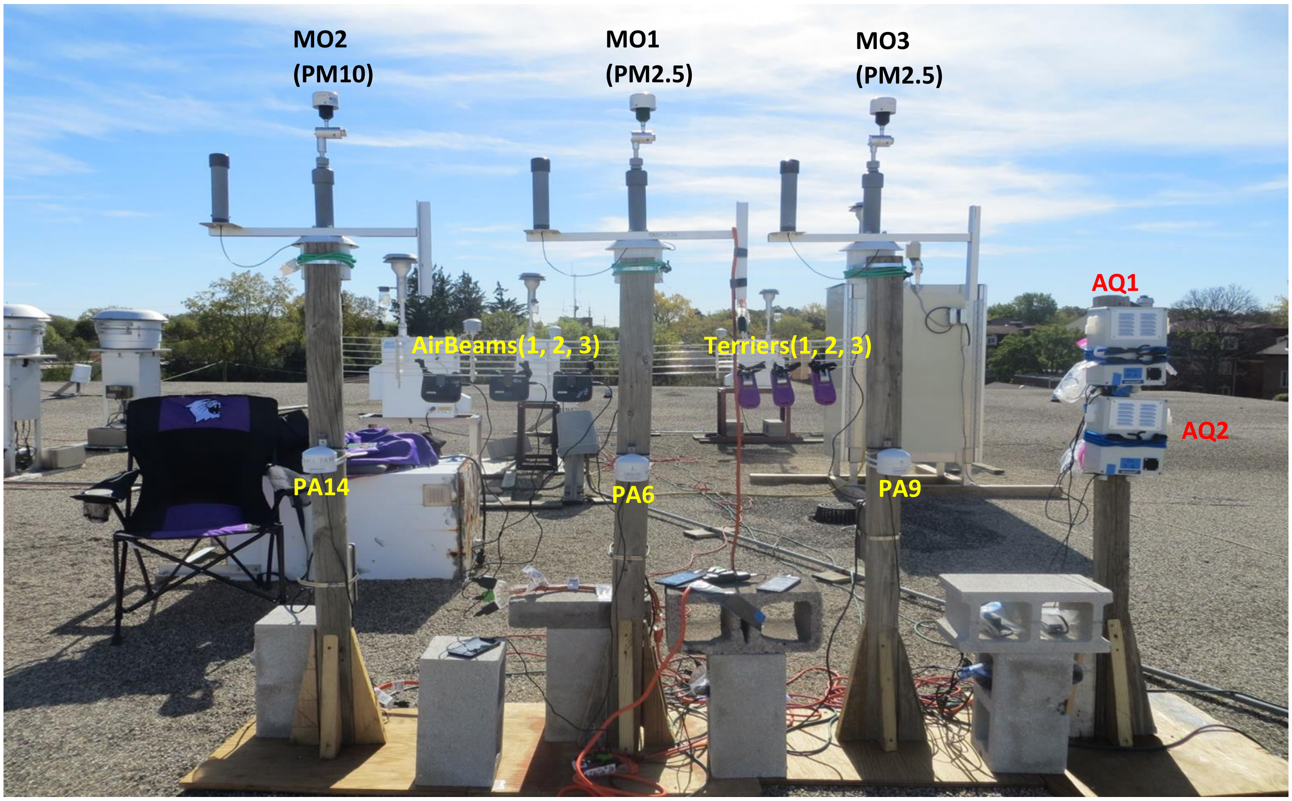


Figure 12. Low-cost sensors were collocated with their respective EPA FRM/FEM monitors at Northbrook air monitoring site, Northbrook, IL from October 6 to December 8, 2017. MO: MetOne PM Neighborhood Monitor, PA: PurpleAir PM sensor, AirBeam: PM Sensor, Terrier: Terrier NO/CO/CO_2 Sensor, AQ: AeroQual NO_2/O_3 Sensor.

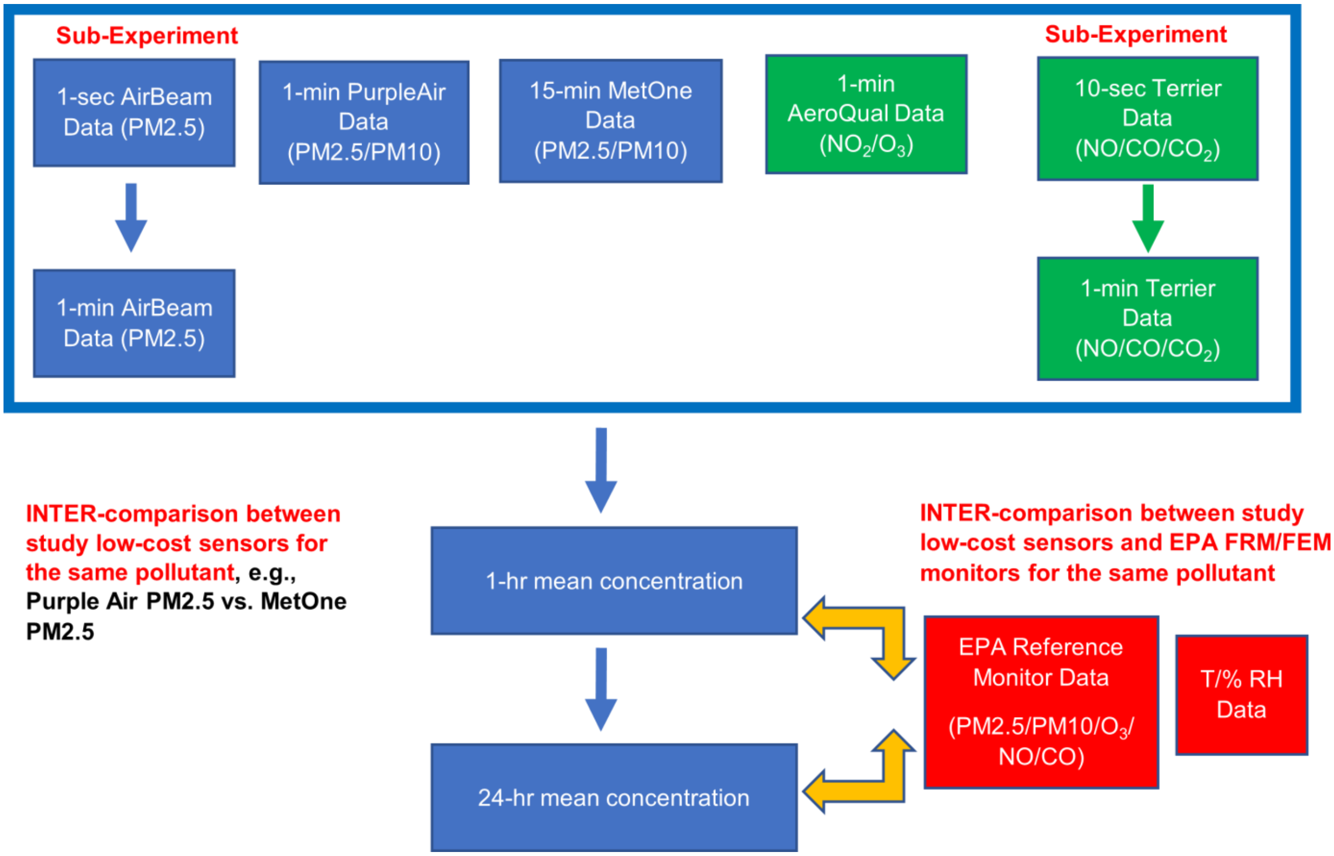


Figure 13. Data management and intra- and inter- comparison analyses flow chart

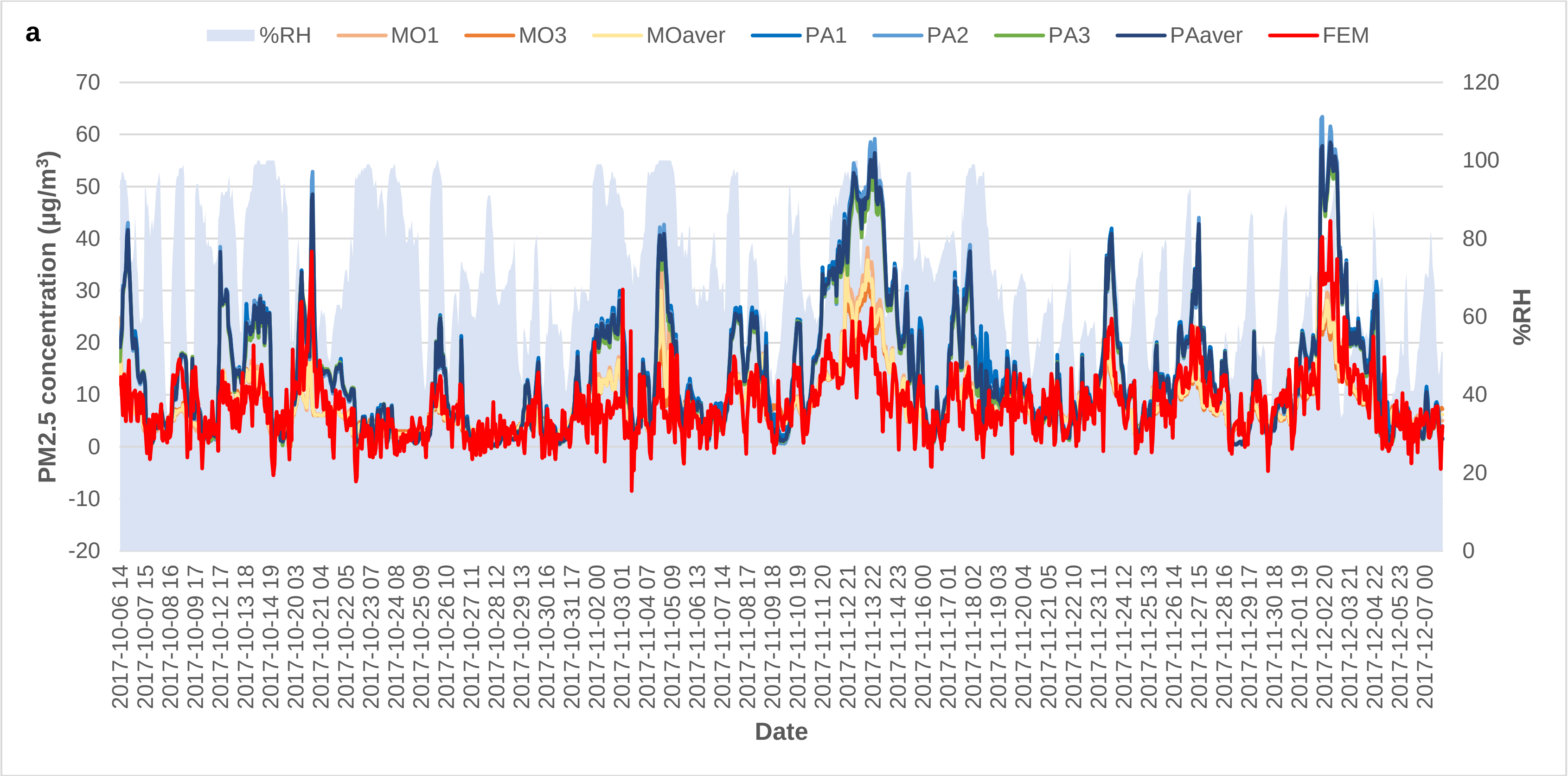


Figure 14. Sample time series of PM2.5 concentrations measured by low-cost sensors and FEM plotted with %RH (a) and temperature (b).

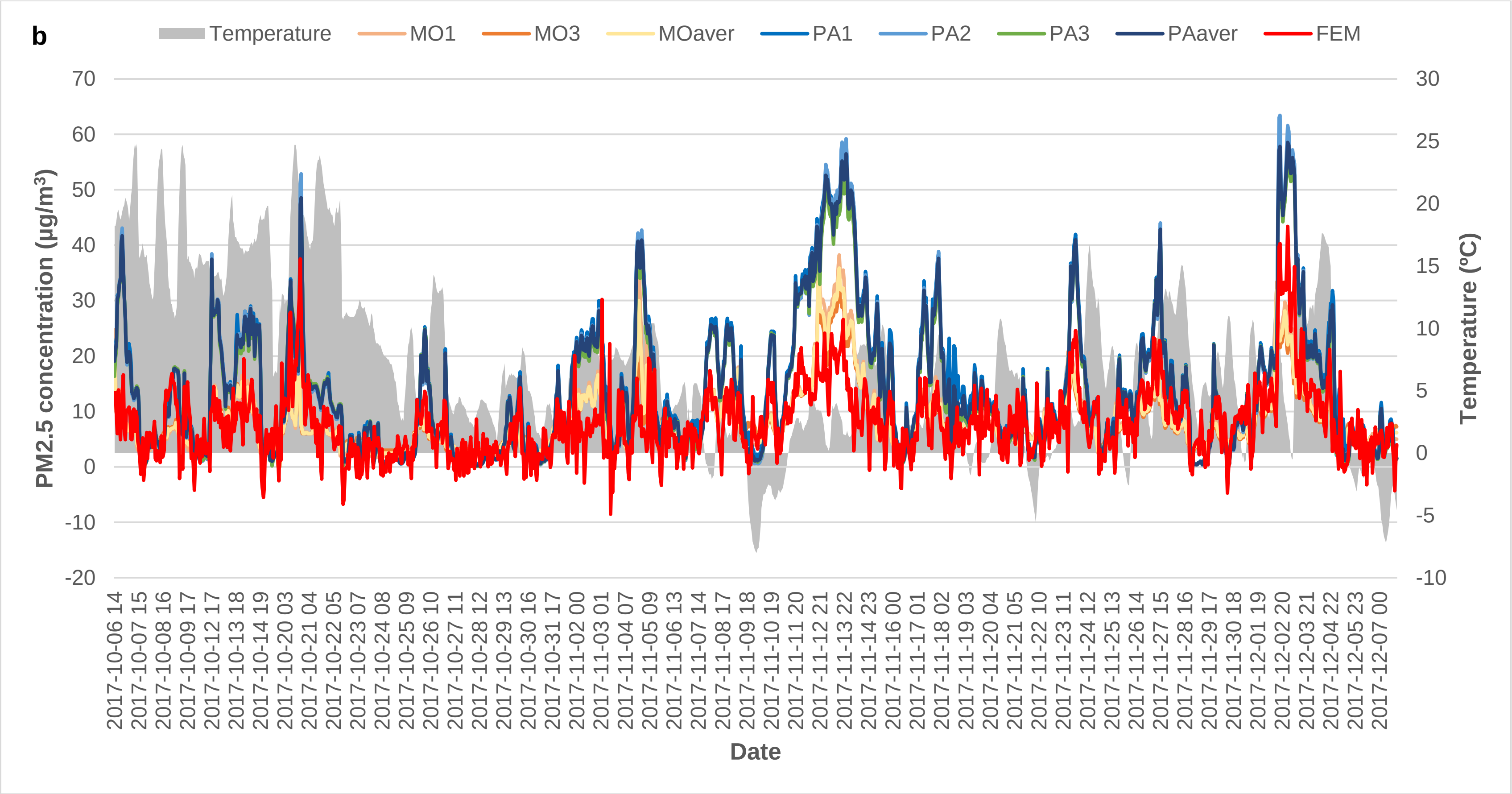
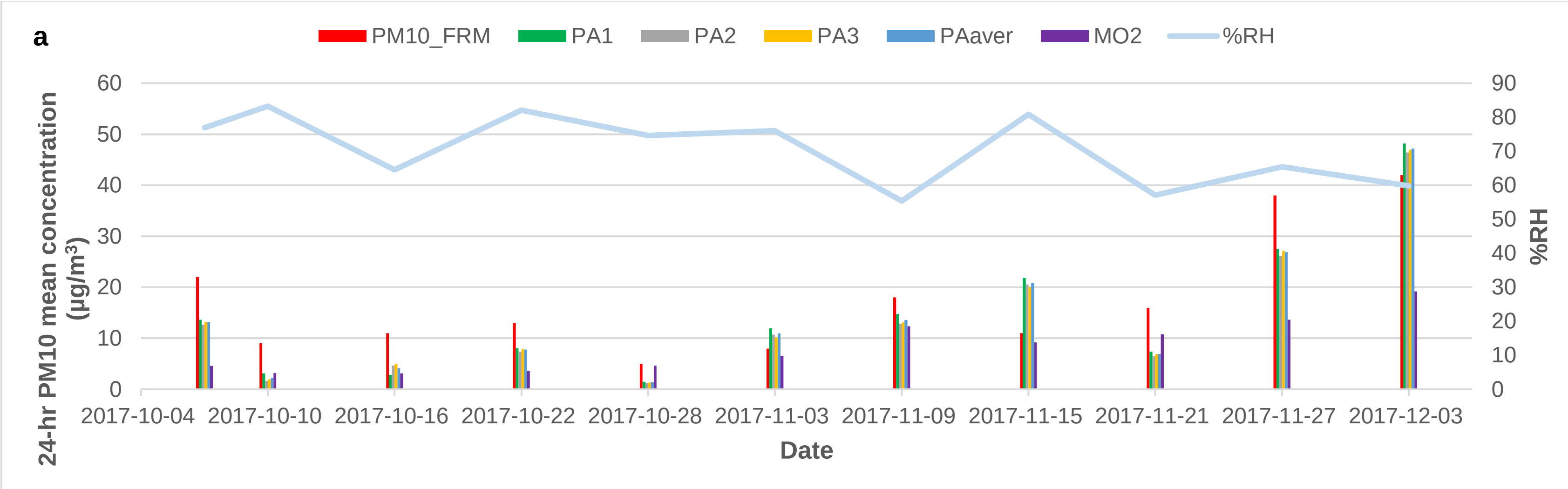


Figure14. Sample time series of PM2.5 concentrations measured by low-cost sensors and FEM plotted with %RH (a) and temperature (b). (continued)



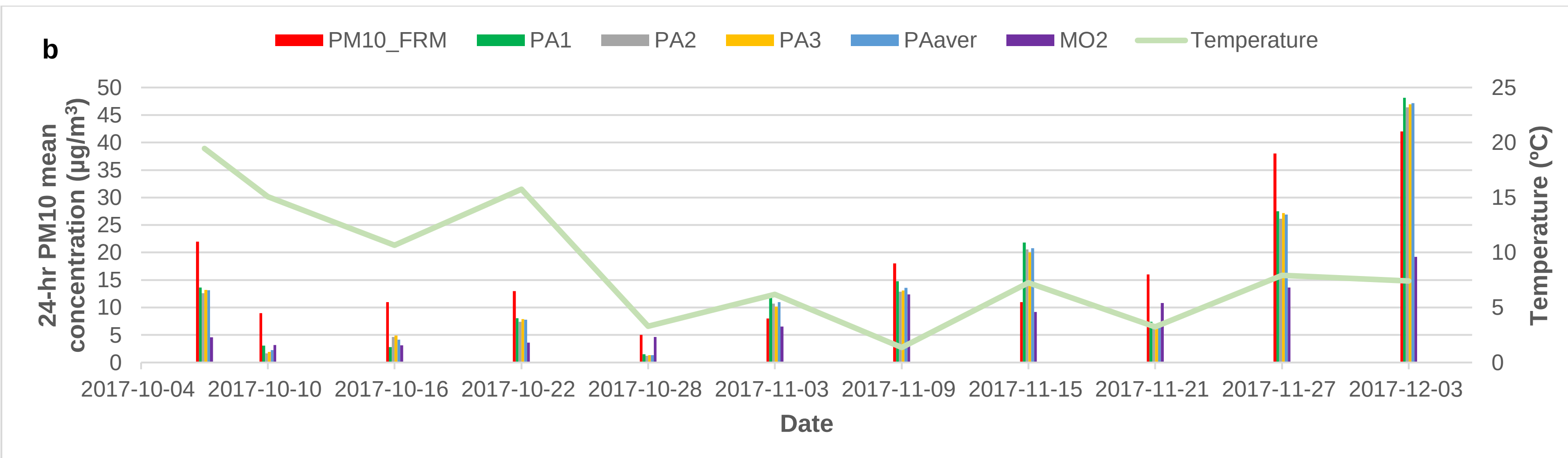


Figure 15. Sample time series of PM10 concentrations measured by low-cost sensors and FRM plotted with %RH (a) and temperature (b).

a

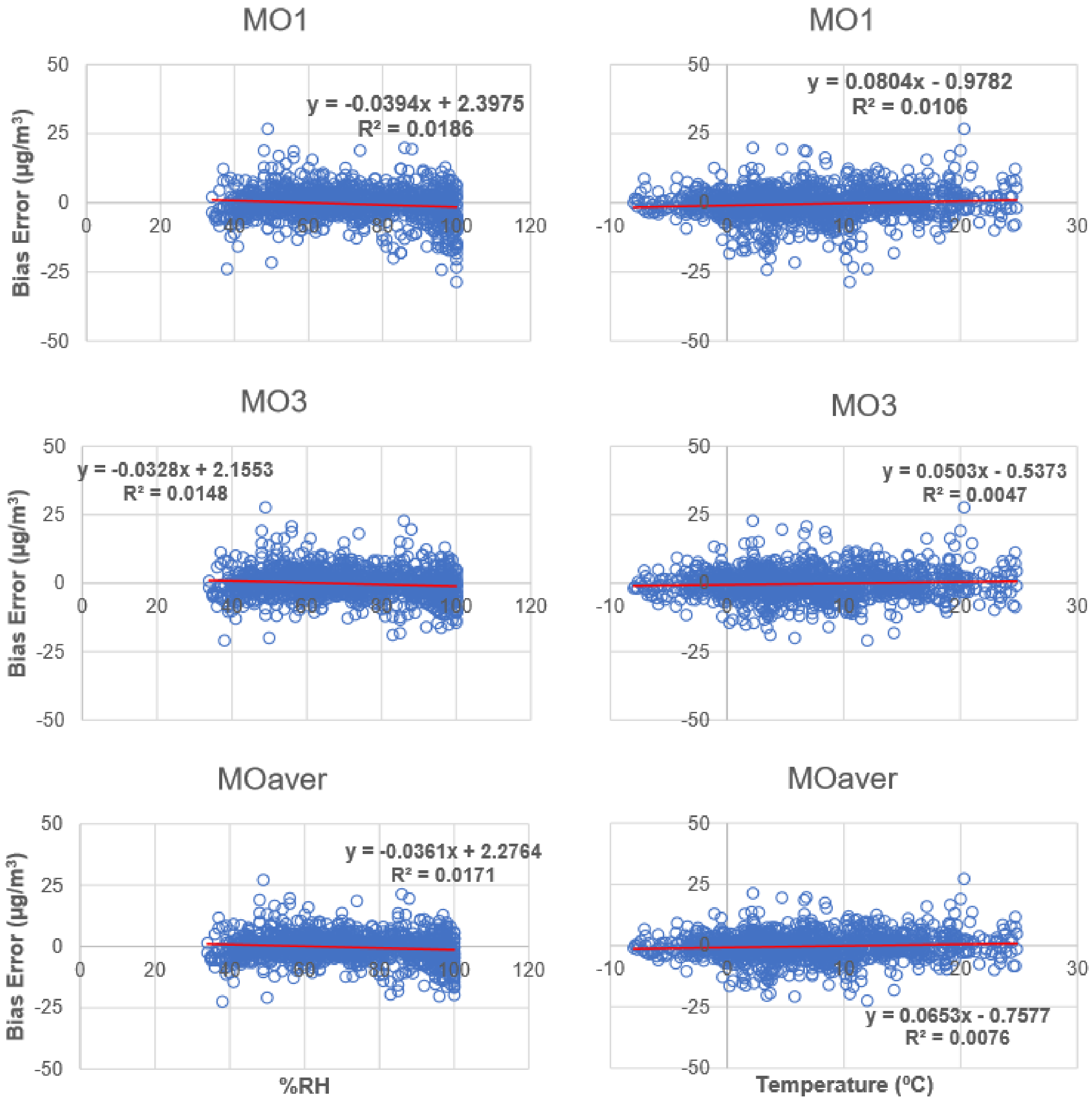


Figure 16. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM (a) or FRM (b) and MetOne measuring PM2.5. MO1 and MO3: MetOne unit#1 and #3; MOaver: average measurements across MO1 and MO3.

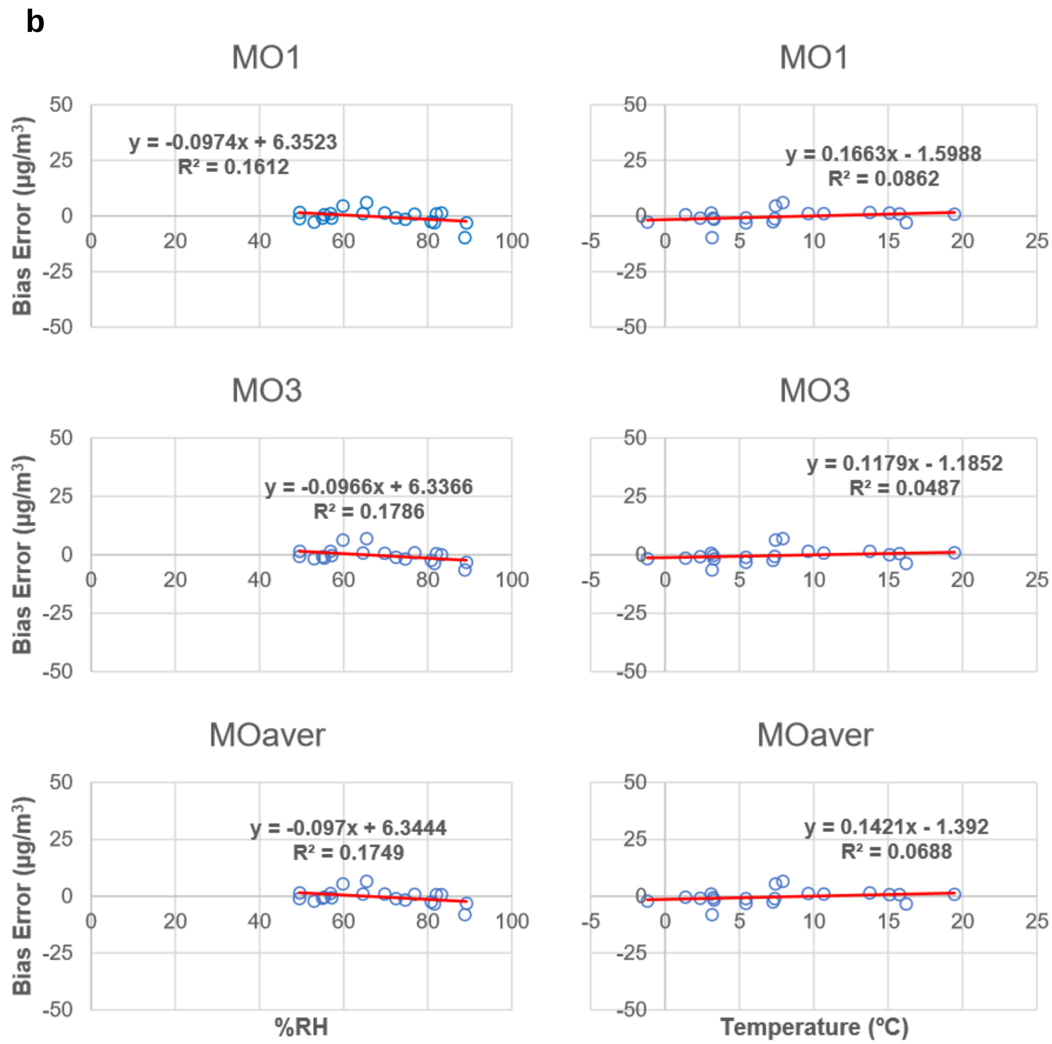


Figure 16. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM (a) or FRM (b) and MetOne measuring PM2.5. MO1 and MO3: MetOne unit#1 and #3; MOaver: average measurements across MO1 and MO3 (continued)

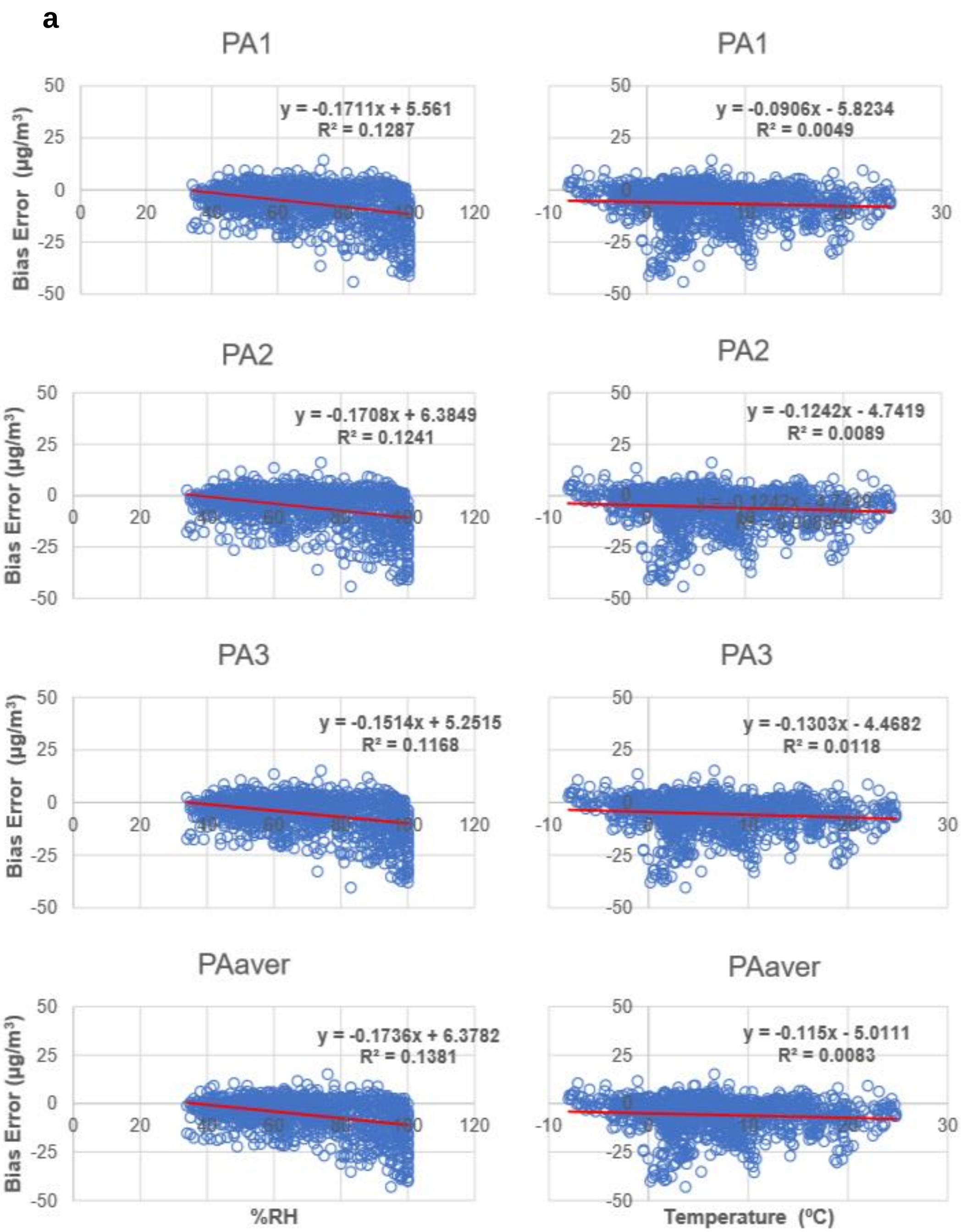


Figure 17. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM (a) or FRM(b) and PurpleAir measuring PM2.5. PA1, PA2, and PA3: PurpleAir unit#1, #2, and #3; PAaver: average measurements across PA1, 2, and 3.

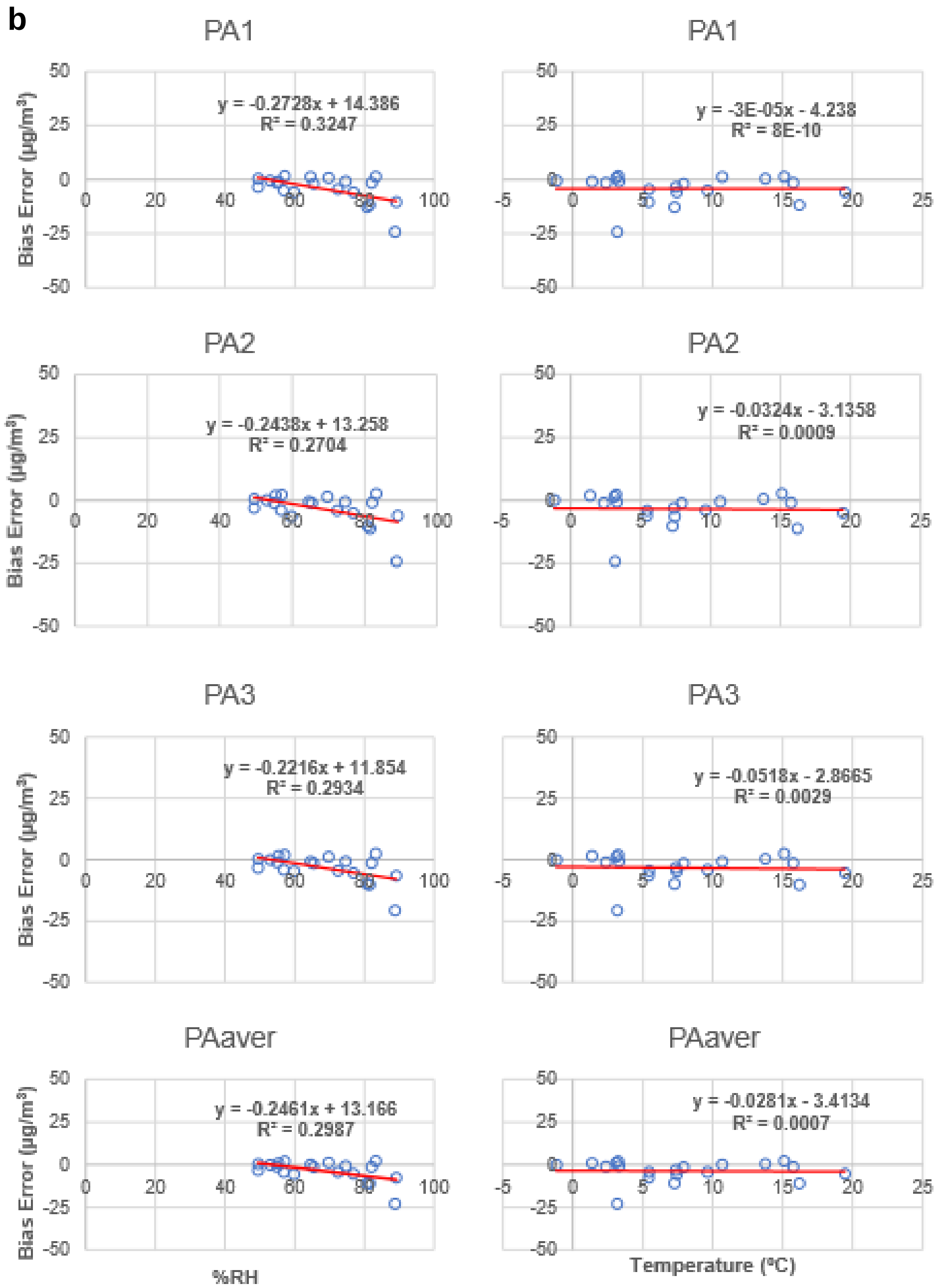


Figure 17. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM (a) or FRM(b) and PurpleAir measuring PM2.5. PA1, PA2, and PA3: PurpleAir unit#1, #2, and #3; PAaver: average measurements across PA1, 2, and 3. (continued)

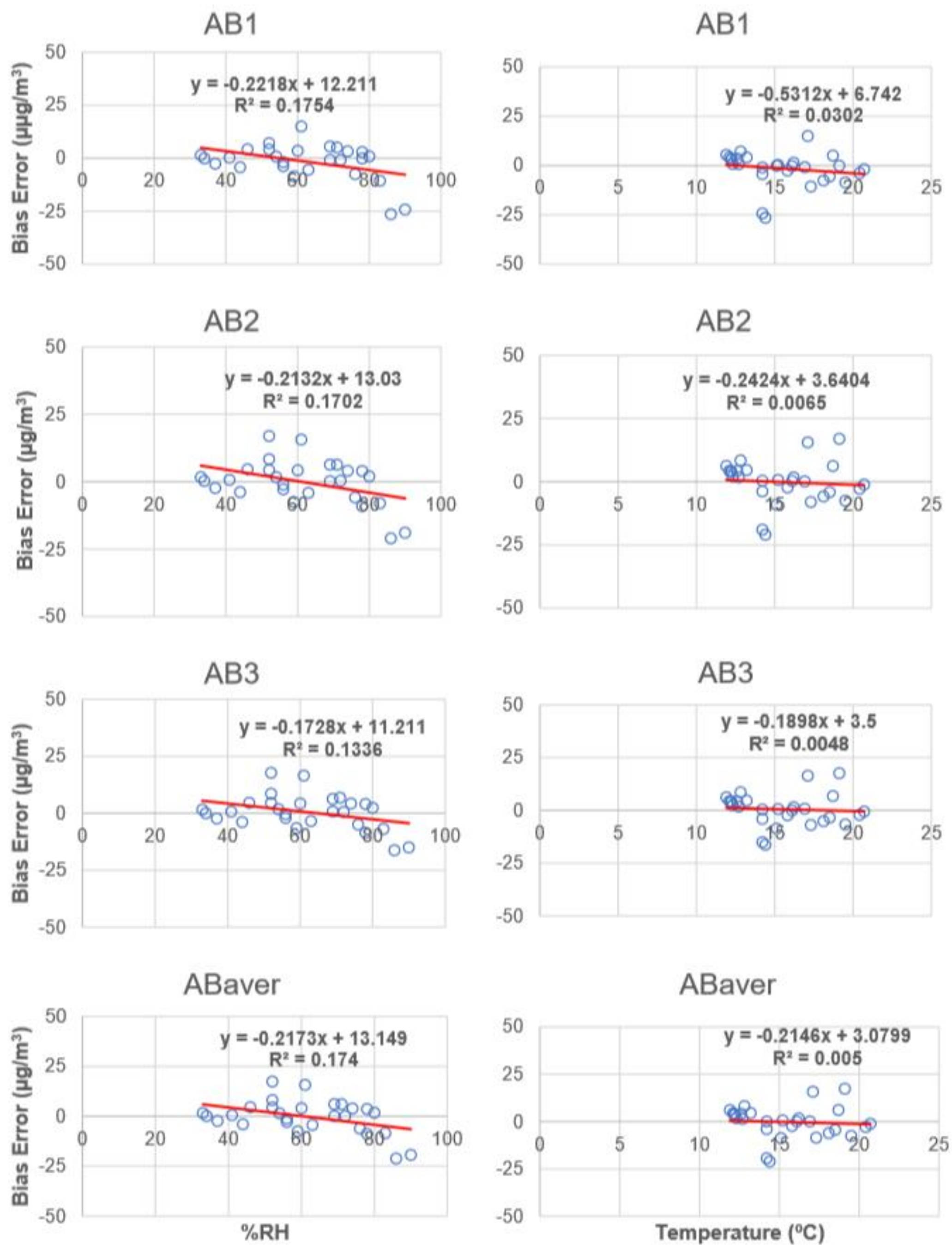


Figure 18**.** Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM and AirBeam measuring PM2.5. AB1, AB2, and AB3: AirBeam unit#1, #2, and #3; ABaver: average measurements across AB1, 2, and 3.

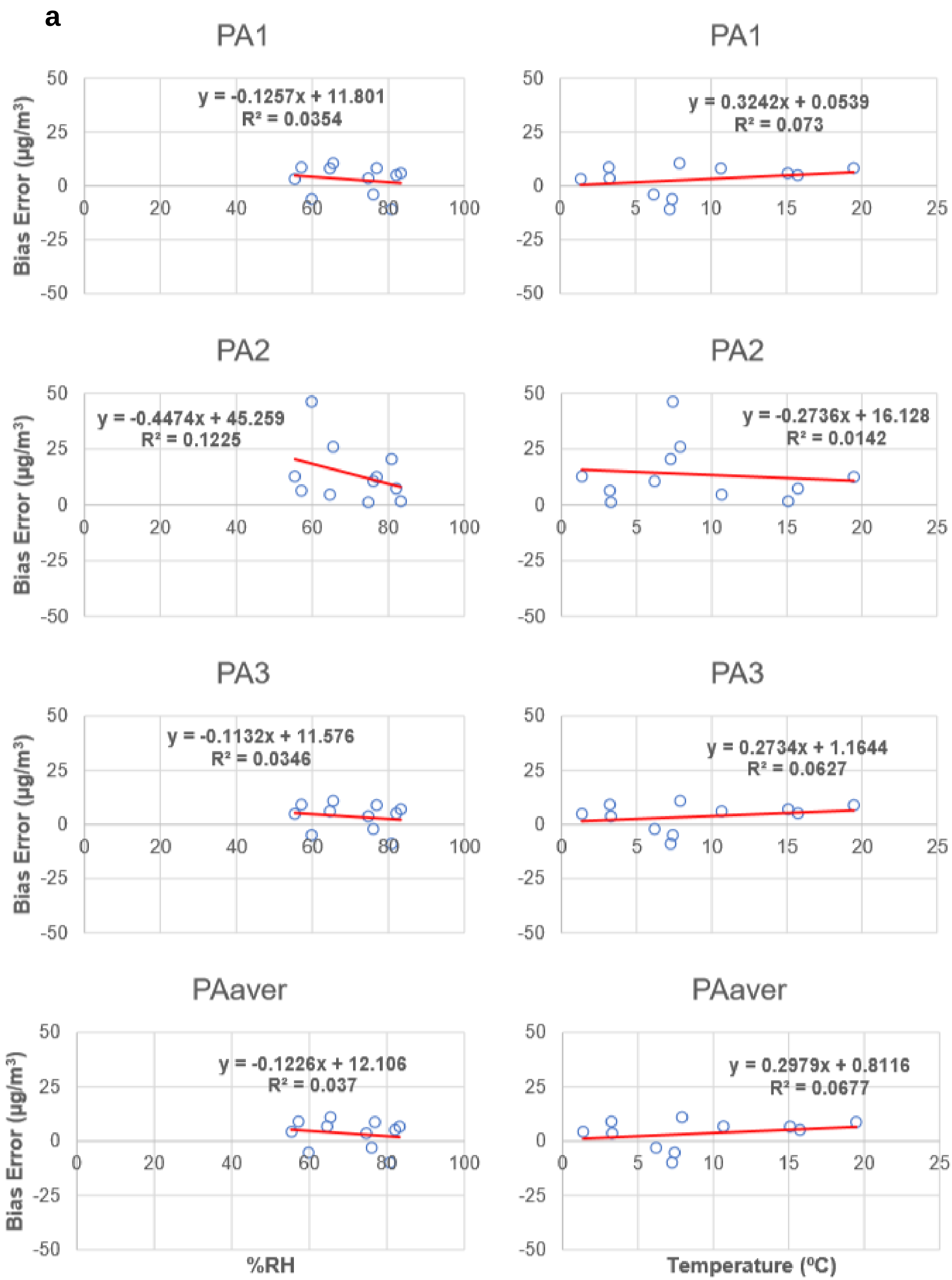


Figure 19. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FRM and PurpleAir (a) or MetOne (b) measuring PM10. PA1, PA2, and PA3: PurpleAir unit#1, #2, and #3; PAaver: average measurements across PA1, 2, and 3; MO2: MetOne unit#2.

b

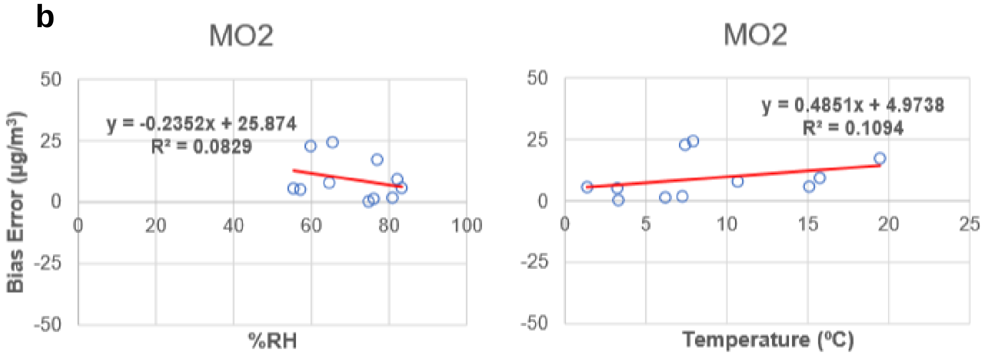


Figure 19. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FRM and PurpleAir (a) or MetOne (b) measuring PM10. PA1, PA2, and PA3: PurpleAir unit#1, #2, and #3; PAaver: average measurements across PA1, 2, and 3; MO2: MetOne unit#2. (continued)

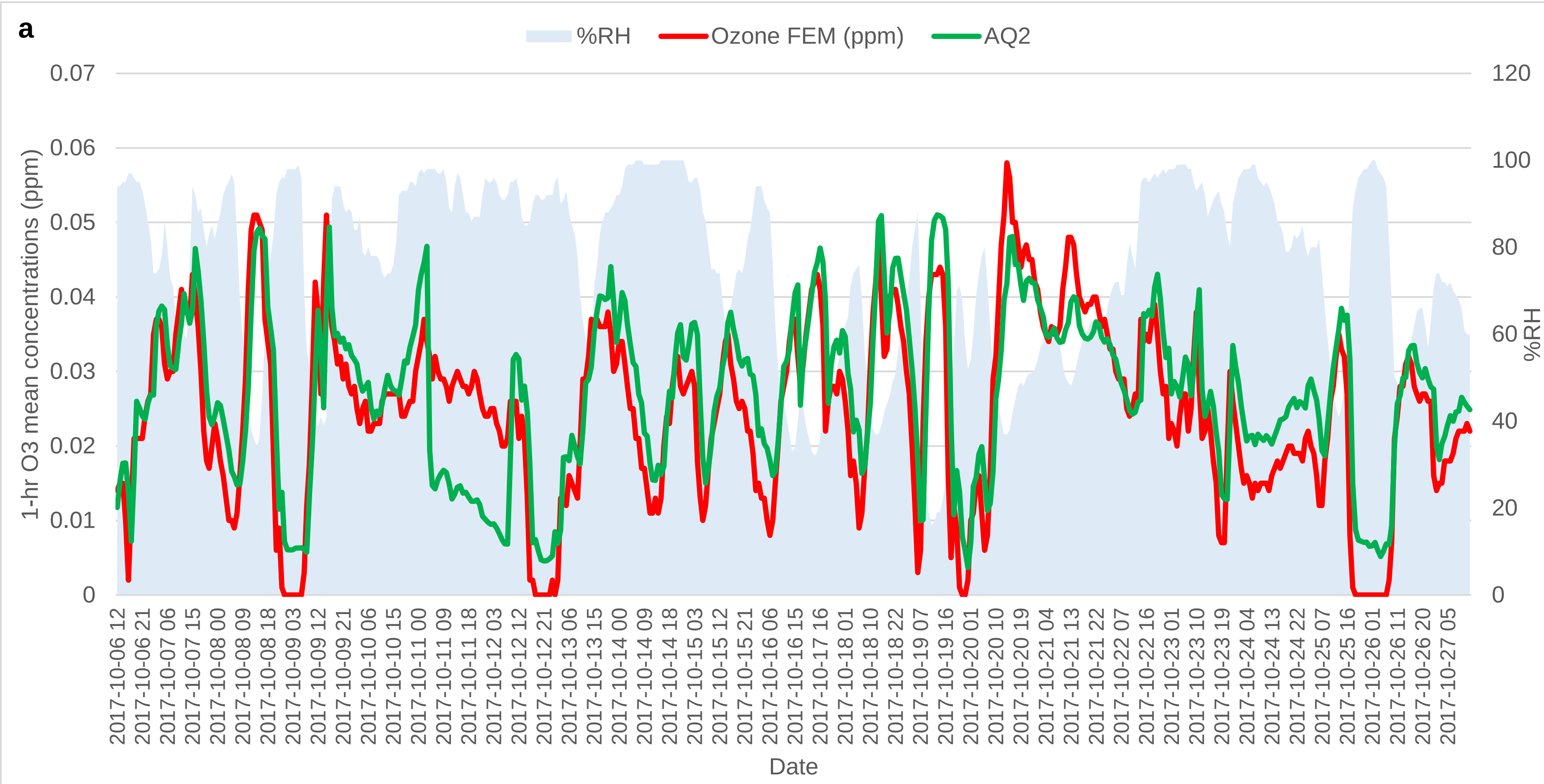


Figure 20**.** Sample time series of O_3 concentrations measured by low-cost sensors and FEM plotted with %RH (a) and Temperature (b).

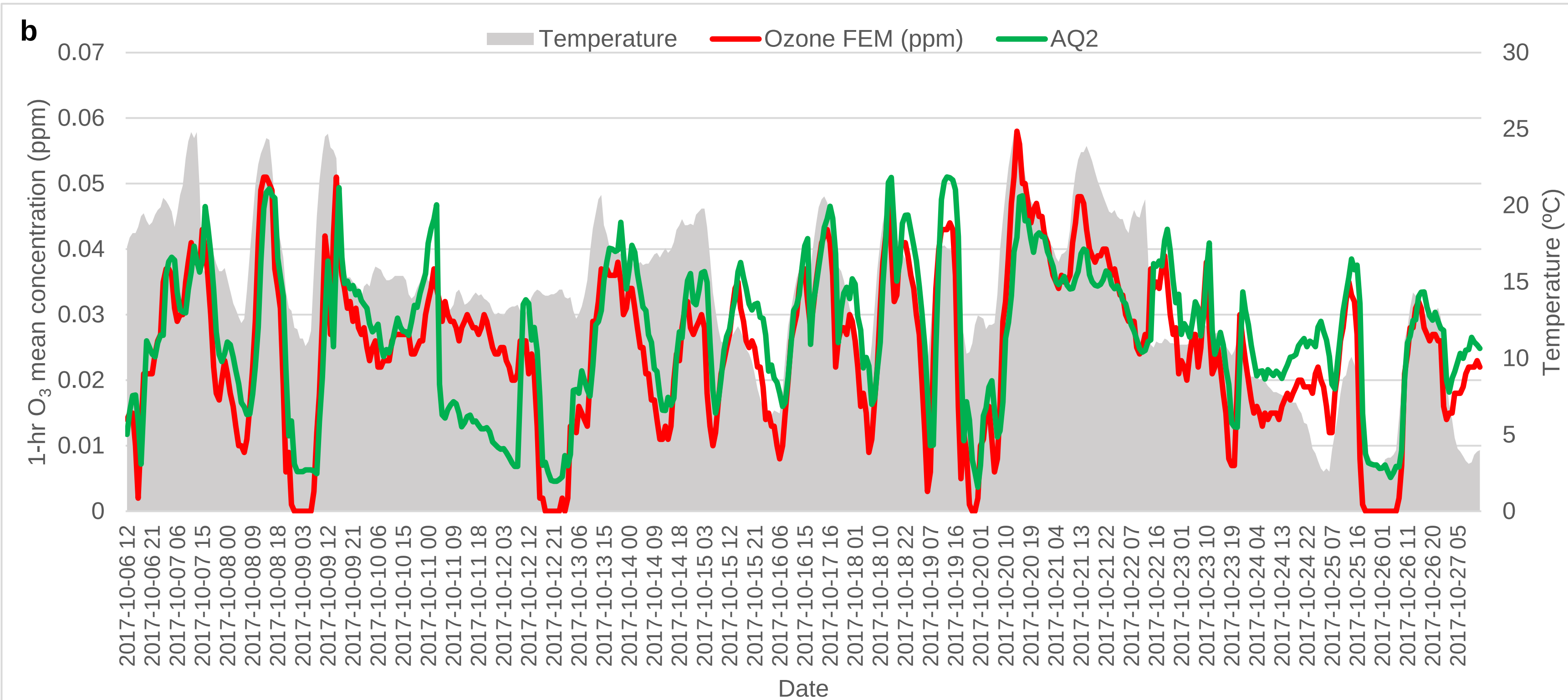


Figure 20. Sample time series of O3 concentrations measured by low-cost sensors and FEM plotted with %RH (a) and Temperature (b). (continued)

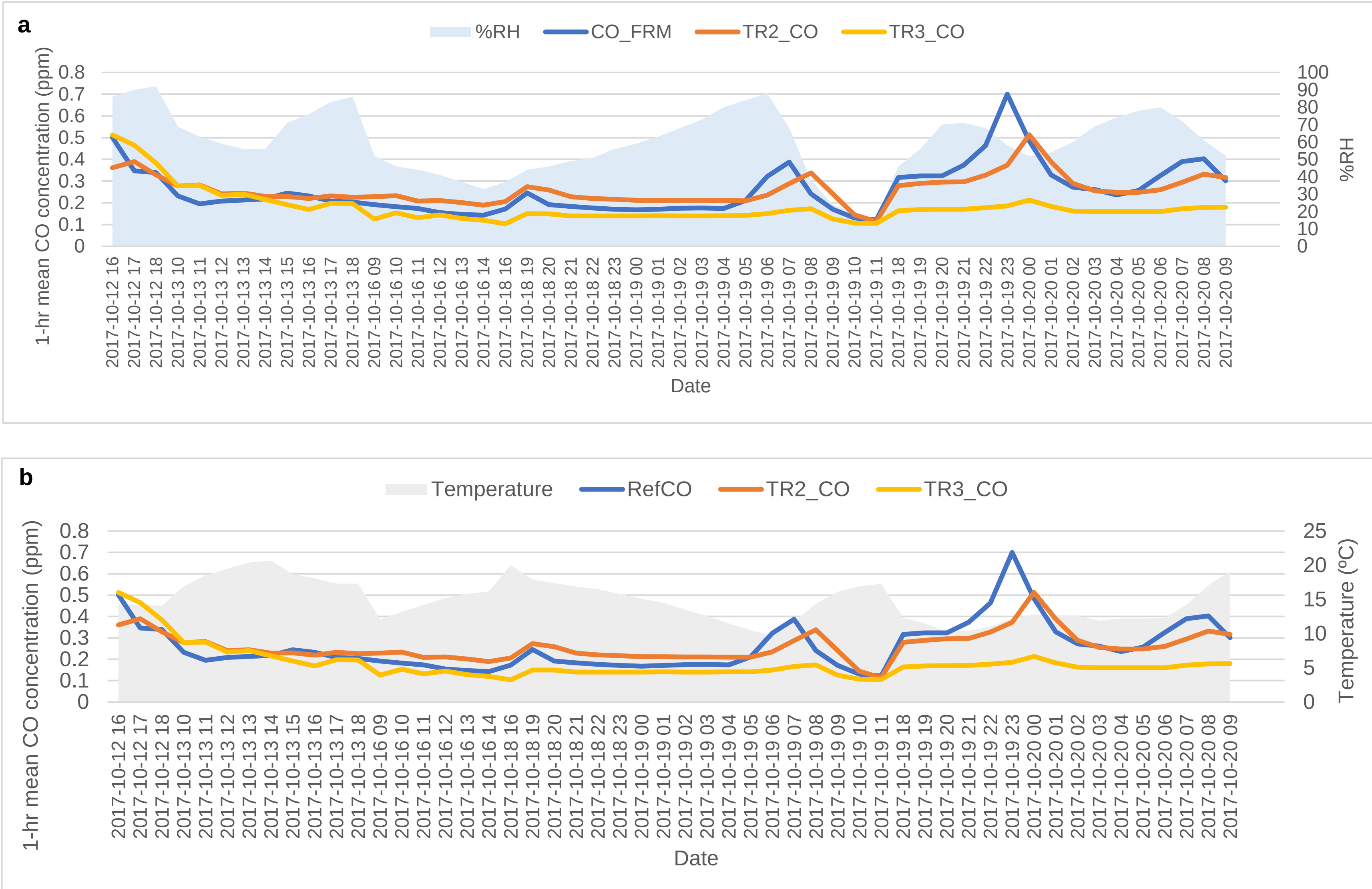


Figure 21. Sample time series of CO concentrations measured by low-cost sensors and FRM plotted with %RH (a) and Temperature (b).

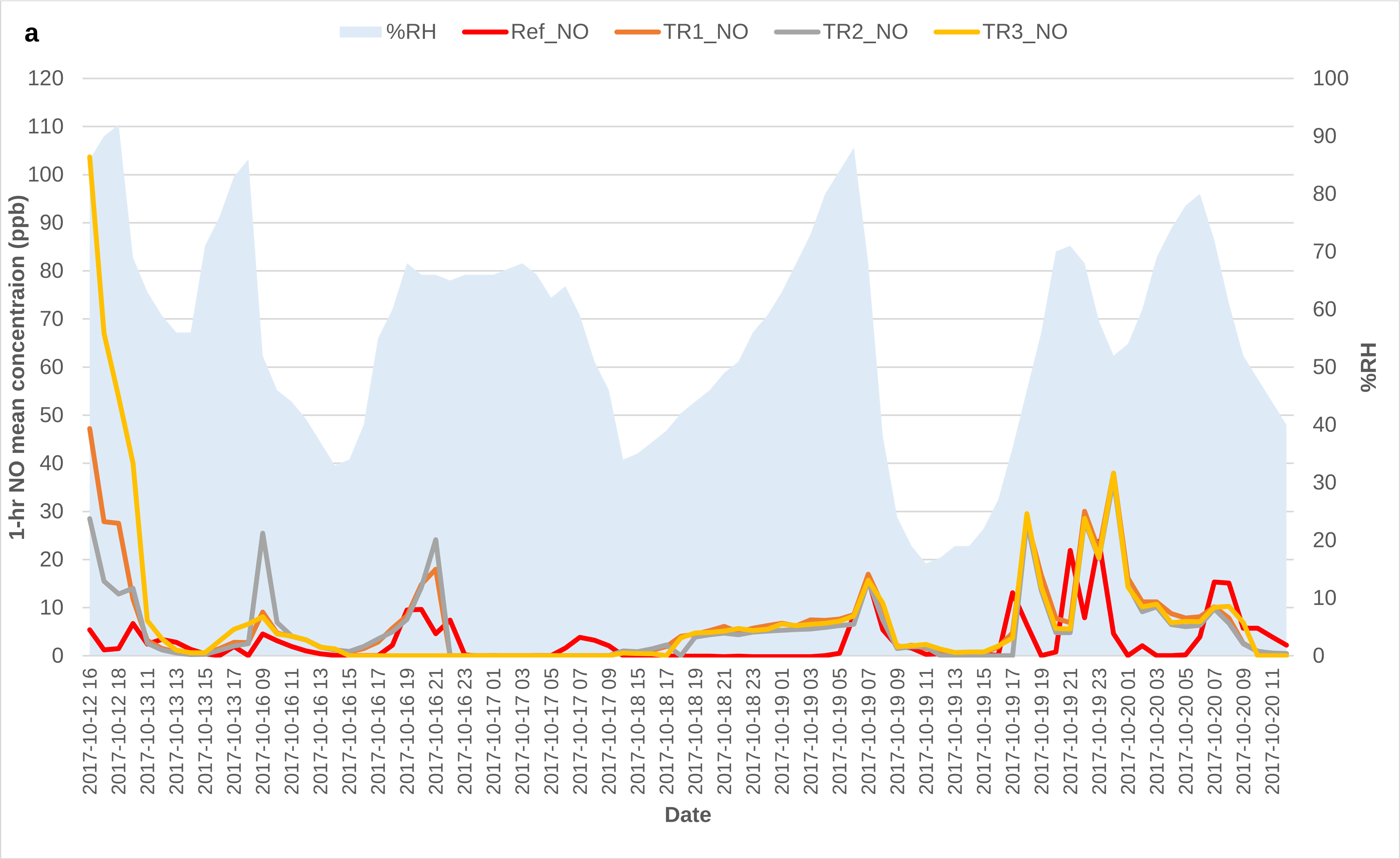


Figure 22. Sample time series of NO concentrations measured by low-cost sensors and the reference monitor (Non-federal reference method) plotted with %RH (a) and Temperature (b).

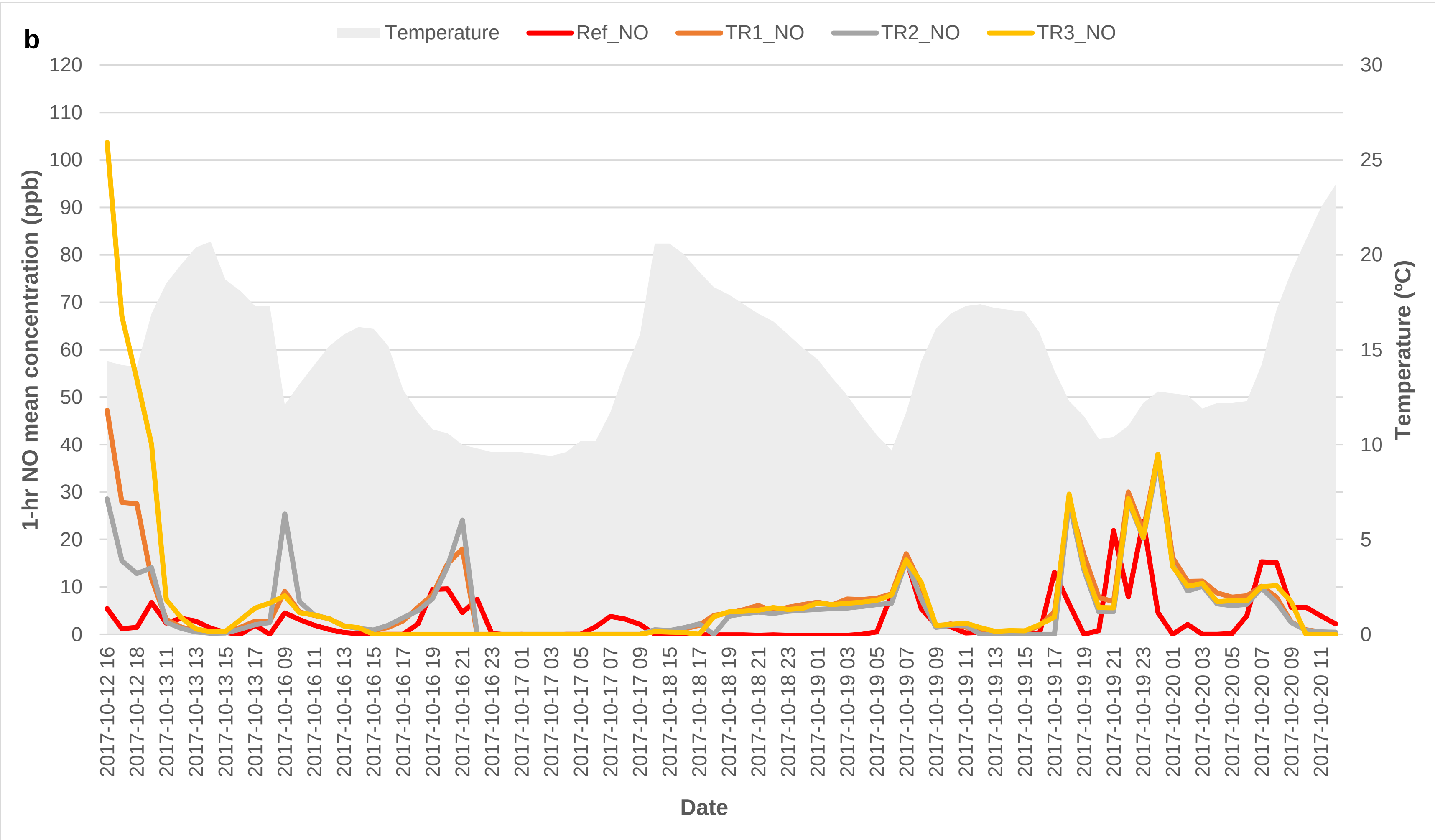


Figure 22. Sample time series of NO concentrations measured by low-cost sensors and the reference monitor (Non-federal reference method) plotted with %RH (a) and Temperature (b). (continued)

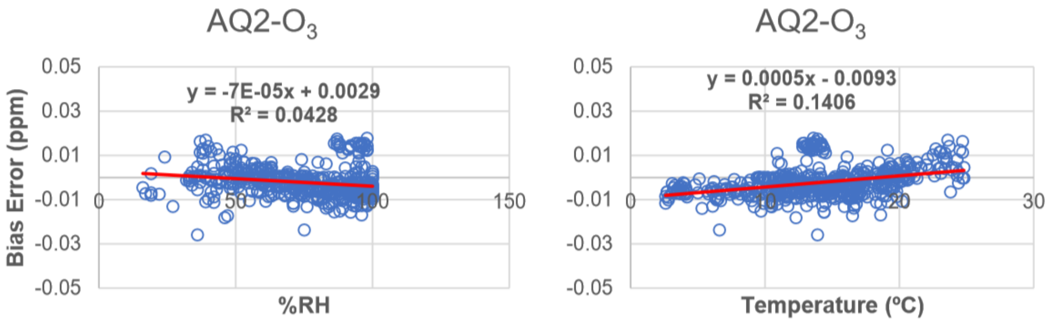


Figure 23. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FEM and AeroQual measuring O_3. AQ2-O_3 indicates AeroQual unit#2 measuring O_3.

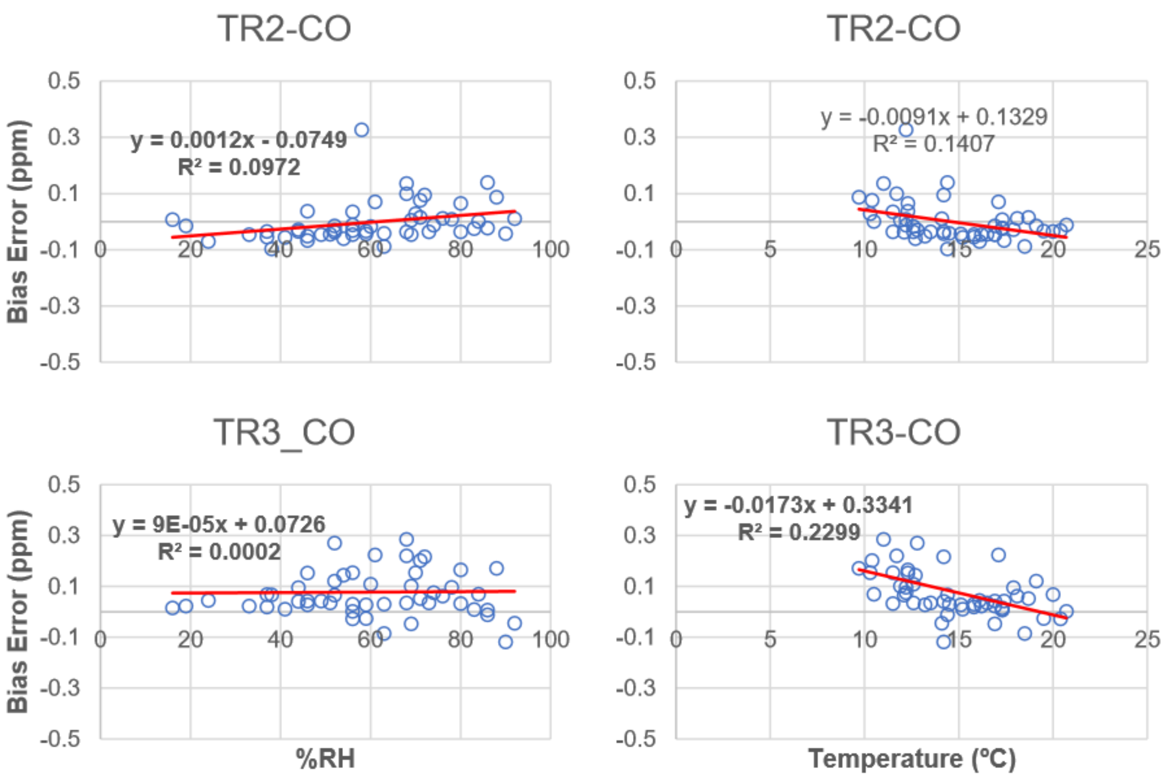


Figure 24. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of FRM and Terrier measuring CO. TR 2, 3-CO indicates Terrier unit#2 and 3 measuring CO.

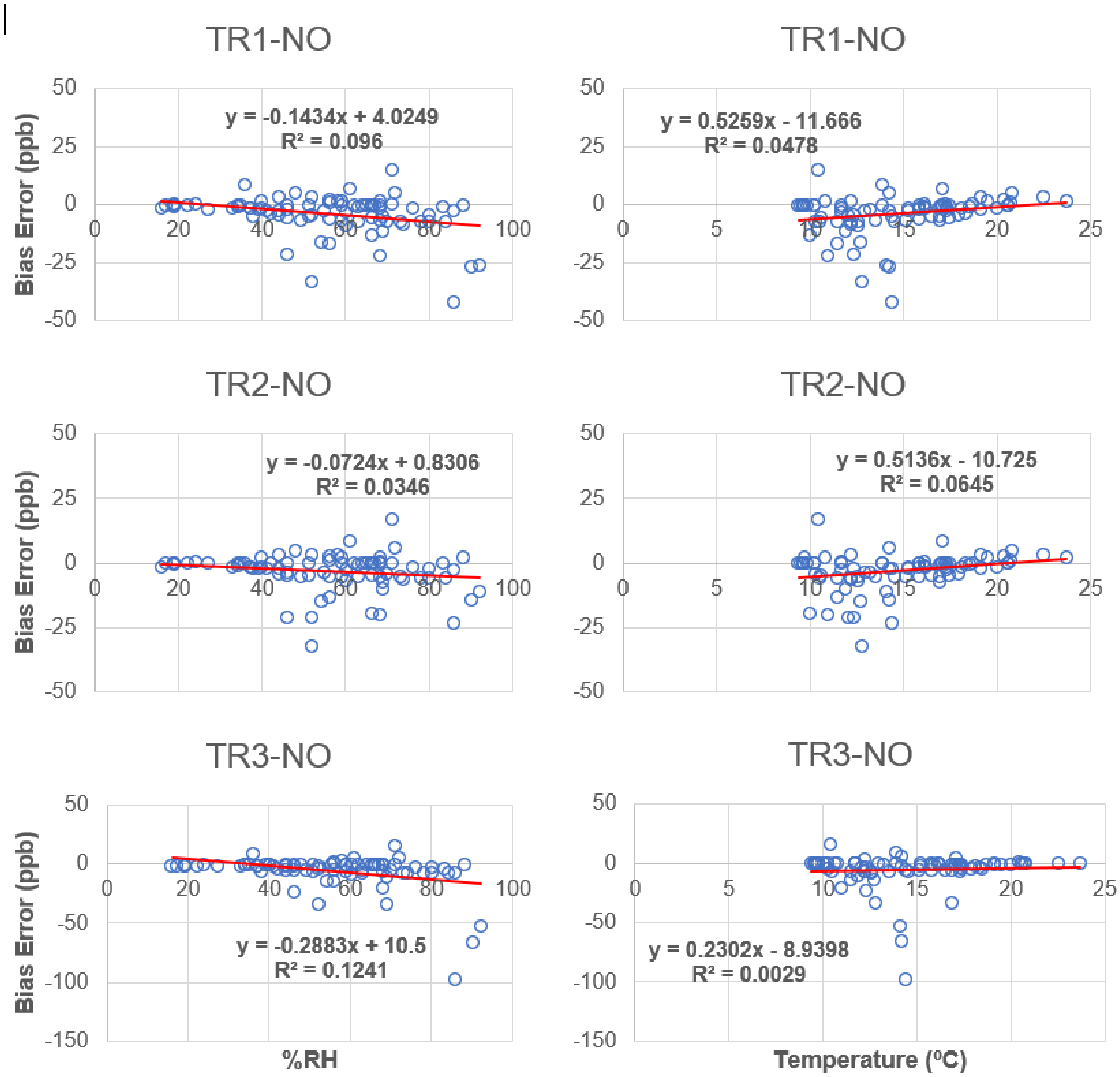


Figure 25. Impacts of humidity, %RH, (left panel) and temperature (right panel) on bias error between measurements of the reference monitor (Non-Federal Reference method) and Terrier measuring NO. TR1, 2, 3-NO indicates Terrier unit#1, 2, and 3 measuring NO.

V. FEASIBILITY OF WORKERS TO EMPLOY LOW-COST PARTICULATE MATTER SENSORS IN OCCUPATIONAL PERSONAL EXPOSURE ASSESSMENT IN BREATHING-ZONE

A. Introduction

Particulate Matter (PM) is a mixture of very small solid particles and liquid droplets in the air. Particulate matter is typically measured as coarse, fine or ultrafine particles, designated as PM10, PM2.5, and PM1 respectively, where the numeric subscript refers to the maximum particle aerodynamic diameter measured in micrometers. Several epidemiologic studies have suggested that PM can cause adverse health outcomes including cardiovascular diseases, respiratory issues, lung cancer, and adverse birth outcomes (Brook et al., 2010; Madrigano et al., 2013; Pope et al., 2011; Ristovski et al., 2012).

Motor vehicles are one of the major sources of PM; thus, PM is expected to occur anywhere vehicles are operated, including in parking garages and loading docks. Workers in these settings may be exposed to PM and other gaseous pollutants. A number of studies have suggested that the concentrations of PM and gaseous pollutants in parking garages and loading docks are higher than those in ambient air as expected because these areas are normally partially or fully enclosed. According to Yan and colleagues' report, the average CO and PM10 concentrations in the indoor parking garage were 10.8 ppm and 228 μg/m^3, respectively; and that, at times, the concentrations exceeded the National Ambient Air Quality Standards of 35 ppm CO and 150 μg/m^3 PM10 (Yan et al., 2017). Similarly, Samal et al. measured elevated concentrations of CO (12-164 ppm) and PM2.5 (100-230 μg/m^3) in an enclosed parking area during an 8-hour sampling period and found that concentrations were highest during peak hours of vehicle activities (Samal et al., 2013). Furthermore, the concentrations of CO and PM varied seasonally, i.e., they were higher during winter than other seasons (Debia et al., 2017; Samal et al., 2013; Yan et al., 2017).

Barriers to measure PM include the cost of instruments, and the time and personnel skills required to operate complicated monitoring devices. These issues might be solved by using new, low-cost sensors. Recently, several manufacturers have offered low-cost air monitoring sensors for real-time monitoring of PM2.5 including AirBeam2 sensor (HabitatMap, Brooklyn, NY, USA) and Ultrasonic Personal Aerosol Sampler (UPAS) (Access Sensor Technologies, Fort Collins, CO, USA) which were employed in this study. Both devices are suitable for personal exposure assessment because they are small, lightweight, easy to operate, and do not interfere with job duties.

Since AirBeam had been discontinued, AirBeam2, the new version of AirBeam, launched in spring 2018, was utilized in this study. AirBeam2 and AirBeam have the same measurement method and operating systems. However, AirBeam2 measures PM1, PM2.5, and PM10, while AirBeam measures only PM2.5. AirBeam/AirBeam2 sensor measures PM2.5 using the light scattering method without a need of calibration before sampling efforts. It can run on either AC or rechargeable battery power (10-hour battery lifetime). The collected data can be seen real-time and uploaded to the Cloud (Heimbinder & Besser, 2014; Heimbinder & Lim, 2018). The performance of the AirBeam has been evaluated in several studies and found to be satisfactory. The South Coast Air Quality Management District (SCAQMD) found that, overall, AirBeam measurements had good correlation with FEM instruments i.e., BAM and GRIMM with R^2=0.66-0.67 and R^2=0.68-0.70. AirBeam mass data was largely overestimated, while the particle count showed a good agreement (SCAQMD, 2015). Sousan and colleagues conducted an AirBeam sensor performance evaluation in laboratory settings to measure PM generated from salt, welding, and Arizona road dust; and discovered poor to high correlations between AirBeam sensor and Scanning Mobility Particle Sizer and Aerodynamic Particle Sizer (SMPS-APS) with R^2=0.49-92 (Sousan et al., 2017). Another recent study performed by Mukherjee et al. reported that AirBeam demonstrated a high degree of precision with R^2=0.95-0.99 and a moderate degree accuracy against the reference instrument (i.e., GRIMM11-R) with R^2=0.6-0.76 (Mukherjee et al., 2017). A few published studies that have employed AirBeam2 suggested that AirBeam2 highly correlated with the TSI DustTrack tested in the concentrated air pollutant chamber (R^2=0.88-0.89) (Heimbinder & Lim, 2018). AirBeam2 moderately correlated with GRIMM (R^2=0.70-0.72), FEM BAM (R^2=0.68-0.69), and FEM T640 (R^2=0.78-0.79) (SCAQMD, 2018). The Ultrasonic Personal Aerosol Sampler (UPAS) developed by Volckens and colleagues is designed to measure personal PM2.5 exposures using time-integrated impaction without requiring calibration. It runs on battery power (battery life is greater than 35 hours at operating flow rate of 1 liter/minute). This filter sampler utilizes an ultrasonic piezoelectric pump to drive flow, as opposed to a traditional diaphragm pump, which has the advantage of being small in size, light weight, and accompanying low noise (Volckens et al., 2017). The UPAS performance was conducted against FEM i.e., URG cyclone and a Personal Environmental Monitor (PEM), which is widely used in occupational exposure assessments. The findings showed stronger correlations between UPAS and FRM (R^2=0.99) compared to the correlation between PEM and FRM (R^2=0.96). The coefficient of variation was less than 10%, in addition, the average mass measured by UPAS was in agreement with FEM (7% difference) (Volckens et al., 2017). UPAS is very new and has been utilized in a very few published studies. Arku and colleagues conducted a previous pilot study characterizing exposure to household air pollution in multiple urban and rural communities by using UPAS and Harvard Impactor. Inter-sampler comparison analysis between UPAS and Harvard Impactor sensor suggested a high correlation between the two sensors with R^2=0.83 (Arku et al., 2018). The UPAS sensor was employed in the recent household air quality study for measuring the personal exposures to PM2.5 among rural Honduran women conducted by Pillarisetti and colleagues. UPAS had a high correlation with a commonly used PM sensor with gravimetric pump, cyclone and filter sampling system (R^2=0.83) (Pillarisetti et al., 2019).

Particulate matter monitoring sensors, including AirBeam/AirBeam2 and UPAS, show great promise for measuring personal exposures, but they have had limited applications in occupational exposure assessments to date. In this study, the feasibility of employing two low-cost PM2.5 sensors (AirBeam2 and UPAS) under the field conditions by University of Illinois at Chicago (UIC) parking and ground-keeping workers was assessed using two approaches. The first approach was based on the assessment of compliance of the sampling protocol by the participating workers using the feasibility assessment tool. The investigators implemented the Relative Compliance Score (RCS), which is unique to this study, that captures the attention/interest level of the participants which may provide the information about the feasibility of employing the low-cost sensors. The second approach involved intra- and inter-sampler performance evaluation of these two PM2.5 low-cost sensors to gain insight into their reliability for air quality and exposure assessment studies in support of occupational personal exposure assessment studies. In addition, the real-time PM2.5 personal exposures of parking and ground-keeping workers on UIC campus were characterized since these two groups of participants who work in close proximity to vehicles and heavy engines that potentially emitting PM2.5; however, their exposures have not been well-characterized as yet. This pilot study provided knowledge to facilitate exposure/health risk mitigation measures for improved occupational health and safety on campus (e.g., safer work policies/procedures).

B. Methods

1. Air Monitoring Sensors

Two low-cost portable PM2.5 sensors, i.e., AirBeam2 ($250) and UPAS ($1300) were selected and employed in the study. These two sensors have different PM2.5 measurement methods. AirBeam2 sensor measures PM2.5 by using the light scattering method while the UPAS uses time-integrated impaction. Prior to the first sampling event of each day, sensors and cellphones were fully charged. In addition, sampling and blank filters for UPAS were prepared and pre-weighed. Each unit of the UPAS was loaded with a pre-weighed filter and measured for the flow rate before the first sampling session of each day. AirBeam2 and UPAS sensors were connected to the cellphone and operated through the mobile applications i.e., AirCasting (for AirBeam2) and UPAS (for UPAS). After completing each air monitoring session, sensors were retrieved from the participants and recharged. UPAS was replaced with a new pre-weighed filter in preparation for the next air sampling session. The detailed explanation delineating the preparation and treatment of sensors and filters is provided in the data collection protocol enclosed in Appendix K.

2. Participant Recruitment

There was a collaboration with UIC Facilities Management and Campus Parking Services to access workers as potential participants. Ten workers (i.e., five of each UIC parking and ground-keeping) participated in the study. The study has been approved to be exempted by Institutional Review Board under protocol# 2019-0018. The IRB approval is enclosed in Appendix L The investigators informed the prospective participants about the study with a provided information sheet (see Appendix M). All participants provided their informed consents (see Appendix N) before participating. Each participant was asked to participate in a 2-hour training session on how to use and operate the sensors, in addition to performing six 1-hour air monitoring sessions on six different days. During two out of the six 1-hour sampling sessions, the participants were shadowed by the investigator while performing their routine work and wearing four units of sensors in their breathing-zone. During the other four 1-hour sampling sessions, they were asked to perform the air monitoring while wearing two units of sensors in their breathing-zone (i.e., two AirBeam2 sensors on their right shoulder, or two UPAS on their left shoulder, or one AirBeam2 sensor on their right shoulder and one UPAS on their left shoulder).

3. Creating the PM2.5 Exposure Assessment Plan using Two Low-Cost PM2.5 Sensors and Collecting Air Quality Data

From April-May 2019, the investigators collaborated with the staff at the UIC Facilities Management and Campus Parking Services to finalize the personal exposure air-monitoring plan. Initially, air monitoring efforts were aimed to capture time-periods and locations of concern for potentially higher PM concentrations and associated exposures. Logistically, the air sampling plan was scheduled based on convenience and weather. Each participant was scheduled for six 1-hour long air-monitoring sessions from May-June 2019. Out of the total six sessions, two (i.e., first and fourth sessions) were for the purpose of Quality Assurance/Quality Control (denoted as Q), which each participant wore two AirBeam2 units on the right shoulder and two UPAS units on the left shoulder in their breathing-zone (see Figure 26) for one hour and was shadowed by the investigator. To access the inter-sensor variability, each participant wore both the AirBeam2 and UPAS during two of the 1-hour sampling sessions i.e., one AirBeam2 was placed on the right shoulder and one UPAS on the left shoulder in their breathing-zone (denoted as X). To access the intra-sensor variability, each participant wore two units of AirBeam2 or UPAS during two of the 1-hour sampling sessions i.e., two AirBeam2 units were placed on the right shoulder (denoted as Y), or two UPAS units on the left shoulder (denoted as Z). Furthermore, each participant was asked to record time-activity data at every five-minute interval. In particular, they were asked to document any PM2.5 generating activities, e.g., lawn mowing, blowing, fertilizing, mulching, cleaning, machine operating, and working nearby the PM generating sources including heavy-duty vehicles and machines.

4. Training the Participating Workers

All participating workers were trained on how to operate AirBeam2 and UPAS in a step-by-step fashion in one 2-hour in-person training session. To facilitate this, the research team prepared user guides enclosed in Appendix O that documented operation of each sensor in a step-by-step sequence. These user guides were made available to the workers. In addition, the participants were trained on how to record the time-activity data documenting PM2.5 generating tasks/activities and air pollution sources they encountered during their routine work. The participants collected time-activity data either manually documented the time-activity data in a mobile monitoring observation log (shown in Appendix Q) or took a picture of an air pollution source and note on during their sampling sessions using their cell phone that, then, became an electronic record in the AirCasting application and could be downloaded along with the air monitoring data from the AirCasting website. These methods allowed the workers to capture any PM generating tasks/activities, encountered during each sampling event. At the beginning of the training session, workers were asked for their age ranges and education levels. The age responses included: (1) 18-24, (2) 25-34, (3) 35-44, (4) 45-54, (5) 55 and over, and (6) do not want to respond; and the education level responses included: (1) less than a high school diploma, (2) high school degree or equivalent (GED) or some college with no degree, (3) Associated degree, (4) Bachelor’s degree or higher, and (5) do not want to respond. The training session was scheduled before initiation of air monitoring activities.

5. Shadowing the Workers and Observing Time-Activity Patterns and Feasibility of Employing the Sensors

The investigator shadowed and observed each participating worker during their first and fourth air-monitoring events. The purpose of these observations was to collect qualitative information in the following two components. The first component is the participant's level of comfort and capacity in operating the sensors for personal exposure monitoring using the feasibility assessment tool enclosed in Appendix P, that captures information pertaining to participant's compliance with the sampling protocol using the following metrics/indicators: correctly placing the sensors in their breathing-zone; level of comfortable in using the sensors; periodically checking AirBeam sensors during the sampling session; periodically checking UPAS sensors during the sampling session; and level of compliance with the general air sampling procedures. The second component is the participants' time-activity patterns during their regular work. Time-activity patterns i.e., time, location, and activities were recorded at every one-minute interval using the time-activity observation log (enclosed in Appendix Q), in addition to, counts of Heavy Duty Vehicles (HDVs) e.g., trucks, buses, and large SUVs encountered during the sampling sessions.

6. Data Management

a) PM2.5 Concentration Data

The PM2.5 exposure concentration data was collected by AirBeam2 sensor every one second were saved with a specific file naming nomenclature (e.g., P1_0818AM) for each sampling session and these files containing the data for each sampling session were transferred from the instrument to the cloud, AirCasting website, using manufacturer developed algorithms. The AirBeam2 collected data were downloaded from the AirCasting website in a csv format and further managed on MS Excel spreadsheets. We observed missing 1-second data points in the collected AirBeam data files. Consequently, AirBeam2 data were treated and imputed for the missing 1-second data following the criteria delineated in Appendix H. One-minute PM2.5 mean concentrations were computed and utilized for statistical data analysis including descriptive statistics and intra-sampler comparisons.

The filter loaded UPAS sensor was utilized to collect PM2.5 personal exposure mass. The sampling filters were collected and post-weighed by the investigator. The collected PM2.5 mass was calculated by finding the difference between the pre- and post-sampling weights of each filter, then, was corrected by the blank filter utilizing two approaches: 1) weight of a blank filter in each run, and 2) average weight of all blank filters in all runs each day. The average of UPAS flow rate measured before and after the runs of each sampling day was computed (Equation V-1). Finally, the PM2.5 concentrations collected by UPAS were calculated (Equation V-2).

Equation V-1: $V(cubic\ meter) = T(\mathrm{min}) \times F(cubic\ meter\ per\ min)$

Equation V-2: $PM2.5\ concentration = \frac{PM2.5\ collected\ mass\ (\mu g)}{V\ (cubic\ meter)}$

V = volume of air collected by UPAS (m^3), T = sampling duration (minute), F = UPAS flow rate (m^3/minute)

After post-weighing the UPAS collected filters, the PM2.5 mass collected by UPAS was too small to perform reliable weighing, thus, the UPAS measured PM2.5

concentrations were excluded from sensor performance and exposure concentration analyses.

b) Time-Activity Pattern and Feasibility Assessment Data

The time-activity pattern data collected by the investigator (for only shadowing sampling sessions) and the participants (if applicable) was entered into Microsoft Excel spreadsheets. The feasibility assessment tool was utilized to assess the feasibility of employing AirBeam and UPAS sensors among participating workers. Every answer to questions of the feasibility assessment tool were assigned scores (Table XXVIII). For each shadowing sampling session, the Relative Compliance Score (RCS) was computed. The RCS is a product of the summation of raw scores of all questions divided by the total maximum raw scores. RCS was utilized as a tool to determine the attention/interest level of the participants, that captures information pertaining to participant’s compliance with the sampling protocol using the following metrics/indicators described above, as well as the participants’ attention in taking the time-activity data during their sampling sessions.

7. Occupational Exposure and Feasibility of Employing Low-Cost Sensor Data Analyses

a) PM2.5 Personal Exposure Concentrations

The descriptive statistics of 1-minute PM2.5 personal exposure measured concentrations was calculated using ProUCL5.1 (USEPA) and R (RStudio, MA) programs. The spatial and temporal variability of PM2.5 personal exposure concentrations across were analyzed and documented. The 1-minute mean and standard deviation of each real-time PM2.5 personal exposure measured concentration for each sampling session was calculated and summarized by workers, worker types (ground-keeping and parking workers), and worker tasks/activities (picking trash and cleaning parking lots (PTC); mowing (MW); weeding and grass trimming (WWGT); doing cashier work /working in the office (CSOF); and valet parking (VP)). Moreover, the number of Heavy-Duty Vehicles (HDVs) of each sampling event were documented. HDV density (counts/minute) was calculated as the total number of HDVs counted divided by the sampling duration of each sampling event. As shown in Table XXXI, the HDV density values across all sampling sessions were relatively low i.e., three sessions had HDV density 0.03, 0.08, and 0.09 counts/minute, respectively; while seven sessions had a HDV density of 0.00 counts/minute, and four sessions had no records. Since the HDV density across the sampling sessions observed were relatively small, the HDV density was not included in the analyses as one of concerned sources of the PM2.5 concentrations measured in this study due to the HDVs were not likely to impact the PM2.5 exposure concentrations measured. Therefore, an effort was expanded into observing and tracking tasks/activities participants performed during each sampling session.

The collected PM2.5 exposure concentrations did not follow the normal distribution assumption; thus, the Wilcoxon rank sum test (R package stats) was utilized to determine whether the PM2.5 mean exposure concentrations were different between ground-keeping and parking workers. In addition, the Kruskal-Wallis rank test and the multiple comparison based on pair-wise rankings analysis were employed to determine the median differences between each pair of task groups.

b) Sensor Performance Assessment

The correlation between the measured concentrations by two units of AirBeam2 sensor on the right shoulder in the participants' breathing-zone during shadowing sampling events was determined to evaluate sensor intra-variability as an indicator of sensor reliability under field conditions. A coefficient of determination (R^2) was utilized as an evaluation metric, which is accepted as a very strong correlation ($R^2 \geq 0.9$), a strong correlation (R^2=0.7-0.89), a moderate correlation (R^2=0.5-0.69), a weak correlation (R^2=0.3-0.49), a very weak correlation (R^2=0.1-0.29), and a no correlation (R^2=0.0-0.09). In addition, the slope and intercept of the regression line were investigated (Collier-Oxandale et al., 2020). Neither the inter-comparison analysis between AirBeam2 and UPAS nor the intra-comparison analysis for UPAS were able to perform due to a shortage of PM2.5 concentration data measured by UPAS as explained previously.

c) Feasibility of Employing the PM2.5 Low-Cost Sensors

The data collected during each shadowing sampling event in response to questions in the feasibility assessment tool shown in Appendix P were analyzed to gain insight into compliance of sampling protocol by the worker participants who partook in the sampling effort. We calculated percent of participating workers that complied with each measure documented in Appendix P. Furthermore, the RCS of each shadowing session was calculated and reported. The descriptive statistics of RCS were documented and analyzed based on the collected demographic information (occupations, tasks, age ranges, and education levels).

C. <u>Results</u>

1. <u>Summary of Participants and Personal Air Sampling Events</u>

Sixty personal air monitoring sessions took place from March 22 to June 21, 2019 at UIC. The ten participants were UIC ground-keeping or parking employees. Most of the participants aged 25-34 (50%) and had a high school degree or equivalent or some college with no degree (70%) (see Table XXIX). The complete/incomplete sampling events were documented based on the criteria of successfully completing the total hour air monitoring and retrieving collected data from two units of AirBeam2 operated side-by-side during each sampling event. Since the PM2.5 mass, which was collected by UPAS, was too small to determine the difference between pre- and post-sampling weights of each filter, the UPAS measured PM2.5 concentrations were not available and the complete sampling events for UPAS could not be evaluated. Based on the AirBeam2 collected data (N=50), 48 (96%) of the AirBeam2 total sampling sessions were successful. The rationale behind the two incomplete sessions included: 1) data was not recorded by one unit of the AirBeam2 or the session was not saved; 2) data was not recorded properly by one unit of the AirBeam2 i.e., the sensor discontinuously communicated with the AirCasting application resulting in four short period data collection with less than one-minute recording sampling duration.

2. <u>Analysis of PM2.5 Exposure Concentrations Collected by AirBeam2 Sensors</u>

The average of 1-minute PM2.5 mean personal exposure concentrations varied from 0.3 µg/m^3 to 26.3 µg/m^3 (ground-keeping) and 0.0-11.9 µg/m^3 (parking) (see Appendix R). The variations of PM2.5 exposure concentrations among task groups were observed shown in the bar plots in Figure 27. Overall, workers engaged in mowing had the highest 1-minute PM2.5 mean exposures (6.9-26.3 µg/m^3); while the exposures of parking employees (i.e., cashiers and parking valets) were lower (0.0-6.4 µg/m^3). The Wilcoxon rank sum test suggested that, at 95% confidence, PM2.5 exposure concentrations were significantly different between ground-keeping and parking workers. The Kruskal-Wallis rank sum test demonstrated that at 95% confidence, PM2.5 median concentrations were significantly different among workers engaging in different tasks (p-value=0.0002). The multiple comparisons based on pair-wise rankings analysis demonstrated that, at 95% confidence, PM2.5 exposure concentrations among workers who were mowing (MW) were significantly greater than those who were doing cashier jobs and/or working in the office (CSOF), and valet parking (VP). In addition, PM2.5 exposure concentrations among workers who were picking trash and cleaning parking lots (PTC) were significantly greater than those who were doing cashier jobs and/or working in the office (CSOF) and valet parking (VP) (see the box plots in Figure 28).

3. AirBeam2 Sensor Performance

The sensor performance was analyzed based on the sampling sessions in which workers wore two units of AirBeam2 in their breathing-zone i.e., the Q and Y sampling sessions during May-June 2019 (N=29). The percentage of the data recovery of AirBeam2 recorded measurements was ≥75 with an exception of two units of AirBeam2 (26 and 37%, respectively). Approximately 70% of the total sampling sessions that two AirBeam2 sensors were operated, excepting nine sampling sessions i.e., Q11, Q14, Y13, Q31, Q34, Q44, Q61, Q81, and Q91, two units of AirBeam reported similarly 1-minute PM2.5 mean measured concentrations as data shown in Tables XXX and XXXI. The correlation plots between the 1-minute PM2.5 mean concentrations measured by two units of AirBeam2 demonstrated a very weak to very strong correlation (R^2=0.11-0.99) with a moderate correlation (R^2=0.64) across all Q and Y sampling sessions. Sixty-five percent of the total sampling sessions included in the analysis demonstrated strong to very strong correlation between two units of AirBeam2 (R^2>0.7). However, the agreement between the measurements of two AirBeam2 units was relatively low as the slope and intercept values deviated from the perfect value of 1 (for slope) and 0 (for intercept) (see Table XXXII). The variation of AirBeam2 sensor performance was noticed regardless of the occupational or task groups. Although the UPAS performance was not determined due to the shortage of collected PM2.5 mass data, the documented flow rates demonstrated that the pre- and post-sampling flow rate differences were less than 10%. In addition, the UPAS flow rates were less than 4% different from the designated flow rate (1lpm) indicating some degree of reliability of the UPAS sensor in support of occupational personal exposure assessment in the outdoor work environment.

4. <u>Feasibility of Employing the Low-Cost Sensors</u>

The feasibility of employing the low-cost PM2.5 sensors among the participants was assessed by utilizing the feasibility assessment tool. The results of the feasibility assessment survey data collected during shadowing sampling session are summarized in Table XXXIII. All participants (100%) correctly placed the sensors in the breathing-zone and complied with the general air sampling procedures. The majority of the total participants had a high level of comfort in using the sensors (60%) and periodically checked the AirBeam2 sensors (65%) and UPAS (50%) during the sampling sessions. Among the participants who demonstrated a medium and a low level of comfort in using the sensors, 42% could not recall the critical steps for operating UPAS i.e., configuring devices and starting and stopping the sensors; 33% could not recall the critical steps for operating AirBeam2 i.e., pairing the sensor with the AirCasting application and starting and saving the recording sessions; and 25% asked a few questions pertaining to the sensors e.g., how to check whether the sensors were operating. Fifty-five percent of the total participants who took notes during the sampling sessions utilizing the AirCasting application (25%) and the time-activity monitoring observation log (30%). The calculated RCS for each shadowing sessions (N=20), summarized in Table XXXIV, ranged from 0.42 to 1 with a mean of 0.7. Sixty percent of the total shadowing sampling sessions demonstrated that participants had a high attention/interest level in conducting air monitoring employing the low-cost sensors and complying with the sampling protocol using the criterion of RCS greater than 0.7. Participants aged ≥45 demonstrated lower RCS values (RCS=0.42-0.58) than those aged <45 (RCS=0.58-1). Participants with an associate degree had higher RCS values (RCS=0.67-1) as compared to those with less than a high school diploma (RCS=0.58-0.67) and those with high school degree or equivalent (GED) or some college with no degree (RCS=0.42-0.92). The results suggested the feasibility and the utility of employing the AirBeam2 and UPAS sensors in occupational setting following the training of the workers on how to operate the sensors and conduct personal exposure monitoring.

D. Discussion

The measured PM2.5 personal exposure concentrations were different among workers performing various tasks. The highest PM2.5 concentration as measured by AirBeam2 was observed among ground-keeping workers engaged in mowing (average concentration=12.4 µg/m^3); while, low PM2.5 concentrations were observed among parking workers (average concentration <3 µg/m^3). The recommendation based on the findings includes the UIC Facilities Management implements personal protection to those workers exposed to higher particulate matter during their routine work. PM exposure concentrations among parking workers were expected to be high based on previous studies (Debia et al., 2017; Samal et al., 2013; Yan et al., 2017) which was not aligned with the results from the present study. This could be explained by the low number of vehicles in some parking locations; several locations were outdoor parking lots; and most vehicles were cars and rarely pick-up trucks, thus the accumulation of PM2.5 in the working areas was less than that observed in the previous studies. In addition, in several sampling days, the weather was cold and windy; thus, parking workers who were doing cashier jobs closed their booths' doors and/or windows during sampling sessions which could minimize PM2.5 exposures from outdoors. Parking valets could be exposed to PM2.5 during their routine work when picking up and dropping off the vehicles. They walked between the buildings and the parking facilities/lots. The sampling sessions might not occur during busy hours reflecting low PM2.5 exposure concentrations observed. In addition, during several sampling days with cold and windy conditions, the workers cut through the buildings; thus, their exposures to PM2.5 was relatively low due to less exposure to the roadside traffic. It was also observed that during their routine work, they did not open the vehicles' windows while driving or idling the vehicles. In the present study, the sampling events were based on convenience, weather, as well as, the availability of the sensors. The locations and tasks of each participant were announced right before their shifts started each working day; as a result, the observation on various tasks was limited. The time-activity data was missing in several runs, with the exception of the shadowing sessions, which could restrict the discussion about tasks/activities and working environment corresponding to PM2.5 exposure concentrations. The participants were encouraged to record the time-activity data every five minutes during the sampling sessions. However, air quality data recording was very demanding as it required the participants to start, stop, and properly save the session, as well as to check whether the recording had occurred or was disrupted (Matkovic et al., 2017). These multitasks, on top of their regular work, might be an intervening factor in their specific time-activity pattern recording. The investigator observed that, in general, the participants' tasks/activities and locations would be similar during a whole hour sampling duration of each sampling session. In the current study, the AirBeam2 sensors demonstrated a moderate intra-sampler variability (R^2=0.64) which was greater than the AirBeam sensor performance of the previous studies (R^2>0.8) (DeWitt et al., 2020; Feinberg et al., 2018; Jiao et al., 2016; Mukherjee et al., 2017; Mukherjee et al., 2019). This might be due to the uncertainties occurring during the mobile air sampling since the present study was a mobile personal air sampling as opposed to a stationary air monitoring in the previous studies. The participants' movement while conducting the air monitoring could slightly shift the sampling orientation of each unit of the sensors resulting in measurement discrepancies between the two units (Mukherjee et al., 2017). However, we could not feasibly compare the intra-sampler performance of AirBeam sensor used in community setting (see chapter III) and at the IEPA Northbrook Air Monitoring Station (see chapter IV) with the AirBeam2 used in this occupational study since AirBeam2 is a modified and improved version of AirBeam that was released Spring 2018. Our study, we believe, is the first study that attempts to assess intra-sampler performance of AirBeam2 in occupational settings with workers working outdoors. Thus, we could not compare our results to those reported in the literature in this case. The UPAS pre- and post-sampling flow rates were consistent and close to the designated flow rate. The accuracy of the flow rate, which is one essential specification pertaining to the air sampling quality, suggested some extent of the reliability of the UPAS sensor. Further studies for evaluating the UPAS sensor performance will require a longer sampling duration, especially in the relatively low concentrations as observed in the current studied conditions, to collect adequate PM2.5 mass on the filter for PM2.5 exposure characterization. It would be beneficial to determine the background concentrations in trial experiments prior to the initiation of the sampling activities to inquire the optimal sampling durations which was not feasible in this study due to the logistical reasons.

Low-cost sensors have facilitated personal exposure assessment in environmental and non-occupational settings to support citizen science projects and intervention programs (Fletcher et al., 2014; Klepeis et al., 2013; Liang et al., 2019; Miskell, Salmond, & Williams, 2018; Semple et al.,, 2015; Steinle et al., 2015). However, the use of low-cost sensors in occupational settings has been limited, for example, the low-cost sensor networks have been deployed in a heavy-vehicle manufacturing facility, for mapping occupational hazards and estimating personal exposures (Zuidema, Stebounova et al., 2019; Zuidema, Sousan et al., 2019). Cattaneo and colleagues highlighted an important need for assessing individual exposures in the workplace by utilizing low-cost sensors in the participants' breathing-zone (Cattaneo et al., 2010). Personal exposure assessment is very crucial since personal exposure concentrations may vary by individual and location (Liang et al., 2019). The advantages of implementing the low-cost sensors including an incorporation of real-time air sampling and GPS locations which have provided a more accurate time-activity data corresponding to measured air pollutant concentrations; in addition to being lightweight, small and generating low-noise are properties that improve the feasibility of employing the sensors in the personal exposure assessment research which is reinforced by the findings from the present study (Koehler & Peters, 2015). The investigator observed a moderate to high degree of RCS (RCS=0.42-1.00) reflecting the feasibility of employing AirBeam2 and UPAS sensors across all participants. The results underscored an importance of the training on how to operate the sensors in a step-by-step fashion with hands-on experiences and provided detailed sensor user guidelines. Most of the participants were highly comfortable in using the sensors. Overall, the results suggested the feasibility and utility of the AirBeams2 and UPAS sensors for personal air quality monitoring in ground-keeping and parking workers' working environments in support of occupational personal exposure studies. The data recovery observed was high (≥75%), even when the AirBeam2 sensors were operated during routine tasks performed, which required excessive body movements and mobilities. The disconnection between AirBeam2 sensor and the AirCasting application occurred once when the participant left the phone in their vehicle while performing tasks approximately 20 feet away. The issue was easily resolved by carrying the phone and the AirBeam2 sensor at close proximity. The connection/data synchronization issue may not be applied to the UPAS sensor since the UPAS application has a different connection procedure and purpose from that of the AirCasting application i.e., after configuring the UPAS sensors with the UPAS application via the phone and starting the sampling session, the phone would not further involve in controlling the sensors/collecting the data. This would lessen the burden of checking the phone during the sampling session. However, the real-time data cannot be retrieved during the sampling session.

E. Conclusion

The findings suggested the AirBeam2 and UPAS sensors were feasible to employ and facilitate the characterization of the real-time personal exposure of parking and ground-keeping workers to PM2.5 on the UIC campus. This study provides information on personal exposure concentration characteristics among the ground-keeping and parking workers. The AirBeam2 sensor demonstrated low to high precision in collecting PM2.5 concentrations among different working microenvironments and tasks. The low-cost sensors were useful in assessing the personal exposures corresponding to time-activity data and addressing the issues pertaining to occupational air quality that warrant the comprehensive evaluation of air pollution relevant to certain individuals’ locations and activities. However, further studies are needed to fill the knowledge gap of the uncertainties impacting the low-cost sensor performance in mobile air monitoring applications in occupational settings.

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TABLE XXVIII. ASSIGNED SCORES OF ANSWERS TO QUESTIONS IN THE FEASIBILITY TOOL

Questions	Assigned scores
Q1. Are the personal exposure sensors correctly placed in the breathing zone? (Y/N)	
Yes (Y)	1
No (N)	0
Q2. Is the participant comfortable in using sensors? (L/M/H)	
Low (L)	1
Medium (M)	2
High (H)	3
Q3. Has the participant periodically checked the cell phone to make sure that the AirBeam are collecting data? (Y/N)	
Yes (Y)	1
No (N)	0
Q4. Has the participant periodically checked the cell phone to make sure that the UPAS are collecting data and nothing blocking the inlet? (Y/N)	
Yes (Y)	1
No (N)	0
Q5. What is the level of compliance with general sampling procedures (e.g., regularly working, not smoking, keeping sensor dry)? (L/M/H)	
Low (L)	1
Medium (M)	2
High (H)	3
How many times they took notes during sampling period?	
8-12	3
4-7	2
1-3	1
no record	0
Total (maximum scores)	**12**

TABLE XXIX. SUMMARY OF PARTICIPANTS' AGE RANGES AND EDUCATION LEVELS

Collected demographic parameters	**N**	**%**
Age ranges		
18-24	2	20
25-34	5	50
35-44	1	10
45-54	1	10
55 and over	1	10
Do not want to respond	0	0
Education levels		
Less than a high school diploma	1	10
High school degree or equivalent (GED) or some college with no degree	7	70
Associated degree	2	20
Bachelor's degree or higher	0	0
Do not want to respond	0	0

TABLE XXX. 1-MINUTE MEAN PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2, Q AND Y SESSIONS, WITH TASKS (GROUND-KEEPING) AND HDV DENSITY

Sampling sessions	Sampling time	AirBeam unit#	Sampling duration (min)	Obs. Number	%data recovery	1-min mean concentration (µg/m^3) Min-Max	Mean (sd)	Tasks	HDV density (units/minute)
Q11	5/22/19 6:39-7:46	1	67	63	94	2.2-16.4	5.6 (4.0)	PTC	0.01
		2	67	56	84	0.4-7.4	1.7 (1.5)		
Q14	6/4/19 6:49-7:59	1	70	69	99	5.5-23.5	10.7 (4.6)	MW	0.00
		2	70	68	97	0.7-9	3.1 (1.8)		
Y13	5/30/19 11:57-12:55	1	58	58	100	0.0-37.4	7.7 (6.9)	MW	NA
		2	58	58	100	1.0-76.1	20.0 (13.7)		
Q21	5/22/19 8:52-9:53	1	61	60	98	1.6-22.3	5.9 (3.6)	WWGT	0.08
		2	61	58	95	4.6-32.3	10.5 (4.6)		
Q24	6/11/19 6:55-8:10	1	75	74	99	4.9-20.2	6.3 (1.8)	PTC	0.35
		2	75	72	96	5.4-20.2	6.7 (1.9)		
Y23	5/30/19 12:03-13:09	1	66	66	100	1.8-51.9	11.5 (9.3)	NA	0.03
		2	66	66	100	2.0-53.5	12.1 (10.0)		
Q31	5/22/19 10:08-11:02	1	54	14	26	2.7-5.2	4.1 (0.7)	WWGT	0.28
		2	54	54	100	0.0-2.1	0.7 (0.5)		
Q34	6/6/19 6:45-8:02	1	77	76	99	1.1-7.1	3.7 (0.9)	PTC	0.00
		2	76	74	97	6.3-24.0	12.7 (2.3)		
Y33	5/30/19 10:02-10:56	1	54	42	78	0.6-21.9	4.1 (3.6)	WWGT	MA
		2	54	42	78	0.4-25.2	4.6 (4.6)		
Q41	5/23/19 10:09-11:11	1	62	23	37	0.0-1.6	0.2 (0.4)	WWGT	0.06
		2	62	61	98	0.0-3.2	0.3 (0.7)		
Q44	6/6/19 8:47-10:07	1	80	78	98	1.8-23.8	6.1 (3.9)	MW	0.01
		2	80	79	99	6.95-43.7	16.6 (6.9)		
Y43	5/30/19 10:04-10:56	1	52	52	100	0.1-16.0	3.5 (4.7)	NA	NA
		2	52	52	100	0.0-4.8	0.9 (1.6)		
Q51	5/23/19 7:09-8:08	1	59	59	100	0.0-15.3	2.7 (3.6)	WWGT	0.19
		2	59	59	100	0.0-13.3	1.3 (2.5)		
Q54	6/11/19 9:14-10:17	1	63	63	100	2.2-32.3	10.8 (5.9)	MW	0.35
		2	63	61	97	3.3-33.6	11.6 (6.4)		
Y53	6/4/19 6:40-7:53	1	73	73	100	3.3-99.3	14.6 (18.4)	NA	NA
		2	73	73	100	2.9-97.4	12.9 (16.9)		

TABLE XXXI. 1-MINUTE MEAN PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2, Q AND Y SESSIONS, WITH TASKS (PARKING) AND HDV DENSITY

Sampling sessions	Sampling time	AirBeam unit#	Sampling duration (min)	Obs. Number	%Data recovery	1-min PM2.5 mean concentration (μg/m³)		Tasks	HDV density (units/minute)
						Min-Max	Mean (sd)		
Q61	5/24/19 10:14-11:00	1	46	46	100	0.0-1.2	0.6 (0.4)	CSOF	0.09
		2	46	46	100	1.5-6.3	4.7 (1.5)		
Q64	6/11/19 13:00-14:02	1	62	62	100	0.9-17.1	2.6 (2.5)	CSOF	0.00
		2	62	61	98	1.6-19.1	3.2 (2.6)		
Y66	6/12/19 9:21-10:18	1	57	57	100	3.5-7.1	5.5 (0.7)	NA	NA
		2	57	57	100	2.9-7.4	4.4 (1.0)		
Q71	5/23/19 13:26-14:31	1	65	65	100	0.0	0.0	CSOF	0.08
		2	65	65	100	0.0-0.4	0.01 (0.04)		
Q74	6/10/19 9:09-10:00	1	61	61	100	0.0-1.3	0.6 (0.3)	CSOF	0.00
		2	61	59	97	0.1-1.5	0.7 (0.3)		
Q81	5/29/19 14:47-15:50	1	63	63	100	0.1-16.7	4.2 (5.3)	VP	0.00
		2	63	61	97	0.0-7.6	1.7 (2.5)		
Q84	6/10/19 11:03-12:07	1	64	64	100	0.0-1.8	0.4 (0.5)	VP	0.03
		2	64	60	94	0.0-1.6	0.4 (0.4)		
Y86	6/12/19 11:02-11:53	1	51	51	100	0.0-8.5	1.7 (2.0)	VP	NA
		2	51	51	100	0.0-11.5	2.1 (2.5)		
Q91	5/24/19 15:05-16:10	1	65	65	100	0.0-1.0	0.2 (0.3)	VP	0.00
		2	65	31	48	0.0-5.05	1.5 (2.0)		
Q94	6/11/19 14:59-15:57	1	58	58	100	0.0-4.1	0.6 (1.0)	VP	0.00
		2	58	56	97	0.0-4.8	0.7 (1.2)		
Y96	6/19/19 11:18-12:08	1	50	48	96	0.0-7.1	2.3 (2.2)	NA	NA
		2	50	48	96	0.0-7.8	2.3 (2.2)		
Q101	6/3/19 12:47-13:55	1	68	58	85	0.1-3.5	0.9 (0.5)	CSOF	0.00
		2	58	58	100	0.1-4.2	0.7 (0.6)		
Q104	6/11/19 11:16-12:15	1	59	59	100	2.7-14.8	6.1 (3.4)	CSOF	0.00
		2	59	59	100	2.5-16.8	6.1 (4.1)		
Y106	6/21/19 10:05-11:02	1	57	57	100	1.4-3.6	2.4 (0.5)	NA	NA
		2	57	57	100	1.6-3.6	2.5 (0.5)		

TABLE XXXII. LINEAR REGRESSION STATISTICS OF THE CORRELATION PLOTS BETWEEN 1-MINUTE PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2-1 AND -2

Occupations	Runs	Obs. number	R^2	Slope	Intercept
Ground-keeping	Q11	55	0.85	0.3405	-0.0962
	Q14	68	0.91	0.369	-0.7592
	Y13	58	0.96	1.9334	5.0965
	All Part#1 runs	**181**	**0.30**	**1.1071**	**-0.456**
	Q21	58	0.94	1.2167	3.3459
	Q24	72	0.87	0.9428	0.6818
	Y23	66	0.98	1.0301	0.2934
	All Part#2 runs	**196**	**0.89**	**0.9866**	**1.8022**
	Q31	13	0.15	0.2741	0.1241
	Q34	74	0.73	2.5207	3.5433
	Y33	42	0.17	0.53	2.4905
	All Part#3 runs	**129**	**0.03**	**0.475**	**7.0878**
	Q41	21	0.92	1.7692	0.018
	Q44	76	0.92	1.6981	6.2282
	Y43	52	0.98	0.3365	-0.2977
	All Part#4 runs	**149**	**0.52**	**1.5339**	**2.0483**
	Q51	58	0.83	0.6545	-0.3899
	Q54	61	0.95	1.0544	0.0335
	Y53	73	0.99	0.9166	-0.4596
	All Part#5 runs	**192**	**0.98**	**0.9311**	**-0.1645**
Parking	Q61	45	0.65	3.0573	2.8946
	Q64	60	0.95	1.0109	0.6118
	Y66	57	0.30	0.7826	0.0433
	All Part#6 runs	**162**	**0.28**	**0.404**	**2.7969**
	Q71	63	NA	NA	NA
	Q74	59	0.01	0.0884	0.636
	All Part#7 runs	**122**	**0.50**	**0.7844**	**0.1253**
	Q81	61	0.69	0.3782	0.044
	Q84	60	0.55	0.5925	0.0831
	Y86	51	0.95	1.1921	0.0966
	All Part#8 runs	**172**	**0.57**	**0.4278**	**0.4049**
	Q91	32	0.81	6.6285	0.4189
	Q94	56	0.95	1.1876	0.0369
	Y96	48	0.96	0.9836	0.0028
	All Part#9 runs	**136**	**0.70**	**0.9371**	**0.4295**
	Q101	59	0.56	0.9425	-0.1047
	Q104	59	0.94	1.1321	-0.8116
	Y106	57	0.11	0.3203	1.6914
	All Part#10 runs	**175**	**0.95**	**1.067**	**-0.2494**
Across all runs		**1614**	**0.64**	**0.9587**	**1.1947**

TABLE XXXIII. PERCENTAGE OF PARTICIPANTS OBSERVED UNDER EACH GROUP OF FESIBILITY ASSESSMENT METRICS

Feasibility Assessment Metrics		**n (%)**
Correctly Placement of Sensors	Yes	20 (100)
	No	0 (0)
Level of Comfortable in Using Sensors	High	12 (60)
	Medium	3 (15)
	Low	5 (25)
Periodically Checking the AirBeam Sensors	Yes	13 (65)
	No	7 (35)
Periodically Checking the UPAS Sensors	Yes	10(50)
	No	10 (50)
Level of Compliance for Sampling Procedure	High	20 (100)
	Medium	0 (0)
	Low	0 (0)

TABLE XXXIV. THE CALCULATED RCS AND COLLECTED DEMOGRAPHIC INFORMATION FOR EACH SHADOWING SESSION[a]

Participant ID	Occupation	Sampling sessions	Age	Education level	Relative Compliance Scores (RCS)
G1	Grounds	Q11	25-34	1	0.58
G1	Grounds	Q14	25-34	1	0.67
G2	Grounds	Q21	18-24	2	0.83
G2	Grounds	Q24	18-24	2	0.58
G3	Grounds	Q31	25-34	3	1.00
G3	Grounds	Q34	25-34	3	0.92
G4	Grounds	Q41	18-24	2	0.75
G4	Grounds	Q44	18-24	2	0.83
G5	Grounds	Q51	45-54	2	0.50
G5	Grounds	Q54	45-54	2	0.42
P1	Parking	Q61	55 and over	2	0.50
P1	Parking	Q64	55 and over	2	0.58
P2	Parking	Q71	25-34	2	0.75
P2	Parking	Q74	25-34	2	0.58
P3	Parking	Q101	25-34	2	0.58
P3	Parking	Q104	25-34	2	0.92
P4	Parking	Q81	35-44	3	0.92
P4	Parking	Q84	35-44	3	0.67
P5	Parking	Q91	25-34	2	0.75
P5	Parking	Q94	25-34	2	0.75

[a]Education levels were categorized into four categories: “1” was less than high school diploma, “2” was high school degree or equivalent (GED) or some college with no degree, “3” was associated degree, and “4” was Bachelor's degree or higher), in addition to “do not want to respond” was also available as one of the answers.

Figure 26. Side-by-side air monitoring sensors in the participant’s breathing-zone, two AirBeam2 (white) and two UPAS (black) sensors

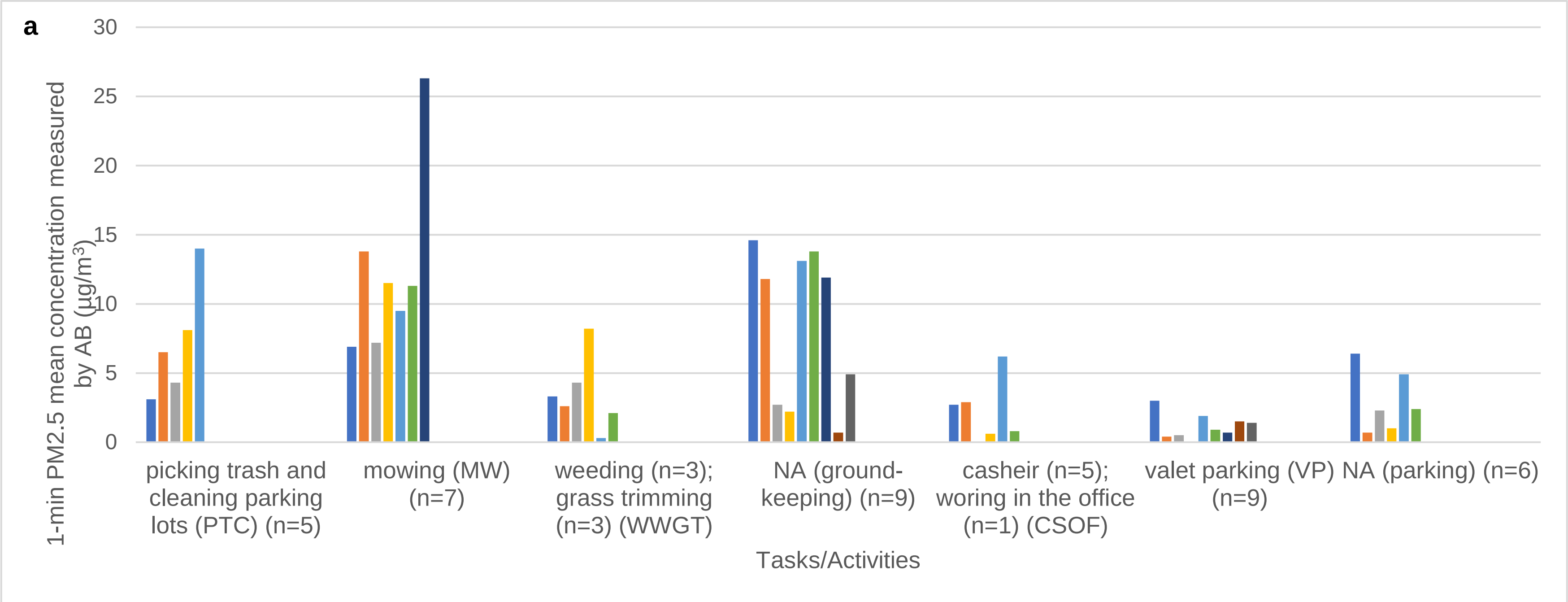


Figure 27. The bar chart showing 1-minute personal PM2.5 mean concentrations measured by AirBeam2 sensors by each task group by each sampling session[a] among UIC ground-keeping and parking employees (a) and across all sampling sessions by each task group (b).

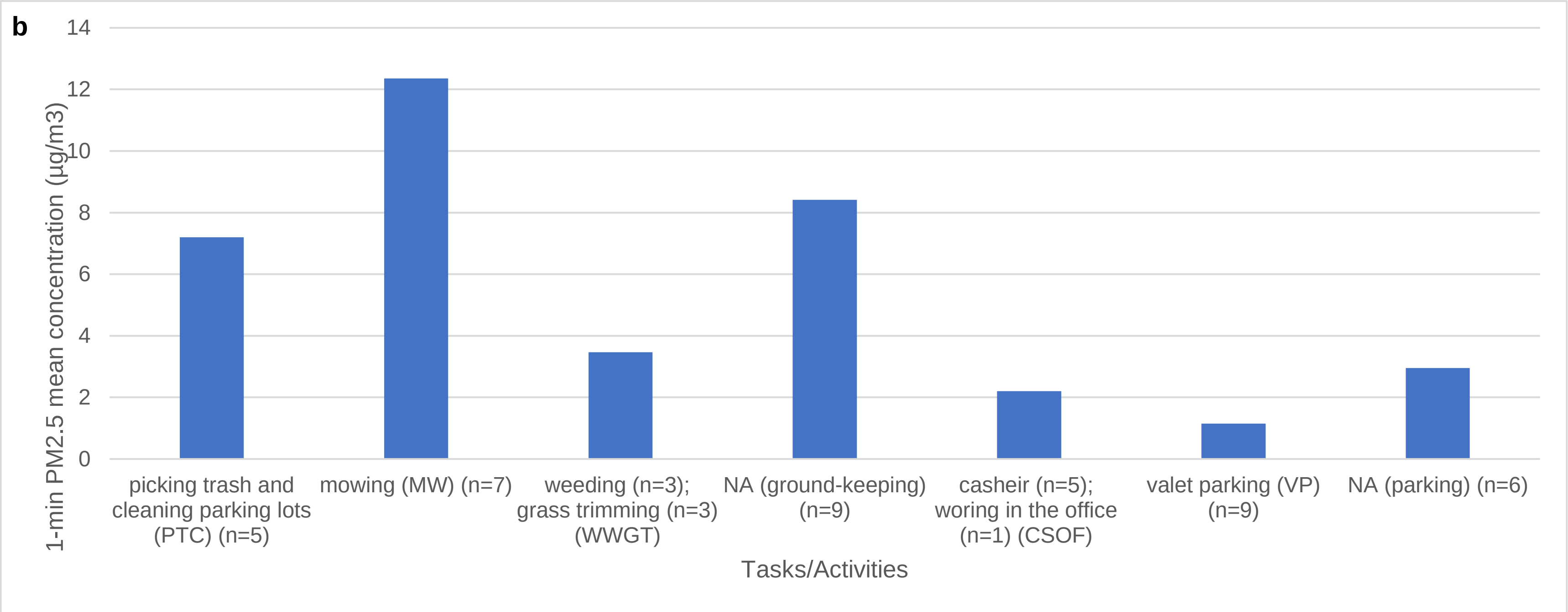


Figure 27. The bar chart showing 1-minute personal PM2.5 mean concentrations measured by AirBeam2 sensors by each task group by each sampling session[a] among UIC ground-keeping and parking employees (a) and across all sampling sessions by each task group (b). (continued)

[a]Sampling sessions included in each task group were indicated in the following list in the order displayed in the bar chart.
PTC: Q11, Q24, X25, Q34, X35
MW: Q14, Y13, X32, Q44, X42, Q54, X52
WWGT: X22, Q31, Y33, Q21, Q41, Q51
CSOF: Q61, Q64, Q71, Q74, Q101, Q104
VP: Q81, Q84, X82, X85, Y66, Q91, O94, X92, X95
NA (not applicable/no record): ground-keeping related tasks (X15, Y23, X45, Y43, X55, Y53); parking related tasks (X72, X75, Y76, Y96, X102, X105, Y106)

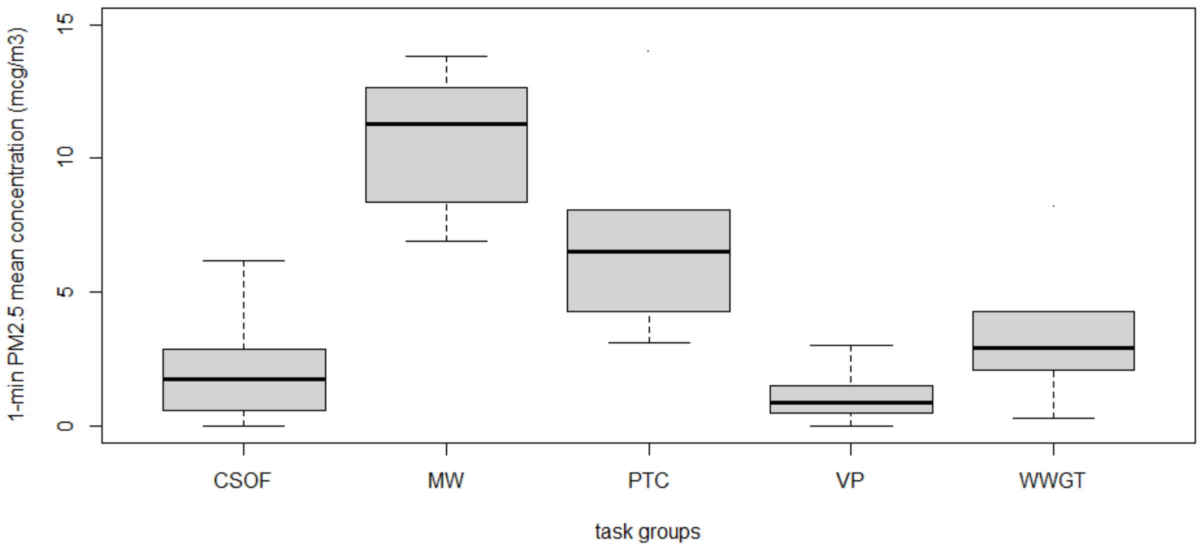


Figure 28**.** Box plots of 1-min PM2.5 mean concentrations measured by AirBeam2 sensors by workers' task groups i.e., doing cashier jobs and/or office work (CSOF), mowing (MW), picking trash and cleaning parking lots (PTC), valet parking (VP), weeding and grass trimming (WWGT)

VI. OVERALL CONCLUSIONS AND RECOMMENDATIONS

The air quality monitoring has been shifting to more miniaturized and low-cost sensors to provide supplemental air quality data in the finer spatial and temporal scales, in addition to advancing personal exposure assessment and characterization. Emerging sensor technologies such as mobile phone applications, the Internet of Things, and portable low-cost sensors empower citizens to create air monitoring networks and collect air quality data to better understand their community and working environments. However, several challenges of employing low-cost sensors including the reliability of the sensors and the feasibility of employing them have not been fully determined. The low-cost sensors do not yet support the regulatory compliance assessment with the National Ambient Air Quality Standards (NAAQS) for criteria air pollutants. Their performance must be thoroughly tested against their respective EPA FRM/FEM monitors both in laboratory and field conditions in different geographic regions across seasons leading to development of correction (or scaling factors). These factors (approved or adopted by USEPA and its state counterparts and the scientific community) could then be applied to low-cost sensor data to assess compliance with the NAAQS in the future. The field of performance assessment for low-cost sensors is its infancy. Furthermore, new sensors and/or new versions of existing sensors are becoming available in the marketplace for consumer use continuously. The continual flux in sensor technology and new generation sensors presents a challenge to sensor performance assessment studies and their ultimate use for regulatory compliance assessment studies. The current study provided valuable information discussing the performance of selected low-cost PM and gaseous pollutant monitoring sensors. The collocated testing results suggested that all investigated low-cost sensors had a very high degree of precision and sufficient accuracy in obtaining air pollutant concentrations at various locations to assess the relative air quality. The low-cost sensors had some degree of correlation and agreement with their FRM/FEM monitors; therefore, the low-cost sensors should not be used for compliance assessment. However, they are very useful tools in determining the locations with higher concentrations (hot spots) that warrant further evaluation using regulatory monitoring tools and methods, and for public education, outreach, and advocacy efforts. The ability to obtain real-time air quality data with at a relatively low cost facilitates air quality data collection at neighborhood level, empowers community organizations and citizens, and fosters policy advocacy and development efforts for improving public health and remedying environmental pollution inequities and disparities.

In order to obtain high quality air quality data, on top of the sensor performance, the proper operation of the sensors and compliance with the general sampling protocol are indeed required. This key point was addressed in the current study. The community residents successfully used the low-cost sensors for personal air quality monitoring in each community. Our study demonstrates that it is feasible to employ the sensors for local air quality assessment in support of citizen science projects, when the citizen scientists are properly trained on how to operate and interact with air sensors and a collaborative relationship is established between the research team and community in each phase of the project. Moreover, the workers successfully used the low-cost PM2.5 sensors for personal air quality monitoring in their work environment. Our study demonstrates that it is feasible to employ the sensors for occupational air quality assessment in support of personal exposure studies, when the workers are properly trained on how to operate and interact with air sensors. The step-by-step training on how to operate each sensor provided to the participants resulted in a high level of comfort in using the sensors and the ability to conduct air monitoring. However, multi-tasking of the tasks during sampling events may influence an accuracy and precision of the time-activity pattern recording during air sampling efforts. Further training of the citizen scientists is necessary to collect representative data for time-activity pattern recording. Furthermore, the findings highlighted the significance of implementing the effective Train-the-Trainer approach in support of community-based research air monitoring projects empowering citizen scientists to perform local air quality assessment for addressing their public health concerns pertaining to air quality in their neighborhoods.

Several challenges of employing low-cost sensors under field conditions have indicated the need for further studies to address the uncertainties impacting low-cost sensor performance. The low-cost sensors were observed to be impacted by the temperature and humidity, which vary among locations and time periods; therefore, an additional correction of sensor measurements for the specific meteorological conditions need to be investigated in order to develop more appropriate and representative correction algorithms for specific locations that take the impact of weather conditions on sampler performance into account. This suggested more collocated studies in diverse temporal and spatial conditions to fill the knowledge gap of the sensor performance in different locations. In addition, the long-term reliability of sensors as air monitoring tools needs to be determined in longer sampling time duration studies. Another opportunity for further research includes the investigation of the uncertainties impacting the low-cost sensor precision in mobile air monitoring in different settings.

APPENDICES

Appendix A. AirBeam and Terrier operational manual guide

AIRBEAM PM2.5 AND TERRIER NO/CO/CO_2 USER GUIDE

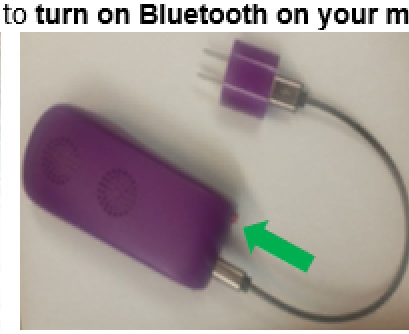
Preparation to Air Monitoring Session in the Community

Description of Sensors: The AirBeam monitors for Particulate Matter 2.5 (PM 2.5), fine particles that are less than 2.5 microns. These particles can enter the lungs and bloodstream. Sources include cars, busses and diesel trucks, metal recyclers, pet coke storage, and other manufacturers. The Terrier monitors three pollutants, Nitrous oxide (NO), carbon monoxide (CO) and carbon dioxide (CO_2). Sources of these pollutants include busses, diesel trucks and cars and any activity that involves fossil fuel combustion.
Calibration: These sensors do not need to be recalibrated.
Charging the battery of the AirBeam sensor, Terrier sensor, and the Android mobile phone: Be sure that the batteries are fully charged prior to sampling. When the AirBeam is fully charged the green light appearing on the side of the AirBeam will disappear. AirBeam battery life is 10 hours. For Terrier, Green LED indicates the sensor is on. After fully charged, the RED light appearing on the top of the Terrier sensor will disappear. The battery lifetime for Terrier is 20 hours. The Terrier sensor works best with a warmup period so that the NO and CO sensors can stabilize. Best practice is to try and keep the Terrier sensor powered while charging. For both sensors, charging time depends on how depleted the battery is.
Reporting Equipment Issues: If the equipment is malfunctioning, please document the issue and how it was addressed in the "Operating Issues Log" (In the Shared Materials subfolder on the Shared Air Shared Action Google Drive). This will help us keep track of problem units. If you would like assistance, or if the equipment is in need of repair/you need to contact the manufacturer, please email the Equipment Health Desk ASAP (send an email to both, Olga Lyandres, olyandres@delta-institute.org, and Caitlin Dillon, cdillon@delta-institute.org to report the problem).

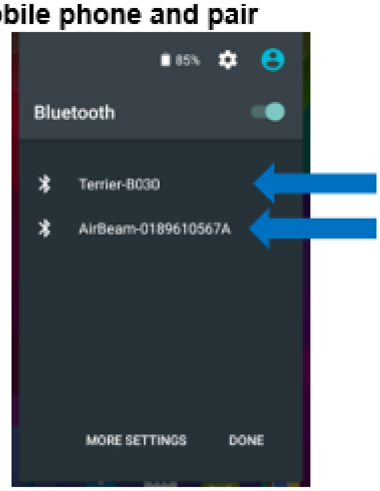
Setting up AirCasting profile.

1. Download AirCasting App: Go to the "Play Store" in an Android phone/Tablet, type "AirCasting", then, click "Install". You may reboot your phone to see the app.
2. Connect the AirBeam and Terrier sensors to your Android mobile phone one at a time: **Press the Square Button at the top of the AirBeam sensor as shown in the picture below (see red arrow), and press the red circle button on the top of the Terrier sensor (see green arrow).** You first need to **turn on Bluetooth on your mobile phone and pair**

AirBeam



Terrier

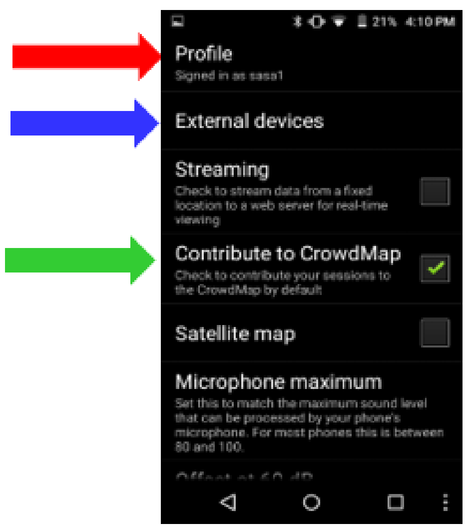


Page for Bluetooth Set Up

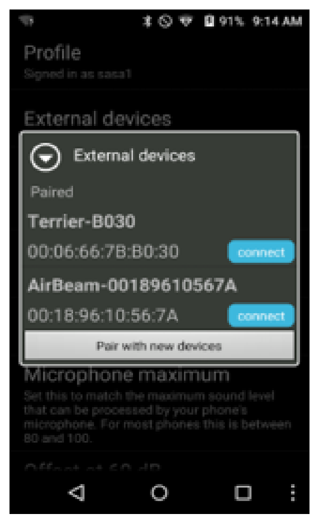
Appendix A (continued)

the Air Beam and Terrier sensors with your phone (see blue arrows). If you would like additional information about your sensors, visit the project google drive, and search for the Equipment Database.

3. **Open AirCasting App on your mobile phone.** AirBeam/Terrier sensors' location accuracy displayed on the AirCasting Map improves outside, so once you begin monitoring, the location appearing on the map will track your actual location. Press the "Setting" button (on a BLU Android phone, "Setting" can be accessed by pressing "vertical three dot" button on the lower right corner of the screen). You will go to another screen. Then, do the following steps:
   a. **First, check your Profile name by pressing "Profile" (see red arrow below):** Check that the profile name matches the one given to you during training or matches the one listed on the Equipment Database for your sensors.
   b. **Second, go to "External devices" (see blue arrow below)", then press "Connect" as shown in the right image, then press "Yes" for both sensors (Terrier and AirBeam).** This ensures successful pairing between AirBeam and Terrier sensors and the mobile phone.
   c. **Third, press "Contribute to CrowdMap" option on the screen (see green arrow)** and make sure there is green checkmark in the box as shown in the left image below).
   d. **Fourth, scroll down further to see the "Show route trace" option on the screen (i.e., further down in the left image shown below). Press on this option** and make sure that there is a green checkmark in the box. **Your AirCasting App is now set up.**



AirCasting Settings Page



Pairing External Devices

Monitoring with AirBeam and Terrier

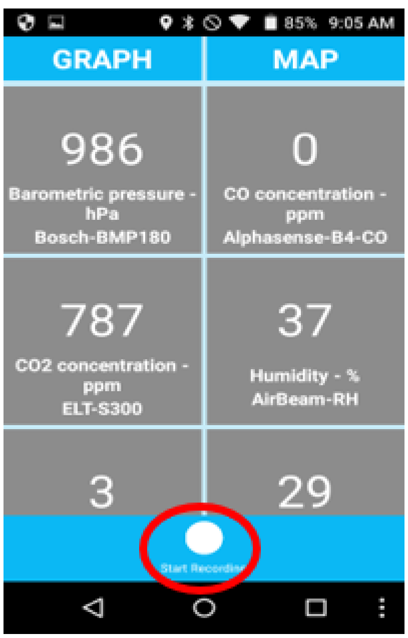
Placement of Sensor in the Breathing Zone: Hang and secure the sensors near the top of the backpack straps, as close to your nose/mouth as possible. The AirBeam should be on your right strap, and the Terrier should be on your left strap. This guidance should be followed in all sampling events.

Appendix A (continued)

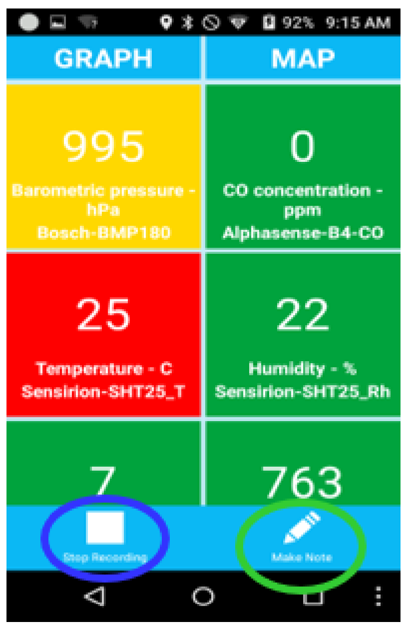
Sampling Location/Route/Time/Duration: Check with your Community Organization contact to make sure that the sampling occurs during predetermined sampling location, route, time and duration.
Location Accuracy: AirBeam/Terrier sensors' location accuracy displayed on the AirCasting Map improves outside, so once you begin monitoring, the location appearing on the map will track your actual location. Please check the accuracy of your location in the map.

Please follow the steps shown below to monitor air quality with AirBeam/Terrier:

1. **Start recording the PM2.5 concentrations by AirBeam and NO, CO, and CO_2 concentrations by Terrier in ambient air by pressing the "Record" button on the left image shown below (see red circle)**. Once the recording starts, you will see the screen image (with two circles) on the right shown below. The ten boxes displayed on the screen are for the ten specific data you are recording (which you will see all if you scroll the screen further down): Pressure, Humidity, Particulate Matter, Temperature (in °C and °F), Sound Level, CO, CO_2 and NO. The square at the left bottom (within the blue circle) is the "Stop Recording" button.



Monitoring screen before recording



Monitoring screen while recording

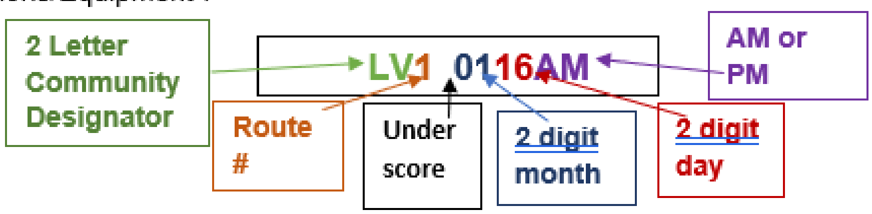
2. This application also has a notes function if you would like to use it. The pencil image close to the right bottom corner of the screen (within green circle on the right image) is the "Make Note" button. As you are recording data, you may want to add some notes and/or save a picture attached to a specific time of your recording of air monitoring data. For example, if a big truck passes by you or you see any smoke generating activity, you may want to add a note and/or take a picture of the truck or any other item generating smoke/dust. In order to do this, press "Make Note" at the bottom right corner (in green circle in the right image shown above). You will see a new screen with a window to type/enter your note. Type your note (e.g., truck), then, press "Attach a photo." You will be directed to the camera of the phone. Press the circle to take a picture of dust/smoke generating activity. Press the checkmark to attach the picture file. Then, press "Save" to save the note you typed and the picture you took. Now,

Appendix A (continued)

you will return to the data recording screen shown above (the image on the right above with ten boxes).

3. **At the end of air monitoring session, stop recoding by pressing the "Stop Recording" button** (within blue circle) on the lower left corner of the screen as shown in the image on the right shown above. You will be directed to a new screen, which will have the following information:

Session details: Title: Enter the session title. Session titles will follow the pattern documented below. For complete information on naming sessions visit the Equipment Database on Google drive, and click the sheet titled 'Labeling Sessions/Equipment".



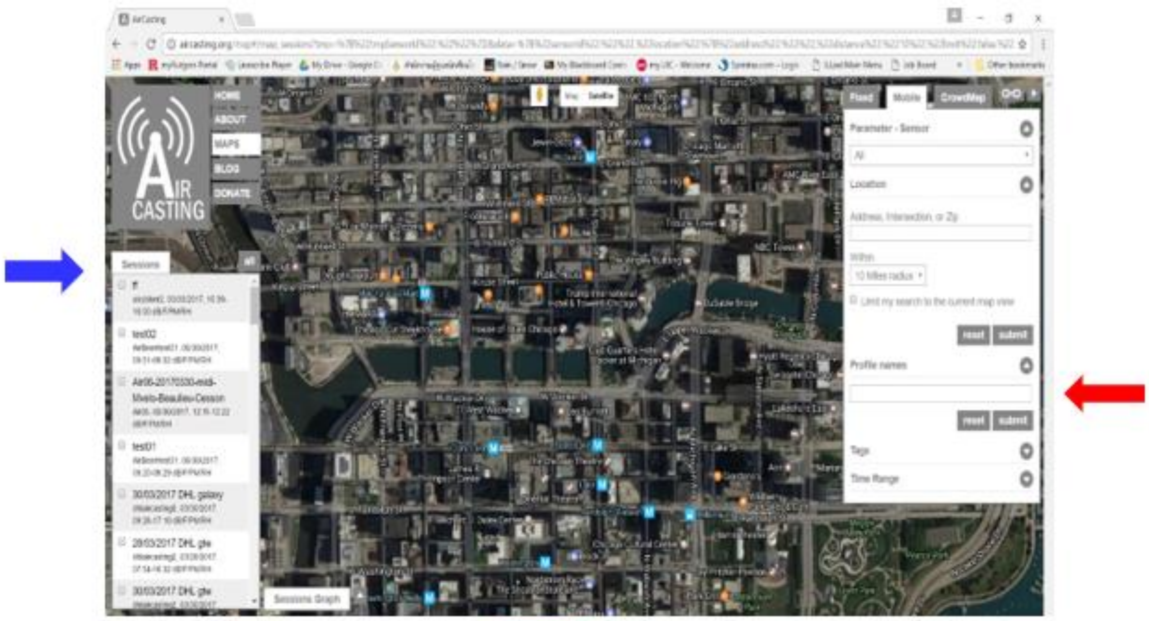
Tags: You can enter 'Mobile' and 'Route #' to help you explore the data on the website, but this is not necessary.

Description: Leave empty

Then, press "Save session" button.

Appendix A (continued)

4. **Now, you can access the air monitoring data you recorded online**. Go to http://www.aircasting.org/ website. Click on "MAPS" on the top left corner of the screen. Next, select "Mobile" option in the menu on the upper right side of the screen. You will see a map similar to the image shown below. Now, enter/type your profile name(s) (which you used to connect with the AirBeam and Terrier sensors) within the "Profile names" box (see red arrow) under the "Mobile" menu. Press submit. Next, choose the air monitoring SESSION or event you would like to view by putting a checkmark at the box for that air monitoring session listed under the SESSION window (blue arrow) on the left.



AirCasting website

Appendix B. Mobile monitoring observation log

Community Organization:		**CODES FOR SOURCES (use in table below in PM Generating Source column)**		
Sampling Date:		**Truck=T**	**Cigarette/Cigar Smoke=CS**	**Industry Source=IS (stack emissions)**
Sampling Time Period:		**Car=C**	**Any Other Smoke= OS**	**Construction Dust= CD**
		Bus=B	**Barbecue=B**	**Any other air pollution source=O**
		Train=TR	**Lawn Mower=LM**	
Session Name: LV#_mmddAM or LV#_mmddPM This is for Little Village, where # = route number; mm = two digit month; dd = two digit day; AM for morning routes; or PM for afternoon routes; if applicable.				
Important Note: If you see any particulate matter or dust generating activity in your immediate vicinity, please enter applicable code(s) for the "PM Generating Source" below as accurately as possible. **Accurate documentation of the time of the PM generating source is very important.**				
Date	**Time**	**PM Generating Source Code (Enter the Codes shown above)**	**Initials**	**Comments/Notes**

Appendix C. Feasibility assessment tool

Questions	Answer			Comments
Sampling Date: **Sampling Time Period:** **Shadowing Time Period:**				
Community:				
Mobile Monitoring Route Number:				
Participant Number:				
Questions	**Answer**			**Comments**
1. Are the personal exposure sensors correctly placed in the breathing-zone? (AirBeam on the right; Terrier on the left)	Y	N		
2. Have the participants followed the sampling route correctly?	Y	N		
3. Are the participants comfortable in using sensors? [1]	L	M	H	
4. Have the participants periodically checked the cell phone to make sure that the sensors are collecting data?	Y	N		
5. Has the participant used his/her A) cell phone (AirCasting platform) or B) hard copy Obs Log or C) Mixed for time-activity records of air pollution sources on mobile monitoring route?	A	B	C	
6. What is the level of compliance for recording time-activity data using the codes provided? [2]	Y	N		
7. What is the level of compliance with general sampling procedures (e.g., walking leisurely, not smoking, keeping sensors dry)? [3]	L	M	H	

Notes:

[1] The ease with which participants use AirBeam and Terrier personal exposure sensors will be quantitatively judged by the number of questions each participant asks the community organizer and/or other participants on the same route in the following manner: Less than 2 questions asked (High-H); 2-5 questions asked (Medium-M); >5 questions asked (Low-L);

[2] The UIC team will qualitatively assess the level of compliance associated with recording time-activity data by the participants in the following manner: Less than 2 instances where air pollution sources (e.g., a smoker passed by or construction dust encountered or a truck passed by) are not recorded (or missed) by the participant (High-H); 2-5 instances where air pollution sources are not recorded (or missed) (Medium-M); >5 instances where air pollution sources are not recorded (or missed) (Low-L). The participants are asked to record data on sources of air pollution on their route (as they are performing mobile monitoring) either electronically (the AirCasting software for AirBeam/Terrier sensors enable the participants taking notes on air pollution sources encountered during mobile monitoring and also taking pictures of these sources and saving notes/pictures along the way) or by documenting this information in time-activity data log in hard copy (see Appendix A) that they each will carry in their backpack. Each participant will decide what form of time-activity data collection effort they would like to undertake.

[3] The UIC team will qualitatively assess the level of compliance (e.g., walking leisurely instead of running; not smoking cigarettes or any other smoke generating substance while sampling; making sure that the equipment is kept dry while sampling) with general sampling procedures outlined in Air Monitoring Check List (see Appendix A) in the following manner: violation of guidelines only once (High-H); violation of guidelines 2-5 times (Medium-M); violation of guidelines >5 times during sampling (Low-L).

Appendix D. Summary of complete/incomplete air sampling events of low-cost sensors with community residents

TABLE XXXV. COMPLETE/INCOMPLETE SESSIONS OF AIRBEAM SENSOR, SUMMER 2017

Communities	Sampling Date	Sampling Time (shadowing time)	Sampling Event	Data Collected Using AirBeam1		Data Collected Using AirBeam2		Rationale for Unsuccessful Events
				Yes	No	Yes	No	
LV	6/15/2017	18:04-19:04	lv4_0615pm	X		X		
	6/16/2017	19:06-19:38	lv1_0616pm	X			X	One AirBeam did not record data.
	6/21/2017	9:13-10:33	lv2_0621am	X		X		
	6/22/2017	18:09-19:13	lv8_0622pm	X		X		
SE	7/19/2017	7:35-8:37	se1_0719am	X			X	One AirBeam did not record data.
	7/19/2017	9:03-10:03	se6_0719am	X		X		
	7/21/2017	9:53-10:41	se4_0721am	X		X		
	7/21/2017	8:43-9:32	se5_0721am	X		X		
SL	9/22/2017	9:00-9:53	sl2_0922am	X		X		
	9/22/2017	8:51-9:49	sl5_0922am	X		X		
	9/25/2017	17:03-17:59	sl4_0925pm	X		X		
	9/25/2017	17:13-18:19	sl3_0925pm	X		X		
PC	8/16/2017	1:49-2:49	pc1_0816pm	X		X		
	8/28/2017	12:26-13:17	pc3_0828pm	X			X	One AirBeam did not record data.
	8/18/2017	12:34-13:34	pc4_0818pm	X			X	One AirBeam did not record data.
	8/18/2017	16:05-16:31	pc1_0818pm	X			X	One AirBeam did not record data.
Total (16 runs)				16 (100%)	0 (0%)	11 (68.75%)	5 (31.25%)	

Appendix D (continued)

TABLE XXXVI. COMPLETE/INCOMPLETE SESSIONS OF TERRIOR SENSOR, SUMMER 2017

Communities	Sampling Date	Sampling Time	Data Collected Using Terrier 1		Data Collected Using Terrier 2		Rationale for Unsuccessful Events
			Yes	No	Yes	No	
LV	6/15/2017	18:04-19:04	X		X		
	6/16/2017	19:06-19:38	X			X	One Terrier did not record data
	6/21/2017	9:13-10:33	X		X		
	6/22/2017	18:09-19:13	X		X		
SE	7/19/2017	7:35-8:37	X			X	One Terrier did not record data
	7/19/2017	9:03-10:03	X			X	One Terrier did not record data
	7/19/2017	9:53-10:41	X			X	One Terrier provided all readings for CO as zero
	7/21/2017	8:43-9:32	X			X	One Terrier provided all readings for CO as zero
SL	9/22/2017	9:00-9:53	X		X		
	9/22/2017	8:51-9:49		X		X	The correlation coefficient was not able to be computed since two units of Terrier did not record data simultaneously
	9/25/2017	17:03-17:59	X			X	One Terrier provided all readings for CO as zero
	9/25/2017	17:13-18:19	X			X	One Terrier provided all readings for CO and NO as zero
PC	8/16/2017	1:49-2:49	X			X	One Terrier did not record data
	8/28/2017	12:26-13:17	X			X	One Terrier provided all readings for CO as zero
	8/18/2017	12:34-13:34		X		X	One Terrier provided all readings for CO as zero; One Terrier did not record data.
	8/18/2017	16:05-16:31		X		X	One Terrier provided all readings for CO as zero; One Terrier did not record data.
Total (16 runs)			13 (81.25%)	3 (18.75%)	4 (25%)	12 (75%)	

Appendix D (continued)

TABLE XXXVII. COMPLETE/INCOMPLETE SESSIONS OF AIRBEAM SENSOR, WINTER 2018

Communities	Sampling Date	Sampling Time	Sampling Event	Data Collected Using AirBeam1		Data Collected Using AirBeam2		Rationale for Unsuccessful Events
				Yes	No	Yes	No	
LV	3/26/2018	17:00-18:00	lv8_0326pm	X			X	Only one AirBeam were utilized for air sampling
	3/23/2018	18:00-18:59	lv9_0323am	X			X	Only one AirBeam were utilized for air sampling
	3/26/2018	7:00-7:38	lv1_0326am	X			X	Only one AirBeam were utilized for air sampling
	3/23/2018	6:29-7:06	lv6_0323am	X			X	Only one AirBeam were utilized for air sampling.
SE	3/23/2018	9:55-10:36	se1_0323am	X		X		
	3/23/2018	12:55-13:30	se3_0323am	X		X		
	3/23/3018	11:15-11:45	se5_0323am	X		X		
	3/23/2018	9:13-9:45	se2_0323am		X		X	There was no recorded data file in database/no saved session
SL	4/25/2018	8:35-9:35	sl1_0425amt	X			X	One AirBeam did not record data
	4/25/2018	9:55-10:42	sl2_0425amt	X			X	One AirBeam did not record data
	4/25/2018	11:03-12:10	sl3_0425amt	X			X	One AirBeam did not record data
	4/27/2018	8:49-9:55	sl4_0427amt	X			X	One AirBeam did not record data
	4/27/2018	10:26-10:45	sl2_0427amt	X			X	One AirBeam did not record data
PC	5/4/2018	10:13-10:47	pc1_0504amt	X			X	One AirBeam did not record data
	5/4/2018	11:10-11:56	pc4_0504amt	X			X	One AirBeam did not record data
	5/4/2018	12:26-13:10	pc8_0504pmt	X			X	One AirBeam did not record data
	5/4/2018	13:46-14:31	pc9_0504pmt	X			X	One AirBeam did not record data
Total (17 runs)				16 (94%)	1 (6%)	3 (18%)	14 (82%)	

Appendix E. The box plots of 1-minute air pollutant mean concentration measured by AirBeam/Terrier sensors by five classes of traffic condition

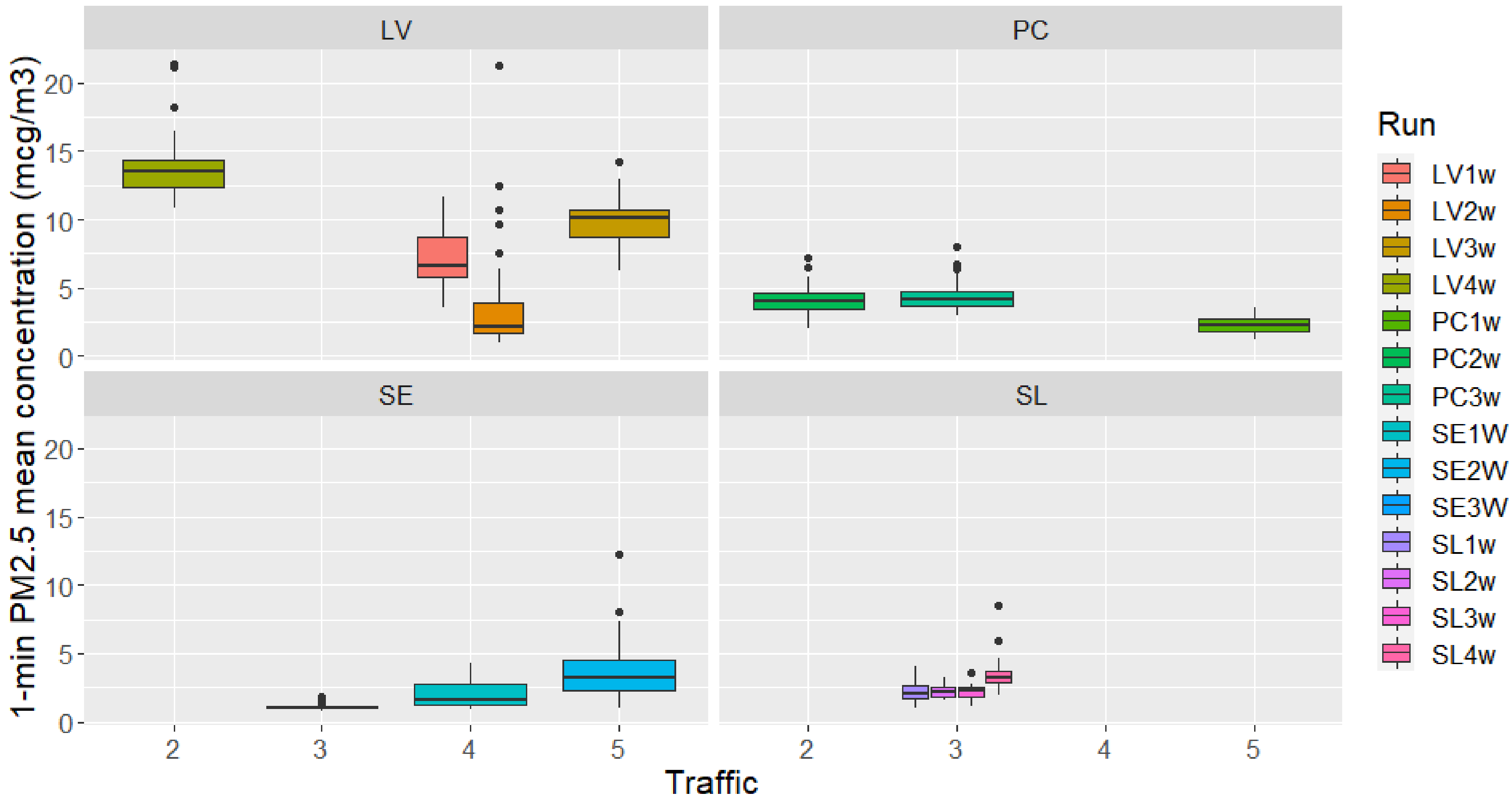


Figure 29. The box plots of 1-minute PM2.5 mean concentration (μg/m^3) measured by AirBeam sensor by five classes of traffic condition (class 1: light, class 2: light to medium, class 3: medium, class 4: medium to heavy, class 5: heavy).

Appendix E (continued)

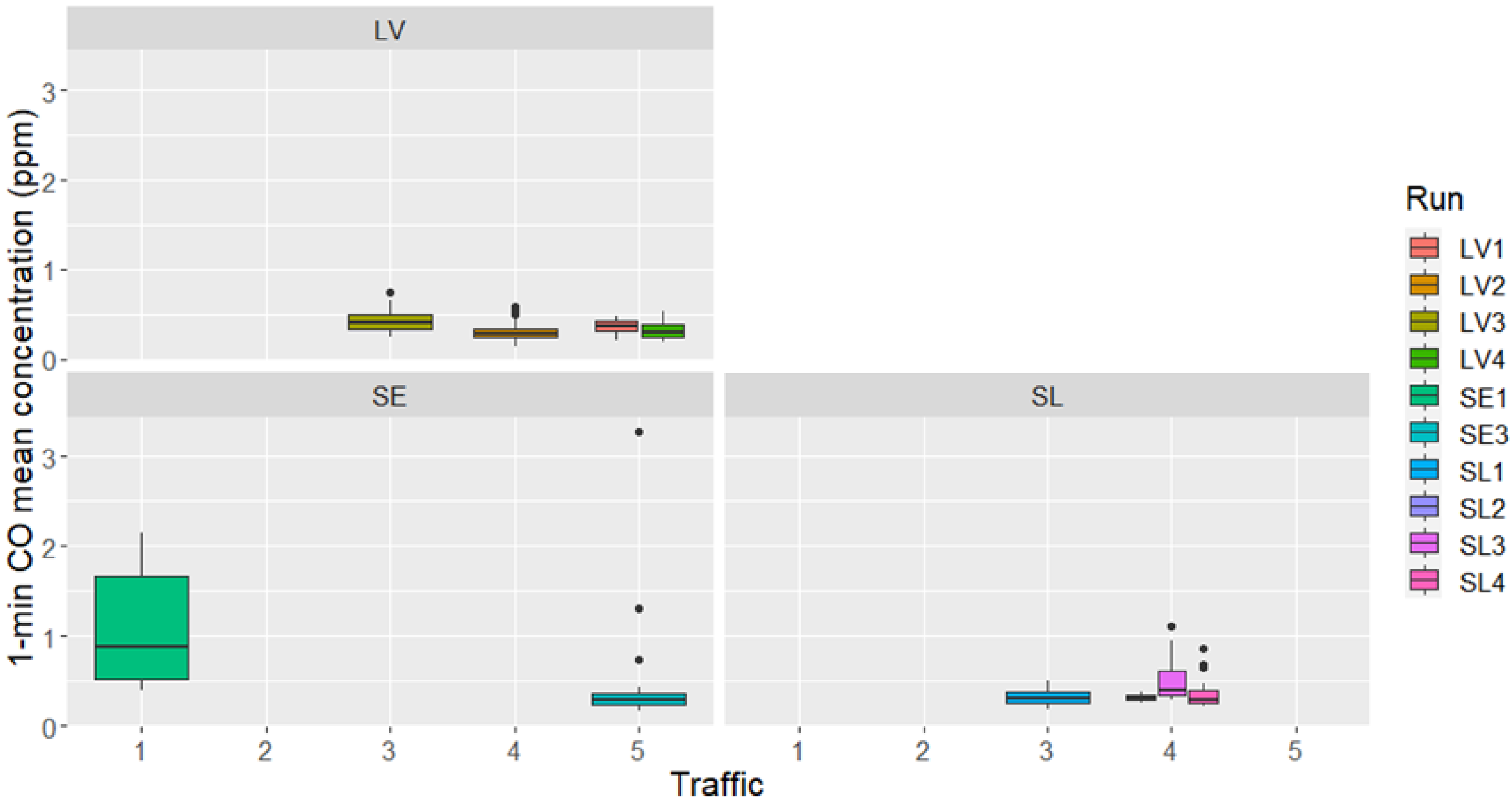


Figure 30. The box plots of 1-minute CO mean concentration (ppm) measured by Terrier sensor by five classes of traffic condition (class 1: light, class 2: light to medium, class 3: medium, class 4: medium to heavy, class 5: heavy).

Appendix E (continued)

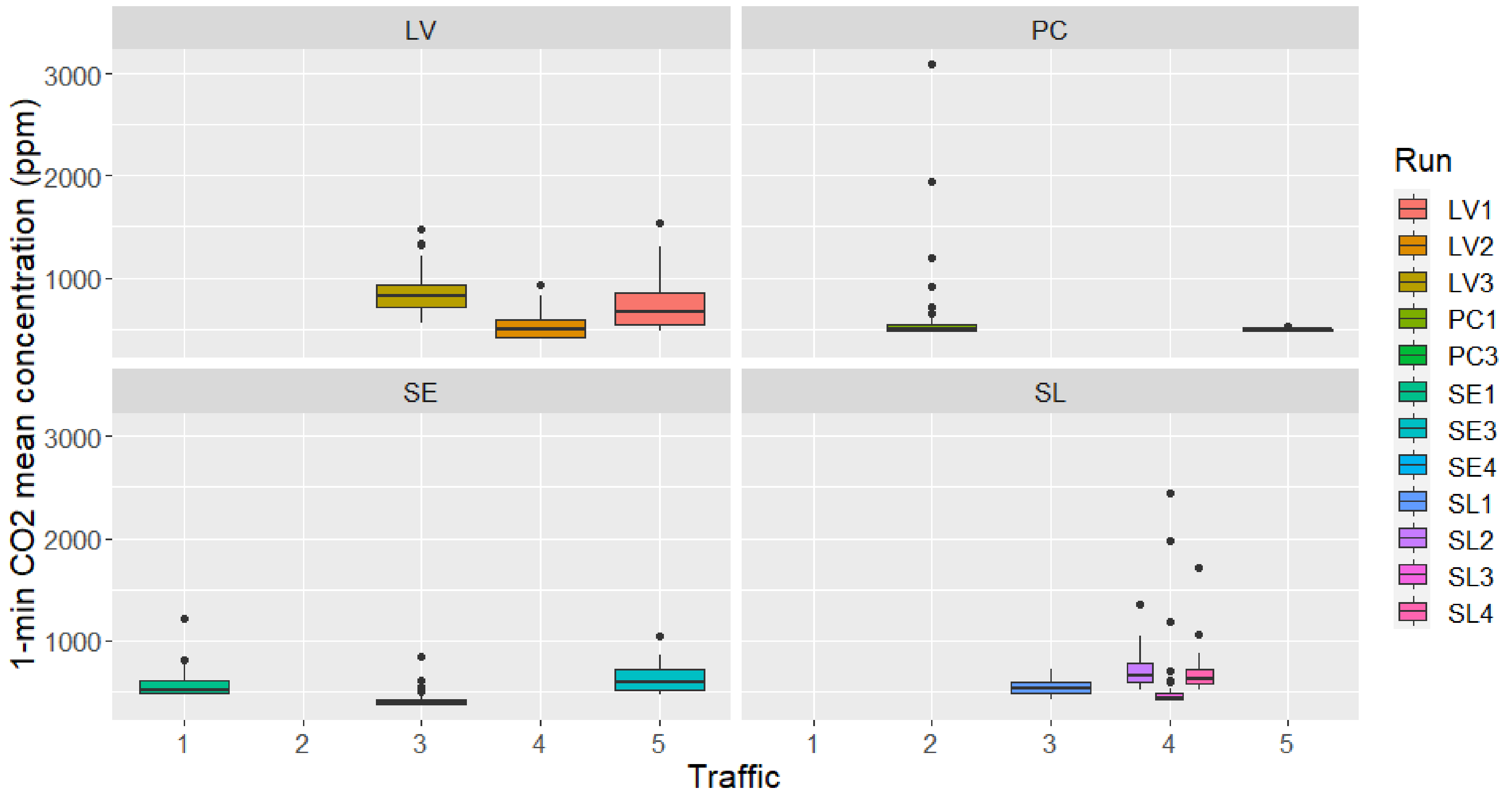


Figure 31. The box plots of 1-minute CO_2 mean concentration (ppm) measured by Terrier sensor by five classes of traffic condition (class 1: light, class 2: light to medium, class 3: medium, class 4: medium to heavy, class 5: heavy).

Appendix E (continued)

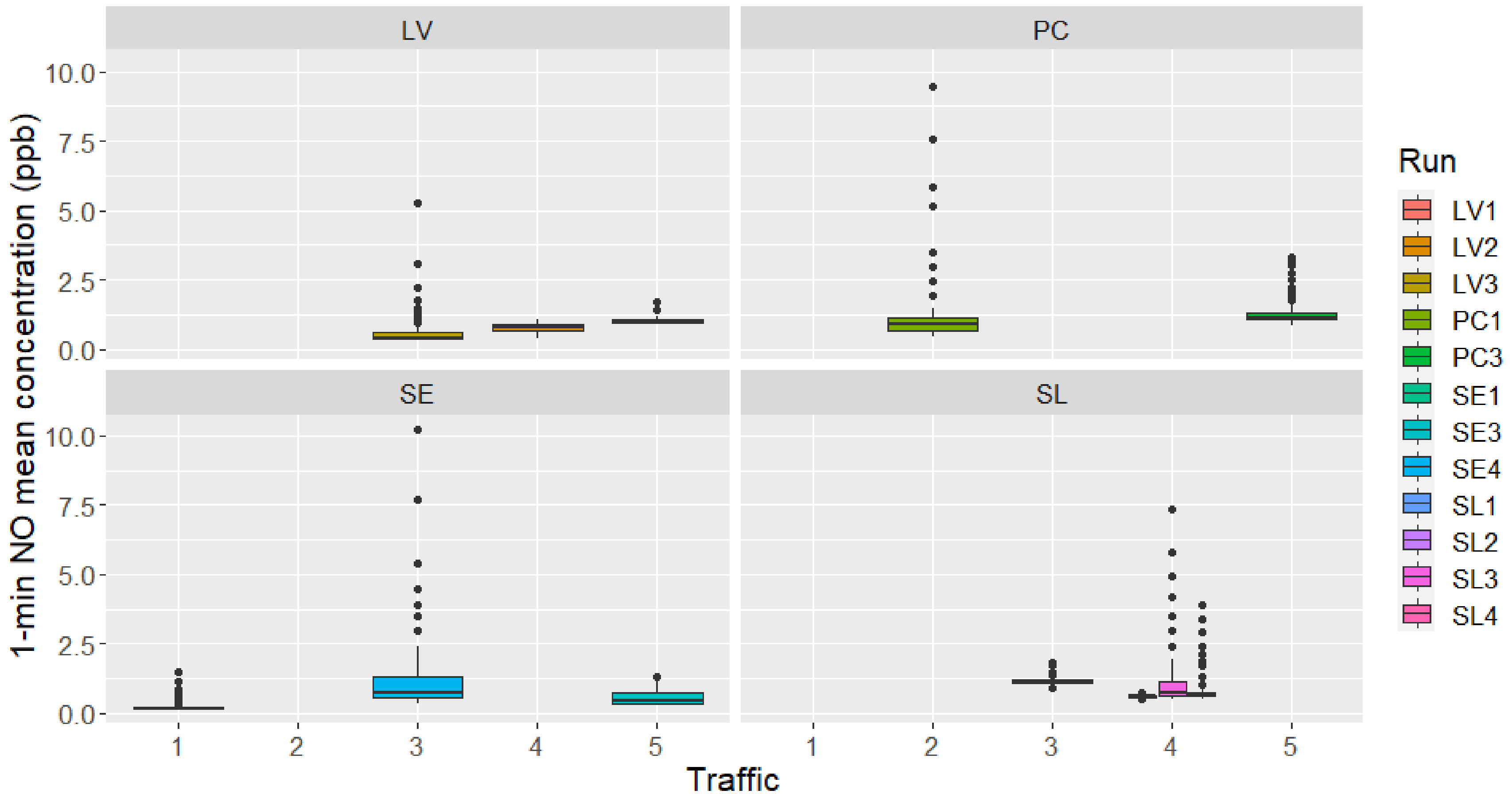
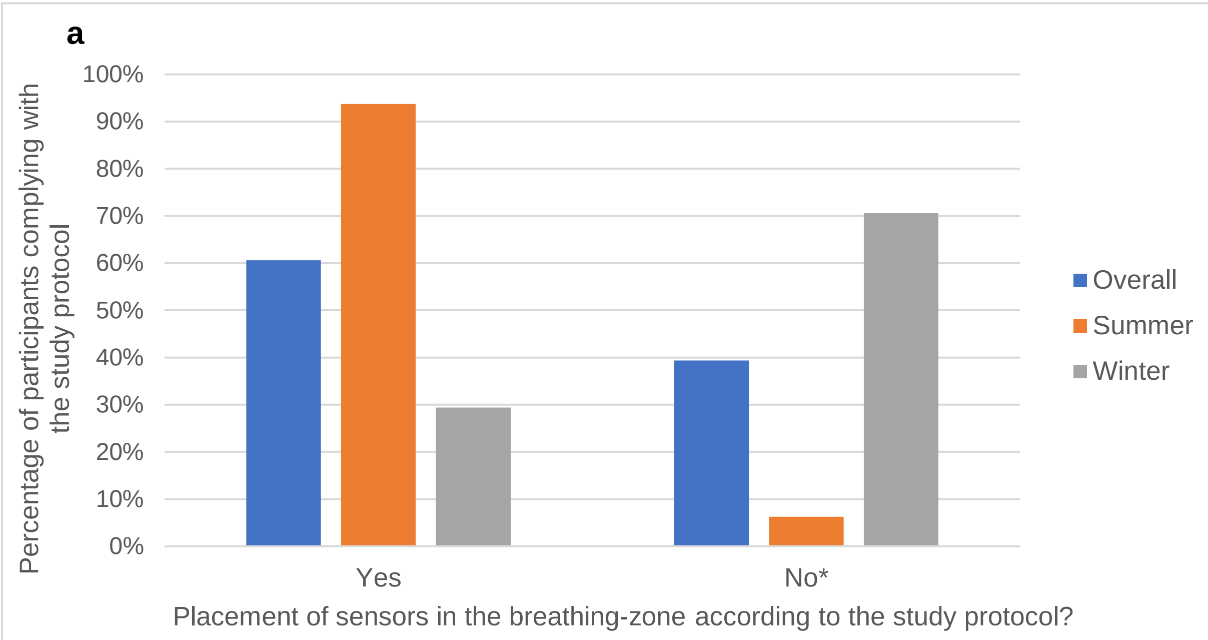


Figure 32. The box plots of 1-minute NO mean concentration (ppb) measured by Terrier sensor by five classes of traffic condition (class 1: light, class 2: light to medium, class 3: medium, class 4: medium to heavy, class 5: heavy)

Appendix F. Bar charts displaying a percentage of each answer of each feasibility assessment tool question (Appendix C)



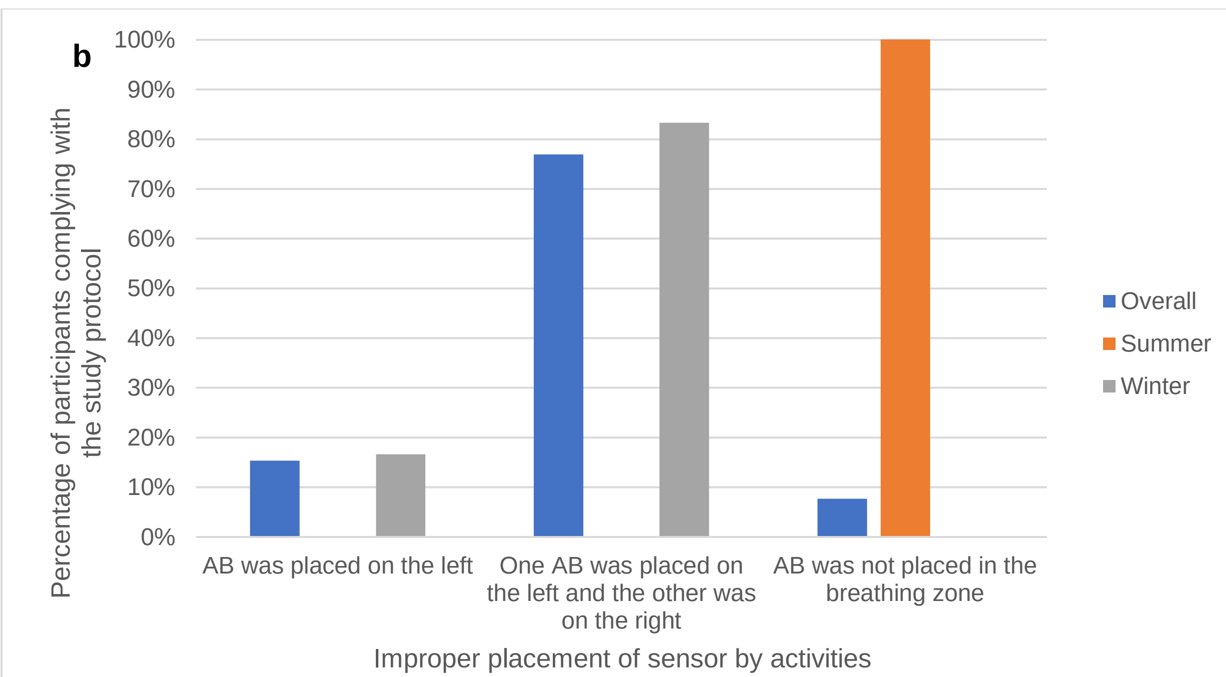


Figure 33. Bar charts displaying percentage of correctly/incorrectly placement of sensors (Question 1) among total participating community residents (a) and percentage of improper placement of sensors by activities (b)

Appendix F (continued)

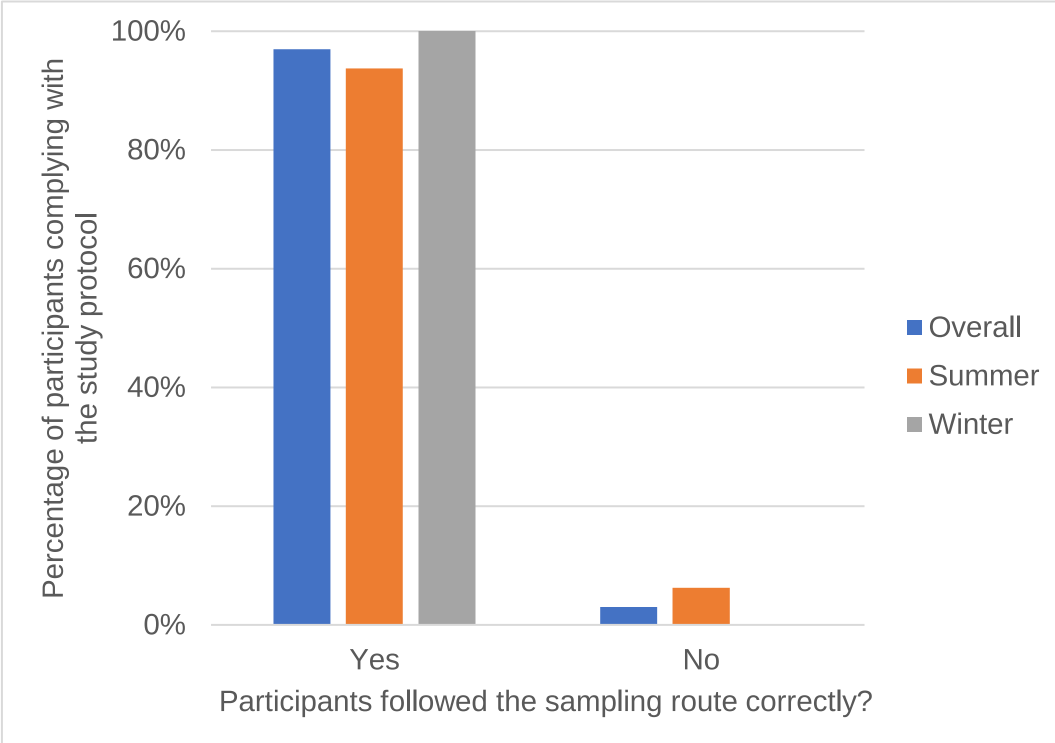


Figure 34. Bar charts displaying percentage of correctly/incorrectly following sampling route (Question 2) among total participating community residents

Appendix F (continued)

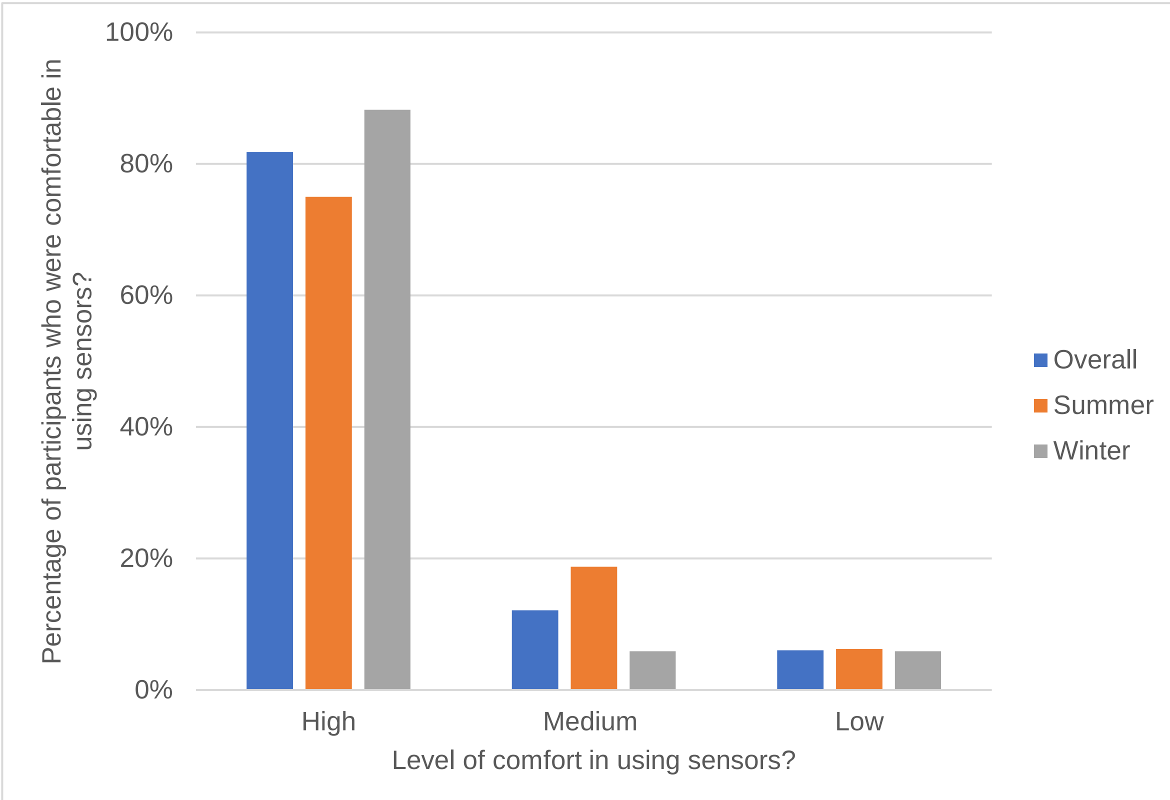


Figure 35. Bar charts displaying percentage of each level of comfortable in using sensors (Question 3) among total participating community residents

Appendix F (continued)

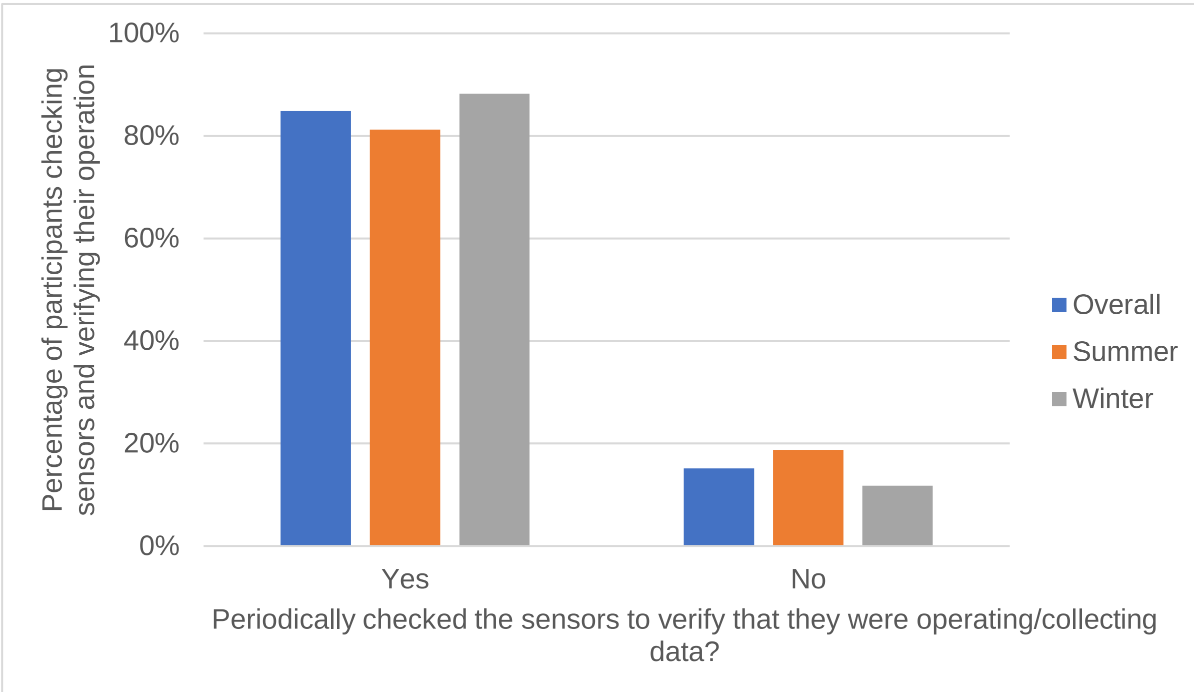


Figure 36. Bar charts displaying percentage of periodically checking sensors (Question 4) among total participating community residents

Appendix F (continued)

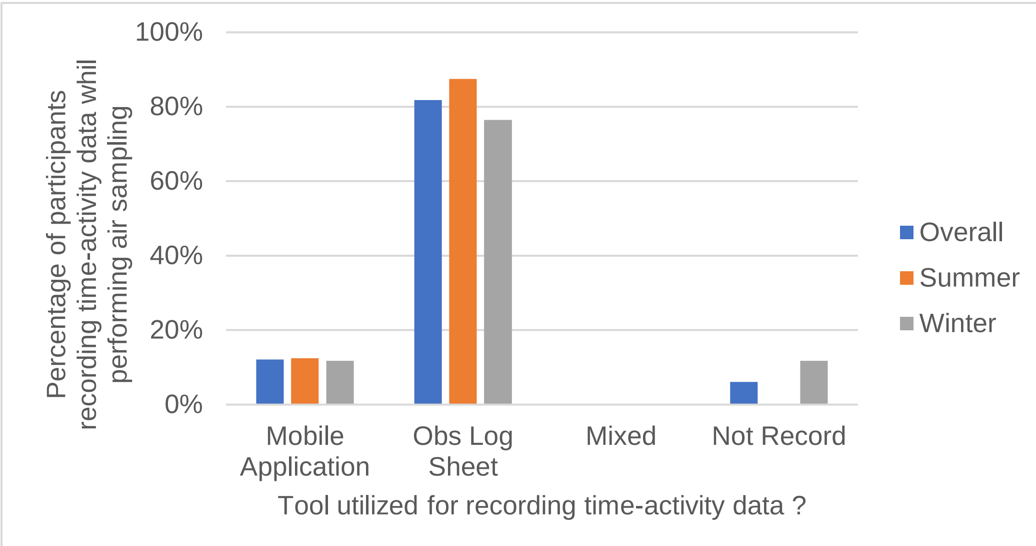


Figure 37. Bar charts displaying percentage of time-activity pattern recording by types of tools utilized (Question 5) among total participating community residents

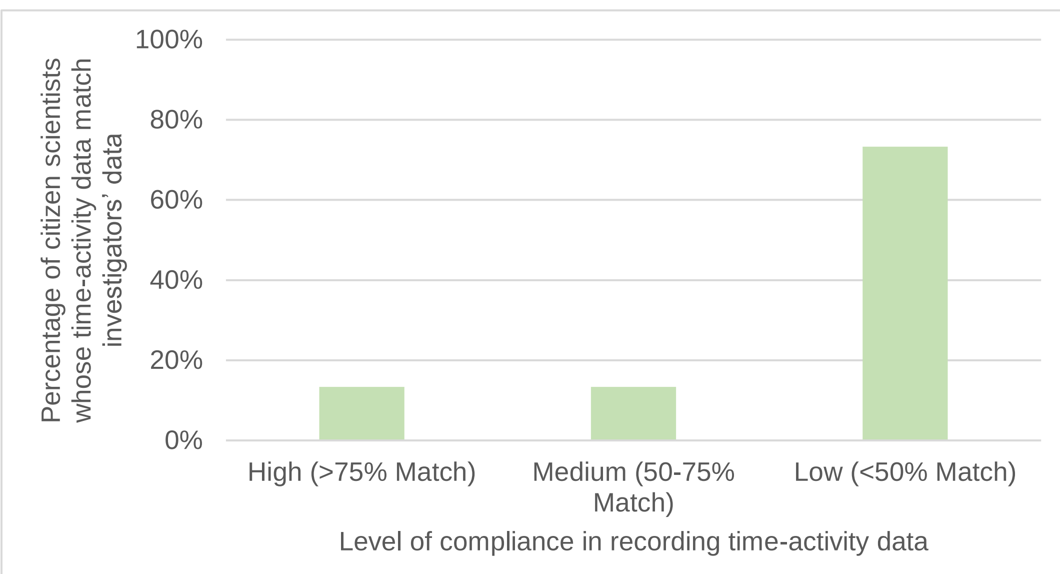


Figure 38. Bar charts displaying percentage of each level of compliance for recording time-activity (Question 6) among total participating community residents. All summer and two runs of the winter sessions were included in this calculation since the records of other winter sessions were missing.

Appendix F (continued)

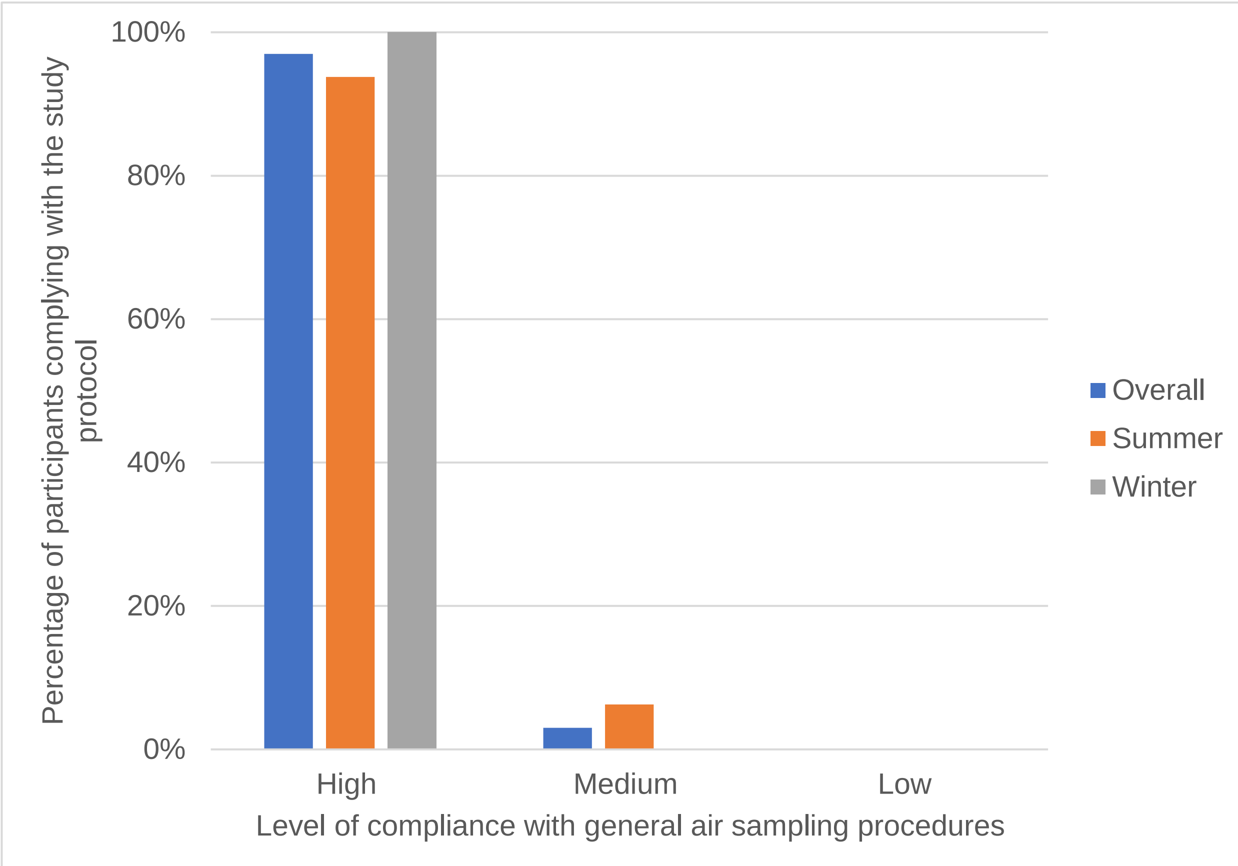


Figure 39. Bar charts displaying percentage of each level of compliance for sampling procedure (Question 7) among total participating community residents

Appendix G. Linear regression line statistics of the correlation plot between the measured concentrations of two units of the low-cost sensors

TABLE XXXVIII. LINEAR REGRESSION STATISTICS OF THE CORRELATION PLOTS BETWEEN MEASURED PM2.5 CONCENTRATIONS BY AIRBEAM SENSORS[a]

Sampling Sessions	**Sampling Date**	**Time**	**Obs. duration (min)**	**AirBeam 1 vs. 2 (PM2.5)**			
				N	R^2	Intercept	Slope
LV1	6/21/2017	9:13-10:33	80	55	0.02	5.5297	0.17
LV2	6/22/2017	18:09-19:13	64	64	0.59	-0.3458	1.0989
LV3	6/15/2017	18:04-19:04	60	60	0.83	-0.5901	0.9827
LV4	6/16/2017	19:06-19:38	32	NA	NA	NA	NA
All LV runs				179	0.23	3.4736	0.4807
SE1	7/21/2017	9:53-10:41	48	48	0.26	5.6028	0.3585
SE2	7/19/2017	9:03-10:03	60	60	0.78	1.1318	0.8167
SE3	7/21/2017	8:43-9:32	49	23	0.94	1.5883	0.9499
SE4	7/19/2017	7:35-8:37	62	NA	NA	NA	NA
All SE runs				131	0.57	2.8145	0.6892
PC1	8/28/2017	12:26-13:17	51	NA	NA	NA	NA
PC2	8/16/2017	1:49-2:49	60	17	0.12	10.164	0.3091
PC3	8/18/2017	12:34-13:34	60	NA	NA	NA	NA
PC4	8/18/2017	16:05-16:31	26	NA	NA	NA	NA
All PC runs				17	0.12	10.164	0.3091
SL1	9/25/2017	17:03-17:59	56	48	0.16	3.8229	0.2935
SL2	9/25/2017	17:13-18:19	66	30	0.22	9.7959	-0.5896
SL3	9/22/2017	9:00-9:53	53	53	0.19	17.112	0.2221
SL4	9/22/2017	8:51-9:49	58	58	0.87	-0.3991	0.8664
All SL runs				189	0.31	5.1551	0.6404
SE1w[b]	3/23/2018	11:15-11:45	30	28	0.88	1.0657	0.1061
SE2w[b]	3/23/2018	12:55-13:30	35	35	0.81	1.0163	0.1017
SE3w[b]	3/23/2018	9:55-10:36	41	39	0.10	0.1984	0.7425
All SE Winter runs[b]				102	0.87	1.0478	-0.0665

[a]NA: not applicable/no record

[b]Only SE community operated two units of AirBeam sensor and successfully retrieved the data from both units during winter air monitoring efforts.

Appendix G (continued)

TABLE XXXIX. LINEAR REGRESSION STATISTICS OF THE CORRELATION PLOTS BETWEEN MEASURED $CO/CO_2/NO$ CONCENTRATIONS BY TERRIOR SENSORS[a]

Sampling Sessions	Terrier-CO				Terrier-CO_2				Terrier-NO			
	N	R^2	Intercept	Slope	N	R^2	Intercept	Slope	N	R^2	Intercept	Slope
LV1	27	0.00	0.2848	0.0706	33	0.88	153.18	0.7361	26	0.04	0.7952	0.5184
LV2	64	0.80	0.1305	0.6834	64	0.92	118.13	0.9606	64	0.92	0.0901	0.5805
LV3	60	0.63	0.2068	1.1656	61	0.51	396.87	0.5822	61	0.98	-0.1518	2.8138
LV4	18	0.92	-0.1224	1.0347	NA	NA	NA	NA	NA	NA	NA	NA
All LV runs	169	0.06	0.2757	0.3628	158	0.78	232.2	0.7296	151	0.33	0.0703	1.1472
SE1	NA	NA	NA	NA	39	0.09	289.82	0.3249	50	0.89	0.0578	0.1808
SE2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
SE3	NA	NA	NA	NA	6	0.68	-66.07	1.2006	31	0.84	0.1835	0.5231
SE4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
All SE runs	NA	NA	NA	NA	45	0.12	255.46	0.4252	80	0.17	0.151	0.1392
PC1	NA	NA	NA	NA	51	0.97	-270.54	1.5781	55	0.96	0.2857	1.9968
PC2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PC3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
PC4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
All PC runs	NA	NA	NA	NA	51	0.97	-270.54	1.5781	55	0.96	0.2857	1.9968
SL1	NA	NA	NA	NA	44	0.0481	715.55	-0.2302	44	0.72	-0.065	1.9669
SL2	NA	NA	NA	NA	17	0.8482	-2725.9	6.1148	NA	NA	NA	NA
SL3	54	0.93	0.07	0.6268	53	0.9938	-150.1	0.9228	54	0.97	0.5636	0.9707
SL4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
All SL runs	54	0.93	0.07	0.6268	114	0.3825	133.76	0.7584	98	0.94	0.6567	0.9673

[a]NA: not applicable/no record

Appendix H. PM2.5 Concentrations Measured by AirBeam Sensor Data Treatment

The AirBeam raw data retrieved from the AirCasting website was 1-second recorded PM2.5 concentrations which were further computed for 1-minute PM2.5 mean concentrations. Data included in the analysis was required to be at least 75% complete in one-minute averaging time intervals. The missing values of air quality data were treated based on the following criteria (Figure 40):

1. The readings of the first and last minutes of each sampling event were disregarded, since they were likely to contain partial data for the entire minute (and less than 75% complete). For example, the sampling session started at 9:00:50 and stopped at 13:59:10; therefore, the first and last minutes contained ten 1-second recorded data points (16% complete), then these data representing the first and last minute of the sampling was disregarded because they were less than 75% complete.

2. If there were ≥75% complete in 1-minute average data set (1-min average data set includes <45 1-second recordings), the 1-second recorded data within that minute was discarded. The data were not included in the data set and were excluded in further data analysis.

3. If there were ≥75% complete in 1-minute average data set (1-min average data set includes 60 1-second recordings), the 1-second missing data points within each minute was determined. If there were 1-second missing data points that occurred ≥3 times consecutively, then no imputation was performed. The missing 1-second data points within a given minute that occur ≥3 times consecutively were treated as missing value (labeled as NA). In summary, we did not make an assumption for those missing data points that occur consecutively ≥ 3 times within a minute since it was

Appendix H (continued)

feasible for those missing 1-second data points to be significantly higher or lower as compared to before or after 1-second recorded values (thus, artificially under or over estimating the mean).

4. If there were 1-second missing data points that occurred one or twice consecutively, the percent difference between before and after one or two consecutive missing 1-second data point(s) was determined whether it is ≤10%. If the percent difference was >10%, then no imputation was performed. These missing 1-second data points within a given minute were treated as missing value (labeled as NA). In summary, we did not make an assumption for those missing data points if the percent difference in before and after missing 1-second data recordings within a given minute are >10% since it was feasible for those missing 1-second data points to be significantly higher or lower as compared to before or after 1-second recorded values (thus, artificially under or over estimating the mean).

5. If the percent difference between before and after one or two consecutive missing 1-second data point(s) was ≤10%, the 1-second missing data point(s) was imputed by the average of the before and after those missing data values within that minute.

After missing data treated, the completed 1-second PM2.5 concentration data set was obtained and calculated for 1-minute and 1-hour PM2.5 mean concentrations, which were utilized for further statistical analyses.

Appendix H (continued)

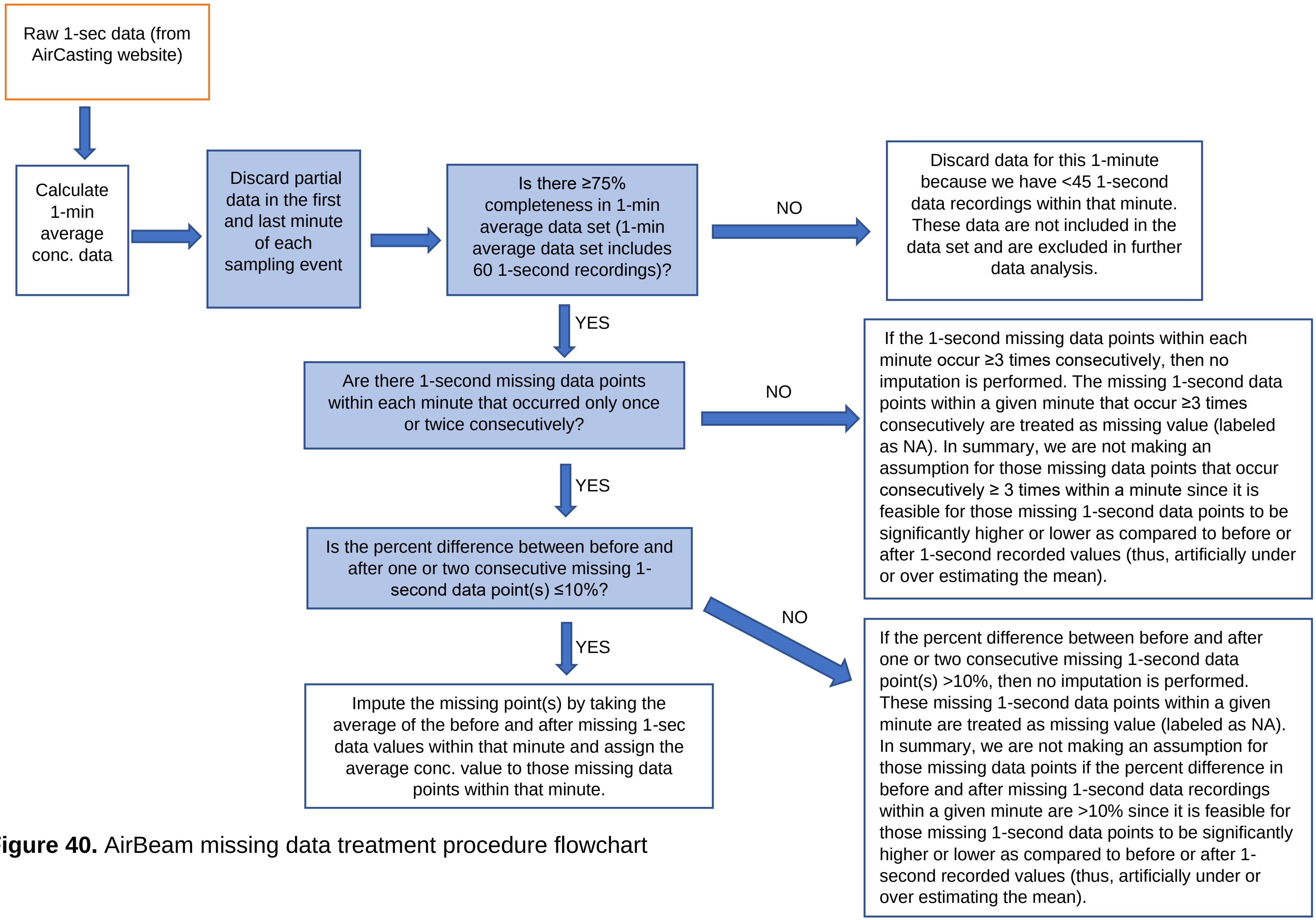


Figure 40. AirBeam missing data treatment procedure flowchart

Appendix I. Correlation Plots Between Channels A and B of Each Unit of PurpleAir Sensor Operated at Northbrook Air Monitoring Site, IL

The correlation plots of measurements of each channel of PurpleAir sensors operated at Northbrook air monitoring site demonstrated a very high degree of correlation for both PM2.5 with $R^2>0.91$ (Figure 41) and PM10 with $R^2>0.94$ (Figure 42)

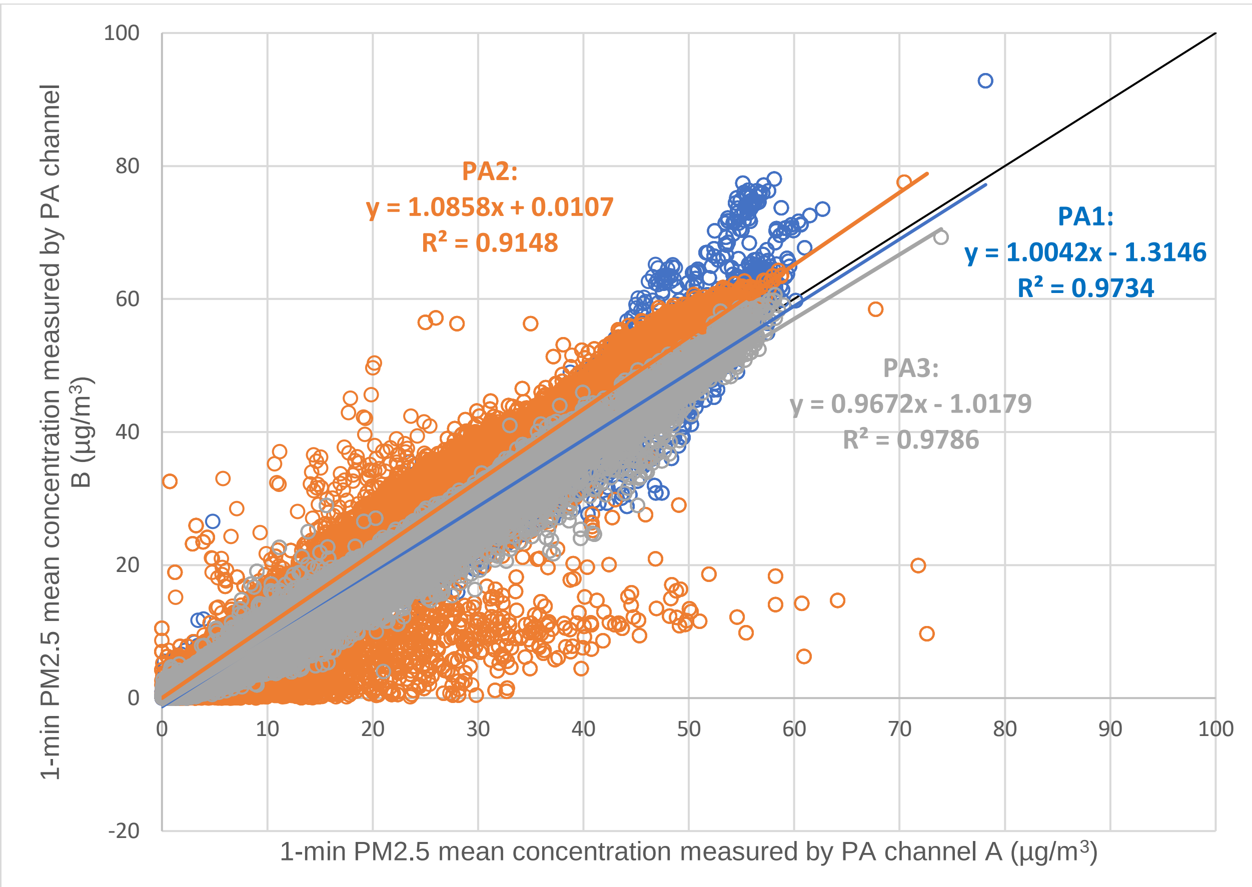


Figure 41. Correlation plot between measurements of channels A and B of PurpleAir measuring PM2.5. Number of observations were 111095 (PA1), 112183 (PA2), and 111022 (PA3).

Appendix I (continued)

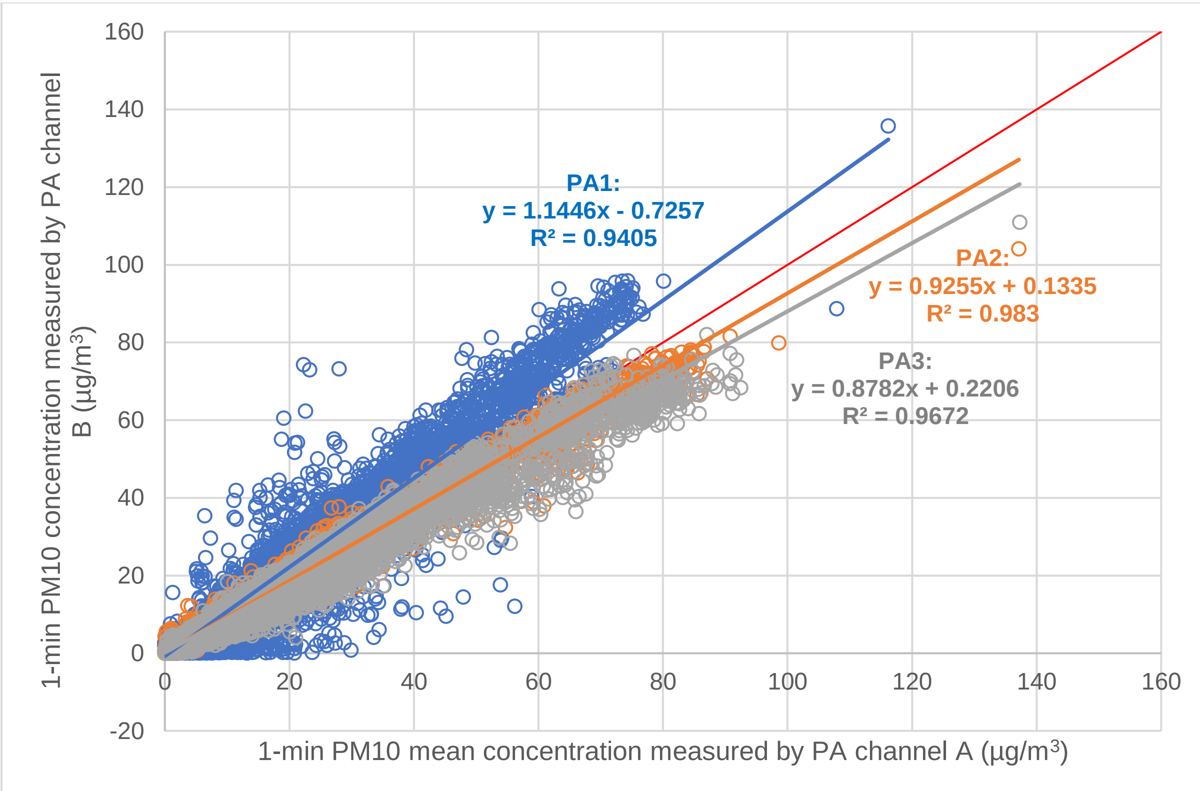


Figure 42. Correlation plots between measurements of channels A and B of PurpleAir measuring PM10. Number of observations were 19774 (PA1), 20445 (PA2), and 20449 (PA3).

Appendix J. Analysis of Non-imputed vs. Imputed PM2. 5 Concentrations Measured by AirBeam at Northbrook Air Monitoring Site, IL

The analysis was conducted to determine the discrepancies between non-imputed and imputed datasets employing the ProUCL 5.1 software. Based on the criteria utilizing for AirBeam data treatment (Appendix H), less than 2% of the dataset for each sensor unit was imputed (Table XXXIX). Descriptive statistics of 1-second and 1-minute PM2.5 concentrations suggested that no discrepancies between the non-imputed and imputed datasets existed (Tables XL, XLI, Figure 43). Thus, we can conclude that imputation procedure employed, as documented in Appendix H, did not alter the nature of the collected data. Hypothesis testing utilizing Wilcoxon-Mann-Whitney Test suggested that, at 95% confidence, the mean of 1-second PM2.5 concentrations of imputed datasets were not statistically significantly different from that of non-imputed ones; in addition, the mean of 1-minute PM2.5 concentrations of imputed datasets were not statistically significantly different from that of non-imputed ones. Intra-comparison analysis using correlation plots employing 1-second and 1-minute unimputed and imputed data suggested similar R^2, slope, and intercept for each of the three AirBeam sensors (Figure 44).

Appendix J (continued)

TABLE XL. DATA SUMMARY OF 1-SECOND PM2.5 CONCENTRATION MEASURED BY AIRBEAM, SUB-EXPERIMENT, NORTHBROOK, ILLINOIS

Sensors	Number of total data points in non-imputed/imputed datasets	Missing data points: N (%)	Imputed data points in the entire air monitoring data set across all sampling events: N (%)
AirBeam1	187200/190692	62318 (25)	3492 (1.4)
AirBeam2	215708/219615	33810 (13.6)	3907 (1.6)
AirBeam3	223006/226696	26512 (10.6)	3690 (1.5)

TABLE XLI. DESCRIPTIVE STATISTICS OF NON-IMPUTED AND IMPUTED 1-SECOND PM2.5 CONCENTRATION MEASURED BY AIRBEAM-1, -2, -3

	AirBeam 1			**AirBeam 2**			**AirBeam 3**		
Parameters	**Non-imputed (N=187200)**	**Imputed (N=190692)**	**% difference**	**Non-imputed (N=215708)**	**Imputed (N=219615)**	**% difference**	**Non-imputed (N=223006)**	**Imputed (N=226696)**	**% difference**
P_{25}	3.5	3.4	2.9	3.3	3.3	0.0	3.2	3.2	0.0
P_{50}	5.7	5.7	0.0	5.2	5.2	0.0	5.1	5.1	0.0
P_{75}	9.5	9.5	0.0	8.8	8.8	0.0	8.2	8.2	0.0
P_{95}	15.1	15.2	0.7	13.2	13.2	0.0	12.2	12.2	0.0
Mean	7.3	7.3	0.0	6.5	6.6	1.5	6.1	6.1	0.0

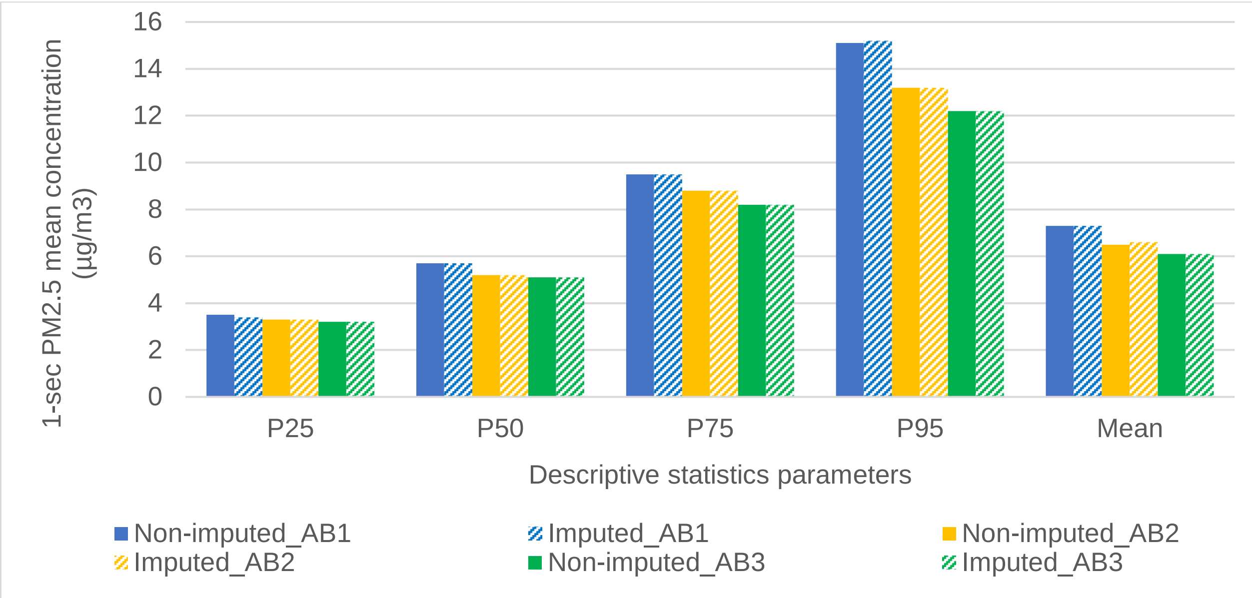
Appendix J (continued)

TABLE XLII. DESCRIPTIVE STATISTICS OF NON-IMPUTED AND IMPUTED 1-MINUTE PM2.5 CONCENTRATION MEASURED BY AIRBEAM-1,-2,-3

	AirBeam 1			AirBeam 2			AirBeam 3		
Parameters	**Non-imputed (N=2944)**	**Imputed (N=2944)**	**% difference**	**Non-imputed (N=3412)**	**Imputed (N=3412)**	**% difference**	**Non-imputed (N=3535)**	**Imputed (N=3535)**	**% difference**
P_{25}	3.5	3.5	0.0	3.4	3.4	0.0	3.3	3.3	0.0
P_{50}	5.4	5.4	0.0	4.9	4.9	0.0	5.0	5.0	0.0
P_{75}	9.1	9.1	0.0	8.5	8.5	0.0	7.8	7.8	0.0
P_{95}	15.0	15.1	0.7	12.9	12.9	0.0	11.8	11.8	0.0
Mean	7.1	7.1	0.0	6.4	6.4	0.0	6.0	6.0	0.0

Appendix J (continued)

a



b

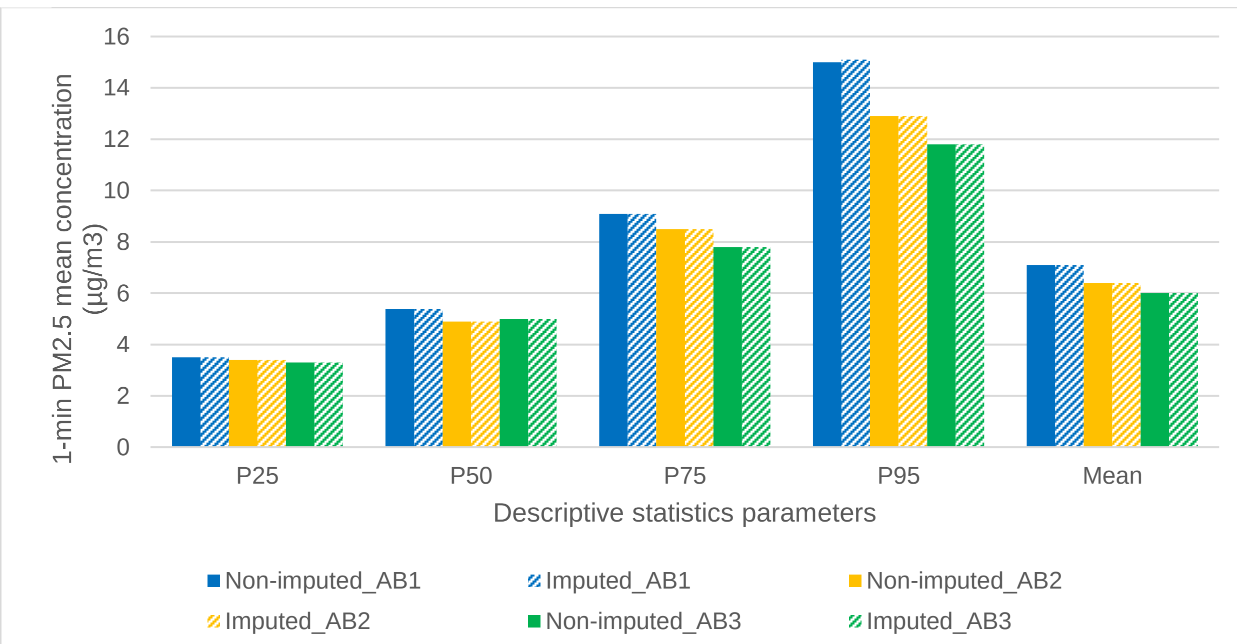
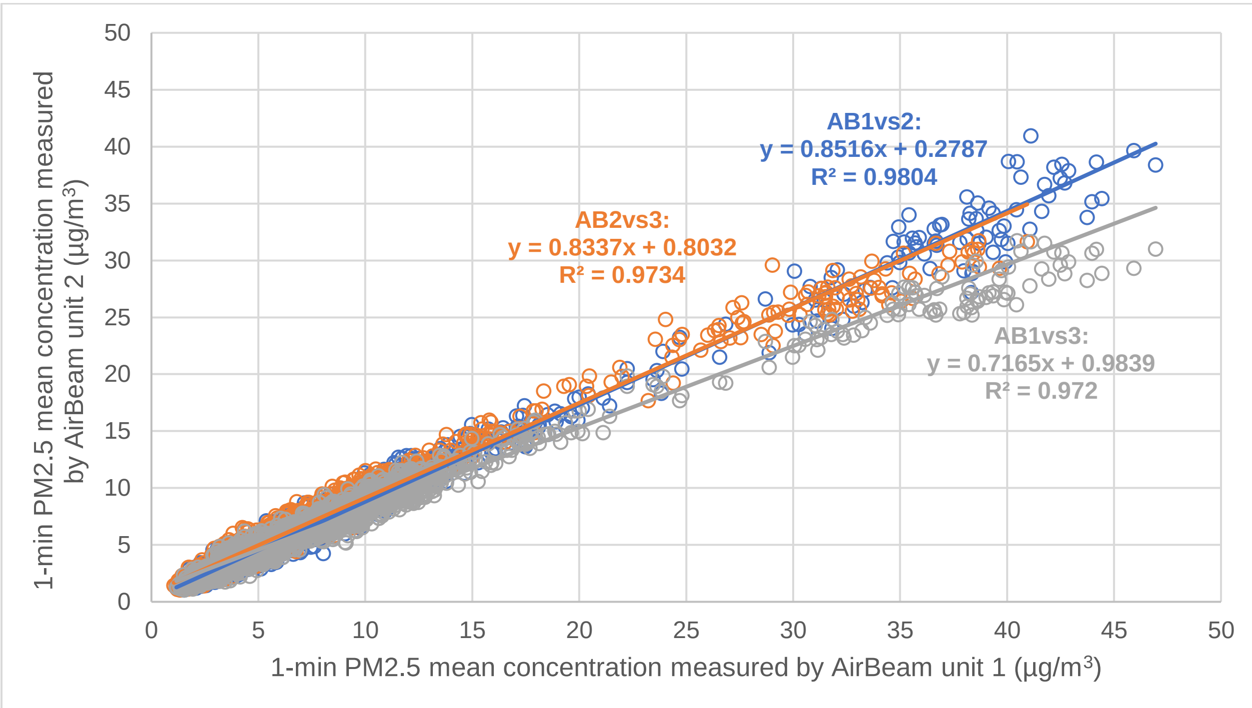


Figure 43. Plots of descriptive statistics parameters of imputed and non-imputed 1-second (a) and 1-minute (b) PM2.5 concentrations measured by AirBeam unit#1, 2, and 3

Appendix J (continued)

a



b

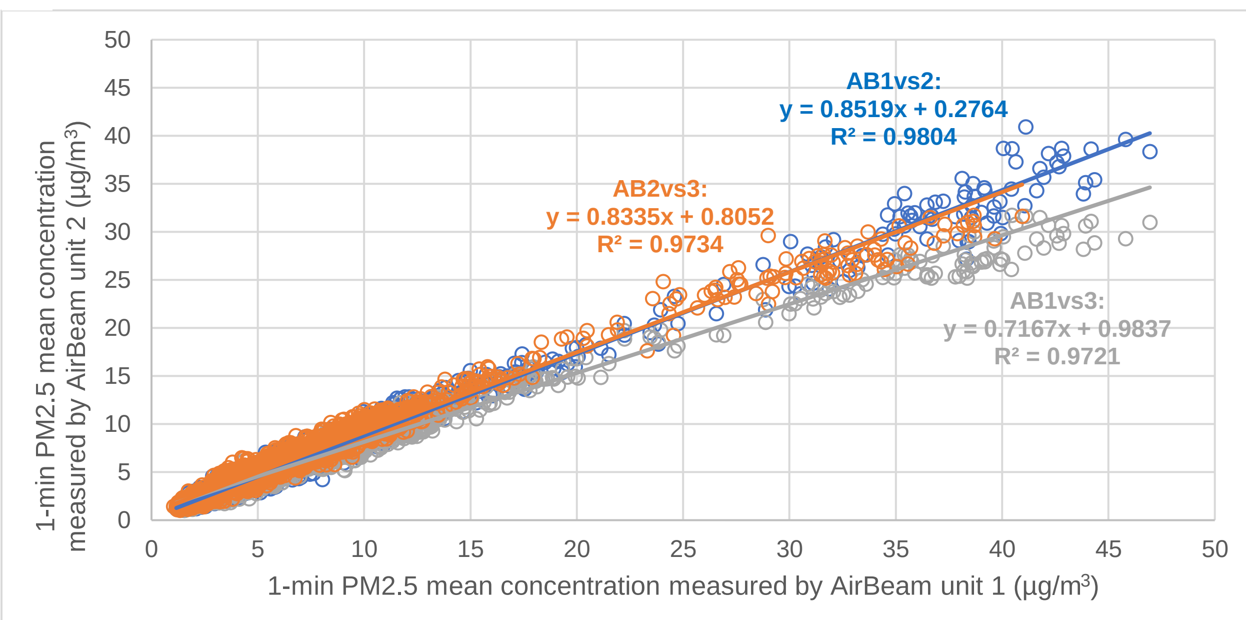


Figure 44. Correlation plots of intra-sensor comparisons of imputed (a) and non-imputed (b) 1-minute PM2.5 concentrations measured by AirBeam unit#1, 2, and 3

Appendix K. Data collection protocol

FEASIBILITY OF EMPLOYMENT LOW-COST PM SENSORS PILOT PROJECT

SAMPLING PROTOCOL

Note: For QA/QC sampling events use two UPAS and two AirBeam units, and 2 phones

1. **Prior sampling event**
    a. Prepare Filters for UPAS
        i. Clean/unused filters will be placed in plastic petri dishes and equilibrated in a desiccator for 72 hours or more with calcium sulfate desiccant
        ii. Each filter will be assigned code "**FP#-mmdd**" # is number of filter e.g., 1,2,3,…; mm-dd is a month and date of day that filter is taken out from the package and put in the petri dish, then equilibrated (document the date and time that start equilibrate the filter)
        iii. Pre-weigh filters after equilibrated for 24, 48, 72 hours, or more
            - 1 sampling filters per sampling event **(for QA/QC event, there will be 2 sampling filters)**
            - 1 field blanks per sampling event
            - 1 Lab blank per weight session

*NOTE: It is expected that the laboratory analyst will be able to duplicate weightings of the same filter to within 15 µg. Make sure to fill out the pre-weighing form (**Table 1**)* KEEP WEIGHING UNTIL THEIR VARIATION OF THREE CONSECUTIVE WEIGHTS ARE LESS THAN 5%. WHEN CALCULATING AVERAGE PRE_WEIGHT, USE THE LAST THREE READING WITH SD LESS THAN 5%.

        iv. place pre-weighted filter into a cartridge—**LOADED CARTRIDGE** [prepare 1 day prior sampling event]
        v. **Each LOADED CARTRIDGE** will be placed in a dust-free plastic zip-lock bag (one for each bag)

*NOTE: Document cartridge#, make sure it matches with filter#; label a ziplock bag with the filter# and cartridge# in the loaded cartridge form (**Table 2**)*

    b. Prepare Samplers (UPAS and AirBeam, and two phones) [prepare one day prior sampling event]
        i. Fully charged and check to make sure it works properly
        ii. CHECK PRESSURE THREE TIMES (AFTER LOADED WITH FILER), then document in the flow rate checking form (*Table 4*)

Appendix K (continued)

c. **1-2 days prior sampling event, confirm with each participant who would do air sampling about time and where to meet (ask contact from Wanda and Carly?)**

2. **On sampling day**
   a. **Sampling Efforts**
      i. **For shadowing efforts** (at 1st and 4th sampling events of each participant)
         - Meet with a participant at the site and give them the air sampling equipment bag

         note: The air sampling equipment bag consists of chest harness attached with two AirBeam and two UPAS units+ a clipboard with a time-activity log sheets (participant code, i.e., P# or G# is already specified in the obs. log sheet) + pens
         - Shadow the participant for 1-hour sampling session (document a time-activity log and feasibility assessment tool)
         - After completing the session, collect all equipment from the participant, take the cartridge with used filters out from the UPAS and secure them in labeled zip-lock bags (1 cartridge/bag)

      ii. **For general air monitoring** (participants do the sampling themselves)
         - Meet with a participant at the site and give them the air sampling equipment bag
         - After they complete the sampling session, meet with participant to collect all equipment from the participant, take the cartridge with used filters out from the UPAS and secured them in labeled zip-lock bags (1 cartridge/bag)
         - Check whether any issues or problems occurred during sampling and whether the sampling session is properly saved; all information in the observation log sheet is documented e.g., date, time, location

   b. **Treatment of used filter in the laboratory**
      i. In the sampling day right after sampling completed (if applicable), take the used filter cartridge to the SPHW325
      ii. **CHECK PRESSURE THREE TIMES (BEFORE UNLOADING THE USED FILTER OF THE LAST RUNS OF EACH DAY), then document in the flow rate checking form (*Table 4*)**

Appendix K (continued)

iii. Transfer each used filter to the petri dish (the petri dish is labeled with the same code appearing on the zip-lock bag)
iv. Equilibrate the filters
Note: document time and date of the start of the equilibrating in the post-weighing form **(*Table 3*)**
v. Clean cartridge and UPAS

c. **Recharge AirBeam units, UPAS units, Phones**

3. **After sampling day**
   a. Used filter post-weighing
      i. Post-weigh the sample filters after equilibrated for 24, 48, 72 hr (72 hr is optional) BUT DO NOT EXCEED 72 hr, otherwise need to keep in the cold storage. Document post-weights in the post-weighing form **(*Table 3*)**
      ii. Insert all documented information into the spreadsheet (Microsoft Excel with same forms i.e., Appendix A to D)
      iii. Keep used filters for 3 days (at least until all information is inserted into the spreadsheets)
   b. Download the data from SD card (for UPAS) and AirCasting website (for AirBeam) and document Date/Time the files completely downloaded in the data retrieving form **(*Table 5*)**

References:

USEPA. (2016). *Quality Assurance Guidance Document 2.12.* RTP, NC: Air Quality Assessment Division, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency. Retrieved from http://purl.fdlp.gov/GPO/gpo69921

Appendix K (continued)

Table1. The filter pre-weighing log

Date	Time	Filter#	Pre-weight-1	Pre-weight-2	Pre-weight-3	Note/comments
						Start Equilibrate filter

Appendix K (continued)

Table 2. The loaded cartridge log

Date prepared loaded cartridge	Time	Filter#	Cartridge# (this number is attached to each cartridge)	Note/comments

Appendix K (continued)

Table 3. The filter post-weighing log

Date	Time	Filter#	Post-weight-1	Post-weight- 2	Post-weight- 3	Note/comments
						Strat Equilibrate filter

Appendix K (continued)

Table 4. The UPAS flow rate recording log

Date	Time	UPAS#	Pre-sampling flowrate (lpm)	Post-sampling flowrate (lpm)	Note/comments

Appendix K (continued)

Table 5. The data retrieving log

Date	Time	Sample Name (for UPAS); Session name (for AirBeam2)	Cartridge# (for UPAS)	Download data from SD card? (Y/N)	Download data from Aircasting application? (Y/N)	Note/comments

Appendix L. Institutional Review Board Approval

Exemption Granted

January 22, 2019

Saisattha Noomnual, MPH
Environmental and Occupational Health
Phone: (732) 519-2377 / Fax: (312) 413-9898

RE: **Protocol # 2019-0018**
"Occupational Personal Exposure to Fine Particulate Matter using Sensors: Feasibility and Performance"

Dear Saisattha Noomnual:

Your application was reviewed on **January 22, 2019** and it was determined that your research meets the criteria for exemption as defined in the U.S. Department of Health and Human Services Regulations for the Protection of Human Subjects [45 CFR 46.104(d)]. You may now begin your research.

Exemption Granted Date:	January 22, 2019
Sponsor:	**NIOSH**
Institutional Proposal (IP) #:	2014-00684
Grant/Contract No:	T42/OH008672
Grant/Contract Title:	Occupational Safety and Health, ERC, University of Illinois at Chicago

The specific exemption categories under 45 CFR 46.104(d) are 2 and 3

You are reminded that investigators whose research involving human subjects is determined to be exempt from the federal regulations for the protection of human subjects still have responsibilities for the ethical conduct of the research under state law and UIC policy.

Please remember to:

→ Use your research protocol number (2019-0018) on any documents or correspondence with the IRB concerning your research protocol.

→ Review and comply with the policies of the UIC Human Subjects Protection Program (HSPP) and the guidance ***Investigator Responsibilities***.

UNIVERSITY OF ILLINOIS AT CHICAGO
Office for the Protection of Research Subjects
201 AOB (MC 672)
1737 West Polk Street
Chicago, Illinois 60612
Phone (312) 996-1711

Appendix L (continued)

We wish you the best as you conduct your research. If you have any questions or need further help, please contact me at (312) 355-2908 or the OPRS office at (312) 996-1711. Please send any correspondence about this protocol to OPRS via OPRS Live.

Sincerely,
Charles W. Hoehne, B.S.
Assistant Director, IRB #7
Office for the Protection of Research Subjects

cc: Lee Friedman
Serap Erdal

UNIVERSITY OF ILLINOIS AT CHICAGO
Office for the Protection of Research Subjects
201 AOB (MC 672)
1737 West Polk Street
Chicago, Illinois 60612
Phone (312) 996-1711

Appendix M. Information sheet for participant recruitment

Project: Feasibility of employing low-cost air monitoring sensors

Principal Investigator: Saisattha Noomnual, School of Public Health (EOHS)

Advisor: Dr. Serap Erdal, School of Public Health (EOHS)

Co-advisor: Dr. Rachel Jones, School of Public Health (EOHS)

Objectives

The purpose of this study is to assess the feasibility of employing low-cost personal sensors for measuring and monitoring fine particulate matter exposures in occupational settings while you are performing your routine work. This pilot study aims to determine the ability to employ these low-cost sensors in field settings and evaluate how well these study sensors perform against each other in field conditions.

Methods

Workers who are eligible to participate in the study are at the age of 18 or above, and you are a UIC parking or ground-keeping employee. Twenty participants will be asked to attend two 1-hour training sessions about how to use and operate the air monitoring sensors. They will be asked to wear two sensors (Fig. 1) for 1-hour during their routine work at UIC on six different days between May to June, 2019. During the first and fourth 1-hour session of wearing the sensors (total of two), they will be shadowed/observed by the investigator. The investigator will collect qualitative data for a number of indicators/variables to assess the effectiveness of training about how to properly use and operate the study sensors performed by the participating workers and an ease with which participants interact with these low-cost sensors. After they complete all six 1-hour air-monitoring sessions, the researcher will evaluate the feasibility of using and operating the sensors.

(a) (b)

Figure 1. Low-cost air monitoring sensors: (a) AirBeam and (b) UPAS

Appendix M (continued)

Significance of the study

The feasibility of employing PM2.5 low-cost sensors in occupational settings will be determined. To our knowledge, the low-cost real-time sensors have not been tested or used in the occupational settings. These sensors have so far been employed in a limited manner in support of community-based environmental air pollution studies and citizen-science projects. As these pollution sensing technologies are being developed, our ability to employ them in field settings remain unanswered from practical, logistical, and technical perspectives. Furthermore, the feasibility to employ and operate them in occupational exposure characterization is so far unexplored. With the performance of this pilot study, the UIC is taking the lead in providing initial answers to these critical research questions and extending their use to occupational exposure assessment. We are hypothesizing that the sensors will capture variability in PM exposure concentrations such that when the workers are engaged in high dust generating activity the sensors will show spikes in concentrations measured. We will also be able to find out how well these two commercially-available samplers perform against each other in field conditions. The performance characteristics and inter and intra-variability of two commercially available sensors in the field conditions will be assessed in order to gain understanding for their reliability for future occupational exposure assessment studies. In summary, this core significance of the study is advancement of occupational exposure assessment science. Depending on the quality of data we generate, we may be in a position to recommend ways or opportunities for particulate matter exposure reduction for UIC grounds-keeping workers.

If you have further questions or comments, please contact Saisattha Noomnual at snoomn2@uic.edu.

Appendix N. Informed consent

Leave box empty - For office use only

University of Illinois at Chicago
Research Information and Consent for Participation in Social Behavioral Research

Occupational Personal Exposure to Fine Particulate Matter using Sensors: Feasibility and Performance

You are being asked to participate in a research study. Researchers are required to provide a consent form such as this one to tell you about the research, to explain that taking part is voluntary, to describe the risks and benefits of participation, and to help you to make an informed decision. You should feel free to ask the researchers any questions you may have.

Principal Investigator Name and Title: Saisattha Noomnual, PhD student
Department and Institution: School of Public Health, UIC
Address and Contact Information: 1603 W Taylor St., Chicago, IL 60612
Sponsor: The study is funded by the National Institute for the Occupational Safety and Health (NIOSH) through University of Illinois at Chicago Education and Research Center (ERC).

Why am I being asked?
You are being asked to participate in a research study that is being conducted by Saisattha Noomnual and Prof. Serap Erdal at the Division of Environmental and Occupational Health Sciences of the University of Illinois at Chicago School of Public Health. You are eligible to participate in the study since you are at the age of 18 or above, and you are a UIC parking or ground-keeping employee.

What is the purpose of this research?
The purpose of this study is to assess the feasibility of employing two different low-cost personal sensors for measuring fine particulate matter exposures in occupational environments. In addition, the research aims to evaluate performance of these two low-cost sensors against one another to advance the science of occupational exposure assessment. You will be one of approximately twenty individuals asked to participate on this study.

What procedures are involved?
You will be asked to attend two 1-hour training sessions on how to use and operate the two air monitoring sensors selected for this study. You will also be asked to wear four sensors for two 1-hour and two sensors for four 1-hour periods (1 hour on six different days) during May to July 2019. The investigator will shadow you as you are routinely working and wearing these two study sensors in your breathing-zone during the first and fourth 1-hour personal air monitoring session. The shadowing effort will be for the entire 1-hour of each personal air monitoring event. The investigator will record how you interact with these low-cost sensors.

Appendix N (continued)

What are the potential risks and discomforts?
There are only minimal risks or discomforts anticipated from taking part in this study because the sensors you will be asked to wear is very small, lightweight, and do not interfere with performing your work. Moreover, you will wear the sensors for only one-hour period in each sampling event. You will be only shadowed/observed by the investigator for three out of six 1-hour air monitoring sessions. Our study will not interfere or affect your routine work.

Are there benefits to taking part in the research?
You will directly benefit from participation in the study in terms of the knowledge gained about how to use and operate personal air monitoring sensors properly in occupational settings. This benefit would also likely to expand to your colleagues in similar institutions and your community via sharing the knowledge generated from our research. Moreover, your participation will facilitate generation of new knowledge about feasibility of expanding the use of low-cost sensors among parking and ground-keeping workers for measuring occupational exposure to particulate matter. Depending on the quality of data we generate, we may be in a position to recommend ways or opportunities for particulate matter exposure reduction for UIC grounds-keeping and parking workers.

What other options are there?
You have the option to not participate in this study.

What about privacy and confidentiality?
The UIC researchers who carry out the research will know that you are a research subject in this study. Subjects will attend two 1-hour training sessions, wear the devices on six different days, and will be shadowed/observed by the researcher for three out of six 1-hour air monitoring sessions. Thus, your supervisors and coworkers will also know that you are participating in the research study. Study information which identifies you (only your name) and the consent form signed by you will be kept in a secure location in a locket cabinet in PI's office in UIC, and can be accessed by only Principle Investigator (PI) and research mentor (i.e., Prof. Erdal) only. This information will be destroyed after the research is completed. You will be assigned a participant code which will be stored with the collected data (i.e., shadowing records, personal exposure concentration measurements, and records of activities you are performing during monitoring periods). The participant code is only linked to your occupation i.e., parking worker (P#) or groundskeeper (G#). Thus, the collected data will be de-identified and cannot be linked back to you in any format.

What are the costs for participating in this research?
There are no costs to you for participating in this research.

Will I be reimbursed for any of my expenses or paid for my participation in this research?
You will receive a $75 gift card for completion of two 1-hour training sessions; wearing two sensors for six 1-hour periods (one hour on six different days); and to be shadowed/observed for two 1-hour periods by the investigator while performing routine work and wearing the sensors. If you do not complete all research activities, prorated compensation would be applied. A $40 gift card will be given to you within ten business days after completing two 1-hour training sessions and wearing sensors for two sampling events during which the investigator will shadow

Appendix N (continued)

you. An additional $35 gift card will be given to you within ten business days after completing the entire study.

Who should I contact if I have questions?
If you have concerns or questions about the study, please contact Ms. Saisattha Noomnual (student PI) at 732-519-2377 or email: snoomn2@uic.edu or Prof. Serap Erdal (faculty mentor) at 312-996-5875 or email: erdal@uic.edu.

What are my rights as a research subject?
If you feel you have not been treated according to the descriptions in this form, or if you have any questions about your rights as a research subject, including questions, concerns, complaints, or to offer input, you may call the Office for the Protection of Research Subjects (OPRS) at 312-996-1711 or 1-866-789-6215 (toll-free) or e-mail OPRS at uicirb@uic.edu.

Can I withdraw from the study?
Your participation in this study is voluntary. Your decision whether or not to participate will not affect your current or future dealings with the University of Illinois at Chicago. **If you decide to participate, you are free to withdraw from the study at any time you wish without affecting that relationship.** You have the right to leave the study at any time without penalty.

What if I am a UIC employee?
Your participation in this research is in no way a part of your university duties, and your refusal to participate will not in any way affect your employment with the university, or the benefits, privileges, or opportunities associated with your employment at UIC. You will not be offered or receive any special consideration if you participate in this research.

Appendix N (continued)

<u>Remember</u>:
Your participation in this research is voluntary. Your decision whether to participate will not affect your current or future relations with the University. If you decide to participate, you are free to withdraw at any time without affecting that relationship.

<u>Signature of Subject</u>
I have read (or someone has read to me) the above information. I have been given an opportunity to ask questions and my questions have been answered to my satisfaction. I agree to participate in this research. I will be given a copy of this signed and dated form.

______________________________ ____________
Signature Date

____
Printed Name

______________________________ ____________
Signature of Person Obtaining Consent Date (must be same as subject's)

____
Printed Name of Person Obtaining Consent

Appendix O. Sensor user guidelines

AIRBEAM AND UPAS PM2.5 SENSORS USER GUIDE

Preparation to Air Monitoring Session in the Working Area

Description of Sensors: The AirBeam and Ultrasonic Personal Air Sampler (UPAS) monitors for Particulate Matter 2.5 (PM2.5), i.e., fine particles that are less than 2.5 micrometers. These particles can enter the lungs and bloodstream. Sources include cars, busses and diesel trucks, metal recyclers, pet coke storage, and other manufacturers and/or air emissions from any source that involves combustion of fossil fuel.

Placement of Sensor in the Breathing Zone: Hang and secure the sensor near the top of the chest harness straps, as close to your nose/mouth as possible. The AirBeam and UPAS should be on your right and left straps, respectively. This guidance should be followed in all sampling events.

Sampling Location/Participant code/Time/Duration: Determine the sampling event (i.e., sampling location, participant code, time and duration) prior to each sampling event and name the sampling saved session correctly.

YOU ARE ASKED TO RECORD THE ACTIVITIES FOR EVERY FIVE-MINUTE INTERVAL USING THE OBSERVATIONAL LOG SHEET WHICH WILL BE PROVIDED TO YOU PRIOR SAMPLE EVENTS. PLEASE DOCUMENT BRIEF DESCRIPTION OF ACTIVITIES YOU PERFORM IN EACH INTERVAL, ESPECIALLY SMOKE OR DUST GENERATED AND OR RELATED ACTIVITIES E.G., WORKING WITH OR NEARBY HEAVY MACHINES AND LAWN MOWING.

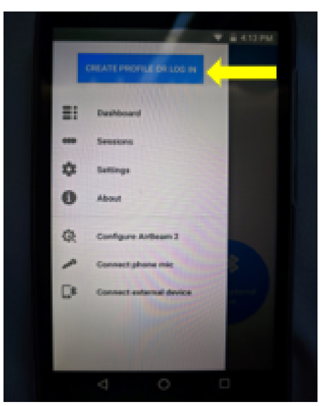
Part I: Step-by-Step Use/Operation Guide for AirBeam, and Air Sampling

1. **Open AirCasting App on your mobile phone and create the profile name.** Once you begin monitoring outside, the location appearing on the map will track your actual location due to improved satellite signal (might take a few minutes). First, open the AirCasting application on an Android phone, next step is "Setting". "Setting" can be accessed by pressing vertical three dashes button on the upper left corner of the screen. You will go to another screen. Then, do the following steps:

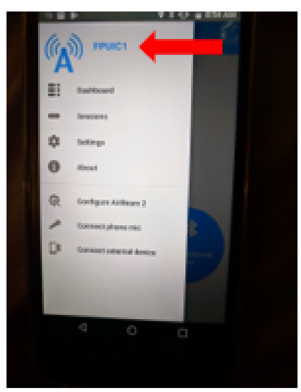
   a. **First, set your Profile name by pressing "CREATE PROFILE OR LOG IN" at the top of the page (see yellow arrow below):** You can create your profile name by pressing "Create Profile". You need to provide the following information i.e., email, profile name, and password, then press "Submit". **[Note: if the profile name (e.g., FPUIC1) has been already created for you (see red arrow below), please check the profile name and document in the observation log sheet before starting each air sampling event.]**

   b. **Second, go to "Setting" (see green arrow in the picture below), press "Contribute to CrowdMap"** Make sure that there is a green checkmark in the box.

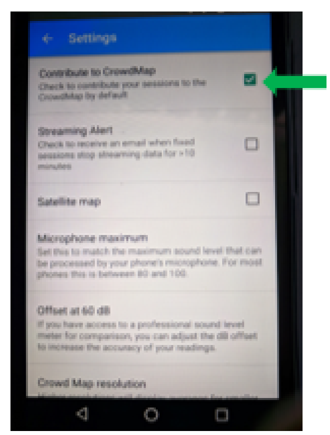
   c. **Third, scroll down further to see the "Show route trace" options on the screen.** Make sure that there is a green checkmark in the box.



Page for Profile name Set Up



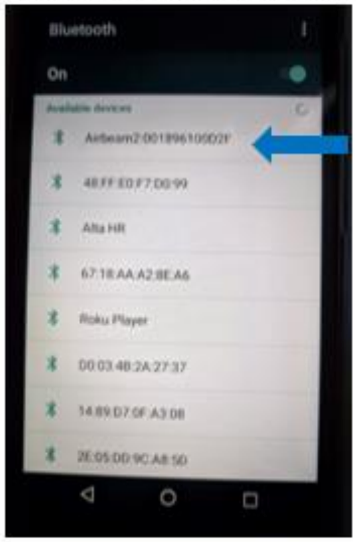
Page for AirCasting Set Up and Profile name



AirCasting Settings Page

Appendix O (continued)

2. **Connect the AirBeam to your Android mobile phone: Press the "Configure AirBeam 2".** The list of **"Available Devices"** will be showed. If you did not see the device that you want to pair in the list, press **"Pair New Device".** You first need to **turn on Bluetooth of your mobile phone and pair the AirBeam 2 sensor with your phone (see blue arrows).** You may access the list of "Available Devices" through "Connect external device". Then, select the device that you want to pair (e.g., AirBeam2:001896100D2F) and then select "Pair".

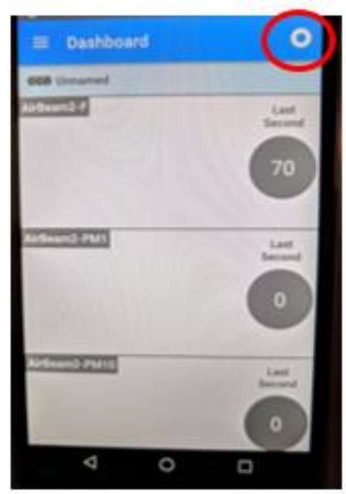


Page for Bluetooth Set Up

3. **Start air sampling:** When the AirBeam Connection Indicator light turns from red to green (see blue circle in the picture on the left below), it means you are ready to connect the phone with the AirBeam. Then press **"Configure AirBeam 2"** on the Dashboard, then press **"Connect"** button and select **"Mobile"**. Wait for five seconds and you will see the AirBeam sensor streams on the Dashboard (see image on the right). Then, **start recording the PM2.5 concentrations by AirBeam in working environment ambient air by pressing the "Record" button on the upper right corner** (see red circle in the right picture). Then, enter a "Session Details" i.e., "Title". Session **Title** will follow the pattern documented below. You always ensure to document the exact same session name in the Time Activity Observation Log. For **Tags**, you can enter 'Parking or Groundskeeping' to help exploring the data on the website, but this is not necessary. Then, press **"Start Session"**.

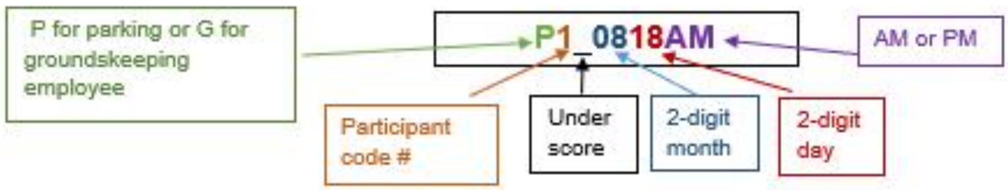
Bottom view of AirBeam

Pairing an external device



Monitor screen before recording

Appendix O (continued)



Pattern of Title

Once the recording starts, the AirBeam sensor streams will become live (the dashboard turns from grey to multiple colors). On the image below, the square at the upper right corner (see red arrow) is the "**Stop Recording**" button and the pencil with speech box image (see blue arrow) is the "**Make Note**" button. As you are recording data, you may want to add some notes and/or save a picture attached to a specific time of your recording of air monitoring data. In order to do this, press "**Make Note**". You will see a new screen with a window to type/enter your note. Type your note (e.g., truck, operated heavy machine), then, press "Attach a photo". You will be directed to the camera of the phone. Press the circle to take a picture of dust/smoke generating activity. Press the checkmark to attach the picture file. Then, press "Save" to save the note you typed and the picture you took. Now, you will return to the data recording screen shown below on the right.

Monitor screen while recording

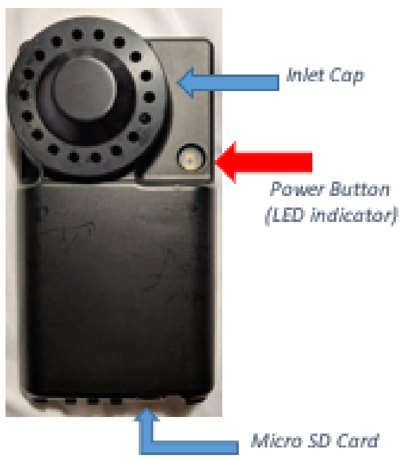
4. **Stop air sampling**: When finishing air sampling, press "**Stop Recording**" button. You will go back to the dashboard with grey color (same screen as you see before start recording).

Appendix O (continued)

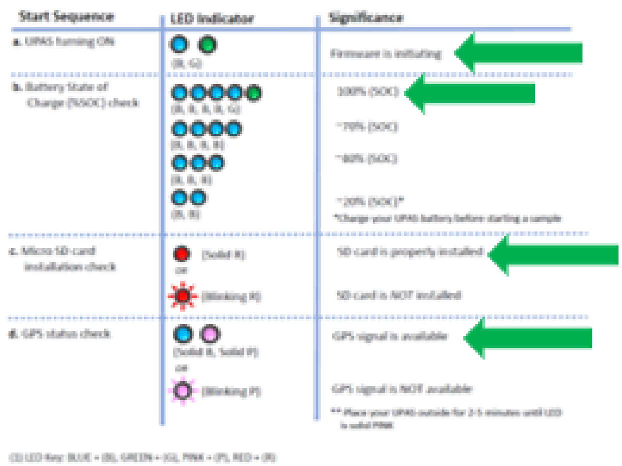
Part II: Step-by Step Use/Operation Guide for UPAS, and Air Sampling

Prior each sampling event, filter will be prepared and installed in the filter cartridge, then placed into the UPAS inlet socket. Before turning on the UPAS, make sure that the filter, filter cartridge and inlet cap are installed.

1. **Initiating the UPAS** **Press the UPAS power button for 5 seconds (see red arrow).** You will see the BLUE LED, indicating the UPAS is turning on. You will see the LED indicator signals following the sequences. You would expect to see the signals (see the green arrows in the right figure below), indicating the UPAS is ready to connect with the phone.



UPAS



Interpreting the LED indicator

2. **Connect the UPAS sensor to your Android mobile phone Application:** **Make sure the UPAS LED indicator is solid PINK, then open the UPAS application.** You first need to **turn on Bluetooth of your mobile phone and pair the UPAS sensor with your phone** (see the red arrow in the left figure on the next page). **To connect the UPAS with the phone, press the three vertical dots button on the top right corner** (see the red circle in the middle figure on the next page)

   A Blue LED indicates the phone is successfully connected to the UPAS. The connection status on the Application changes to "Connected to <UPAS serial number>" and the battery status will show (see the red rectangle right figure on the next page).

Appendix O (continued)

Pairing UPAS to Phone

Connecting UPAS to Phone

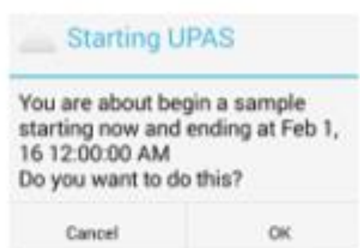
Indication of successfully devices pairing

3. **Setting up parameters in the UPAS App on your mobile phone.** Once you successfully paired the devices, you need to enter/ set up parameters include:

   Sample name: P1_0818AM (same manner as you do for session name for AirBeam sensor)
   Cartridge ID: you will be provided this information prior each sampling event
   Select "GPS ON"
   Select "LED ON"
   Select "NORMAL LOG"
   MICROENVIRONMENT DETECTION: OFF
   FLOW RATE: 1.0 LPM
   FLOW RATE OFFSET: 0.0%
   DUTY CYCLE: 100%
   LOG INTERVAL: 30 SECONDs
   START TIME: NOW
   SAMPLING DURATION: Indefinitely
   START WITH SET TIME: leave it as it is

4. **Start recording the PM2.5 concentrations by UPAS in working environment ambient air.** After set up all parameter, you will start recording PM2.5 concentration by pressing **the "START" button** shown below on the left image (see the red arrow in the left figure below). The "Starting UPAS" dialogue box (see the right figure below) pops up. You press "OK". You will see the indicate light (at the power button) turns green meaning it begins sampling.

Main menu screen



Monitor screen dialogue box

Appendix O (continued)

After starting a sample run with the UPAS application, the LED indicator will turn to solid PINK, and then solid RED for a few moments, then solid GREEN, indicating the UPAS reaches the programmed flow rate. **Make sure the LED indicator is GREEN during sampling event.**

LED Indicator during a sample run

5. **Stop recording the PM2.5 concentration. At the end of air monitoring session, stop recoding by press and hold the power button for 5 second until the LED indicator turns off.**

Appendix P. Feasibility Assessment Tool

Sampling Date: **Sampling Time Period:** **Shadowing Time Period:**				
Location:				
Occupation[a]:				
Participant Code:				
Questions	**Answer[b]**			**Comments**
1. Are the personal exposure sensors correctly placed in the breathing-zone? (AirBeam(s) is placed on the right and UPAS(s) is on the left shoulders)	Y	N		
2. Are the workers comfortable in using sensors? [1]	L	M	H	
3. Have the workers periodically checked the cell phone to make sure that the AirBeam2 are collecting data?	Y	N		
4. Have the workers periodically checked the UPAS to make sure that it is running and anything block the air inlet?	Y	N		
5. What is the level of compliance with general sampling procedures (e.g., regularly working, not smoking, keeping sensors dry)? [2]	L	M	H	

Notes:

[a]Occupation: (1) parking lot assistant, or (2) groundskeeper

[b]Y=Yes; N=No; L=Low; M=Medium; H=High

[1] The ease with which participants use AirBeam and UPAS personal exposure sensors will be quantitatively judged by the number of questions each participant asks the investigator on in each sampling session in the following manner: Less than 2 questions asked (High-H); 2-5 questions asked (Medium-M); >5 questions asked (Low-L);

[2] The investigator will qualitatively assess the level of compliance (e.g., performing routine work while personal exposure monitoring; not smoking cigarettes or any other smoke generating substance while sampling; making sure that the equipment is kept dry while sampling) with general exposure monitoring sampling procedures outlined in the Sampling and Analysis Plan in the following manner: violation of guidelines only once (High-H); violation of guidelines 2-5 times (Medium-M); violation of guidelines >5 times during sampling (Low-L).

Appendix Q. Time Activity Monitoring Observation Log

Participant Code (P# or G#):		**CODES FOR SOURCES (use in table below in PM Generating Source column)**		
Sampling Date:		**Truck=T**	**Cigarette/Cigar Smoke=CS**	**Industry Source=IS (stack emissions)**
Sampling Time Period:		**Car=C**	**Any Other Smoke= OS**	**Construction Dust= CD**
Profile Name:		**Bus=B**	**Any other air pollution source=O**	**Blower=BL; Fertilizing=FT**
		Train=TR	**Lawn Mower=LM**	**Machine Operating= MO**

Session Name:
P#_mmddAM or P#_mmddPM This is for parking employee, where # = code number; mm = two digit month; dd = two digit day; AM for morning routes; or PM for afternoon; if applicable. For Groundskeeping, working use G#.

Important Note: Activities will be documented for every five minutes. Any PM generating activities will be recording at any time it happens. **Accurate documentation of the time of the PM generating source is very important.**

Time	**Activities and/or PM Generating Source Code (Enter the Codes shown above)**	**Comments/Notes**

Appendix R.

TABLE XLIII. SUMMARY OF PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2 SENSORS AMONG GROUND-KEEPING AND PARKING WORKERS[a]

Occ.	Sampling sessions	Start time	Stop time	Sampling duration (min)	1-min PM2.5 mean concentration (µg/m³) Min-Max	Mean (sd)	Tasks/Other comments
Ground-keeping	**Q11**	5/22/19 6:39	5/22/19 7:46	67	1.4-11.3	3.1 (2.0)	picking trash, sweeping parking facilities and lots (at several locations); driving pick-up car from to different locations
	Q14	6/4/19 6:49	6/4/19 7:59	70	3.3-16.2	6.9 (3.1)	mowing using a ride-on lawn mower
	X12	5/31/19 7:00	5/31/19 8:00	60	NA	NA	weed whipping
	X15	6/7/19 6:54	6/7/19 8:04	70	7.8-28.9	14.6 (3.9)	NA
	Y13	5/30/19 11:57	5/30/19 12:55	58	0.5-56.7	13.8 (10.3)	mowing using a ride-on lawn mower
	Q21	5/22/19 8:52	5/22/19 9:53	61	3.2-27.3	8.2 (4.1)	grass trimming using grass trimmer machine (with battery); their co-worker was blowing
	Q24	6/11/19 6:55	6/11/19 8:10	75	5.1-19.7	6.5 (1.8)	picking trash, sweeping at several locations; driving a pick-up car from one location to others
	X22	5/31/19 9:04	5/31/19 10:06	62	0.0-50.9	3.3 (8.0)	garbage picking; weed whipping
	X25	6/12/19 6:53	6/12/19 8:07	74	1.7-18.5	4.3 (2.3)	cleaning; sweeping; picking up garbage; changing garbage bags at several locations
	Y23	5/30/19 12:03	5/30/19 13:09	66	2.3-52.7	11.8 (9.5)	NA
	Q31	5/22/19 10:08	5/22/19 11:02	54	1.7-3.3	2.6 (0.5)	weeding, raking, and spading; their co-worker was doing grass trimming and blowing (portable blower)
	Q34	6/6/19 6:45	6/6/19 8:02	77	3.7-15.3	8.1 (1.5)	picking trash, sweeping parking facilities and lots (at several locations); driving pick-up car from one location to others

Appendix R (continued)

TABLE XLIII. SUMMARY OF PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2 SENSORS AMONG GROUND-KEEPING AND PARKING WORKERSa (continued)

Occ.	Sampling sessions	Start time	Stop time	Sampling duration (min)	1-min PM2.5 mean concentration (µg/m^3)		Tasks/Other comments
					Min-Max	Mean	
	X32	5/31/19 8:59	5/31/19 10:05	66	0.6-29.5	7.2 (6.6)	mowing using a walk-behind mower
	X35	6/7/19 6:48	6/7/19 8:08	80	5.7-26.2	14.0 (3.0)	parking lot cleanup; trash collecting
	Y33	5/30/19 10:02	5/30/19 10:56	54	0.6-16.6	4.3 (3.4)	weed whipping and grass blowing
	Q41	5/23/19 10:09	5/23/19 11:11	62	0-2.4	0.3 (0.6)	raking, grass trimming using brush cutter; their co-worker was doing grass trimming using brush cutter and blowing (portable blower); working by a running ride-on mowing
	Q44	6/6/19 8:47	6/6/19 10:07	80	4.4-33.3	11.5 (5.3)	mowing using a walk-behind lawn mower; their co-workers was mowing by using brush cutter
	X42	5/31/19 7:00	5/31/19 8:00	60	3.3-32.2	9.5 (6.4)	lawn mowing
	X45	6/12/19 6:58	6/12/19 8:00	62	0.0-13.2	2.7 (3.5)	NA
	Y43	5/30/19 10:04	5/30/19 10:56	52	0.0-10.4	2.2 (3.1)	NA
	Q51	5/23/19 7:09	5/23/19 8:08	59	0-15.0	2.1 (3.2)	raking, blowing, grass trimming using brush cutter; their co-worker was blowing
	Q54	6/11/19 9:14	6/11/19 10:17	63	3.0-32.8	11.3 (6.1)	mowing using a ride-on lawn mower
	X52	6/6/19 6:41	6/6/19 8:00	79	8.0-75.3	26.3 (11.5)	mowing
	X55	6/12/19 7:08	6/12/19 8:00	52	2.8-53.9	13.1 (11.9)	NA
	Y53	6/4/19 6:40	6/4/19 7:53	73	3.3-98.3	13.8 (17.6)	NA

Appendix R (continued)

TABLE XLIII. SUMMARY OF PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2 SENSORS AMONG GROUND-KEEPING AND PARKING WORKERSa (continued)

Occ.	Sampling sessions	Start time	Stop time	Sampling duration (min)	1-min PM2.5 mean concentration (µg/m^3)		Tasks/Other comments
Parking	**Q61**	5/24/19 10:14	5/24/19 11:00	46	0.8-3.6	2.7 (0.9)	doing cashier inside the booth (the booth's window was closed but the door was opened.)
	Q64	6/11/19 13:00	6/11/19 14:02	62	1.5-18.1	2.9 (2.6)	doing cashier inside the booth (the booth's window was closed but the door was opened.)
	X62	5/29/19 13:19	5/29/19 14:19	60	7.4-31.0	11.9 (4.7)	NA
	X65	6/13/19 12:00	6/13/19 13:00	60	0.0-1.5	0.7 (0.3)	NA
	Y66	6/12/19 9:21	6/12/19 10:18	57	3.5-7.0	4.9 (0.8)	NA
	Q71	5/23/19 13:26	5/23/19 14:31	65	0.0-0.183	0.003 (0.023)	doing cashier inside the booth (the booth's window and door were opened.)
	Q74	6/10/19 9:09	6/10/19 10:10	56	0.2-1.1	0.6 (0.2)	doing cashier inside the booth (the booth's window and door were closed.)
	X72	5/29/19 12:56	5/29/19 13:56	60	5.8-7.4	6.4 (0.4)	NA
	X75	6/13/19 12:06	6/13/19 13:16	70	0.0-2.7	0.7 (0.6)	NA
	Q81	5/29/19 14:57	5/29/19 15:50	63	0.0-10.7	3.0 (3.8)	valet parking
	Q84	6/10/19 11:03	6/10/19 12:07	64	0.0-1.4	0.4 (0.4)	valet parking
	X82	6/5/19 10:02	6/5/19 11:08	66	0.0-2.1	0.5 (0.5)	valet parking
	X85	6/13/19 12:51	6/13/19 14:00	69	0.0-0.7	0.0 (0.1)	valet parking

Appendix R (continued)

TABLE XLIII. SUMMARY OF PM2.5 CONCENTRATIONS MEASURED BY AIRBEAM2 SENSORS AMONG GROUND-KEEPING AND PARKING WORKERSa (continued)

Occ.	Sampling sessions	Start time	Stop time	Sampling duration (min)	1-min PM2.5 mean concentration (μg/m^3)		Tasks/Other comments
	Y86	6/12/19 11:02	6/12/19 11:53	51	0.0-9.8	1.9 (2.3)	valet parking
	Q91	5/24/19 15:05	5/24/19 16:10	65	0.0-3.0	0.9 (1.2)	valet parking
	Q94	6/11/19 14:59	6/11/19 15:57	58	0.0-4.4	0.7 (1.1)	valet parking
	X92	5/31/19 11:00	5/31/19 12:00	60	0.0-5.6	1.5 (1.5)	valet parking
	X95	6/12/19 11:04	6/12/19 12:00	56	0.0-6.2	1.4 (2.0)	valet parking
	Y96	6/19/19 11:18	6/19/19 12:08	50	0.0-7.4	2.3 (2.2)	NA
	Q101	6/3/19 12:47	6/3/19 13:55	68	0.2-3.8	0.8 (0.5)	working in their office in the parking facilities; traffic lineups for parking payment
	Q104	6/11/19 11:16	6/11/19 12:15	59	2.7-15.8	6.2 (3.9)	doing cashier inside the booth where more intense vehicles coming in and out compared to other locations
	X102	6/10/19 10:58	6/10/19 11:27	29	0.2-4.3	1.0 (0.9)	NA
	X105	6/17/19 12:57	6/17/19 13:51	54	0.0-10.2	4.9 (2.7)	NA
	Y106	6/21/19 10:05	6/21/19 11:02	57	1.5-3.6	2.4 (0.4)	NA

[a]NA: not applicable/no record

VITA

SAISATTHA NOOMNUAL

Education

2020	Ph.D., University of Illinois at Chicago, School of Public Health, Department of Environmental and Occupational Health Sciences
2016	M.P.H. (Environmental and Occupational Health), Rutgers University, Department of Environmental and Occupational Health, *Young adult street vendors and health outcomes affected by traffic-related air pollution*
2013	M.Sc., Chulabhorn Graduate Institute, Environmental Toxicology, *Identification of a novel antimicrobial and anticancer Streptanoate from Streptomyces sp. DC3*
2010	B.Sc. (Biotechnology), Kasetsart University, Department of Agro-Industry

Professional Activities

2017-2018	Research Assistant at Center of Healthy Work, University of Illinois at Chicago
2017-2018	Graduate Hourly work with Shared Air Shared Act project funded by USEPA, University of Illinois at Chicago
Summer 2017	Graduate Hourly work at Center of Healthy Work, University of Illinois at Chicago
2015- 2016	Research assistant at School of Public Health, Rutgers University
Summer 2015	Summer Internship at School of Public Health, Rutgers University
2013-2014	Research assistant at Chulabhorn Research Institute, Thailand

Teaching Experiences

Fall 2020	Teaching Assistant, Determinants of Population Health (Online Course), University of Illinois at Chicago
Spring 2020	Teaching Assistant, Local Citizenship and Community Health Initiatives, University of Illinois at Chicago
Fall 2019	Teaching Assistant, Determinants of Population Health (Online Course), University of Illinois at Chicago

Spring 2019	Teaching Assistant, Local Citizenship and Community Health Initiatives, University of Illinois at Chicago
Fall 2018	Teaching Assistant, Determinants of Population Health (Online Course), University of Illinois at Chicago
Spring 2018	Teaching Assistant, Local Citizenship and Community Health Initiatives, University of Illinois at Chicago
2011	Guest Lecture, General Principle of Carcinogenesis, Kasetsart University
2008	Teaching Assistant, Unit-operation of Agro-Industry I, Kasetsart University

Awards and Honors

2019	Michael Bruton Scholarship
Jun 2018-Jun 19	NIOSH Illinois ERC Pilot Project Research Training Grant
2018	AWMA Air Quality Research and Study Scholarship
2017	AIHF Chicago Local Section Scholarship
2016-present	Student member of national Delta Omega Honor Society in Public Health, Rutgers SPH chapter
2013-2019	Thai Ministry of Science and Technology Master/PhD or PhD Scholarship
2010-2013	The scholarship for Master's degree in Environmental Toxicology program, Chulabhorn Graduate Institute, BKK, Thailand
2010	The Second-Class Honor in Biotechnology program, Kasetsart University, BKK, Thailand

Research Publications AND PRESENTATIONS

2018	Shendell, D. G., **Noomnual, S.**, Plascak, J., & Apostolico, A. A. (2018). Injuries among young workers in career-technical-vocational education and associations with per pupil spending 11 Medical and Health Sciences 1117 Public Health and Health Services 13 Education 1303 Specialist Studies in Education. *BMC Public Health*, 18(1).

2017	**Noomnual, S.** and Shendell, D.G. (2017). Young Adult Street Vendors and Adverse Respiratory Health Outcomes in Bangkok, Thailand. *Safety and Health at Work*, 8: 407-409
2016	**Noomnual, S.** and Shendell, D. G. (2016). Risk of adult street vendor exposure to traffic-related air pollution in Bangkok, Thailand. *Hum Ecol Risk Assess*, 23(2): 1-10
2016	Shendell, D. G., **Noomnual, S.**, Chishti, S., Sorensen Allacci, M., & Madrigano, J. (2016). Exposures Resulting in Safety and Health Concerns for Child Laborers in Less Developed Countries. *J Environ Public Health*, 3985498.
2016	**Noomnual, S.**, Thasana, N., Sungkeeree, P., Mongkolsuk, S., Loprasert, S. (2016). Streptanoate, a new anticancer butanoate from Streptomyces sp. DC3. *J Antibiot*, 69(2):124-127
2012	**Noomnual, S.** S., Loprasert. Isolation and Characterization of Antimicrobial and Anti-nematode Compound(s) from *Streptomyces* sp. DC3 at EHT conference organized by Center of Excellence on Environmental Health and Toxicology, Ministry of Education (June 30th – July 1st 2012, At Chulabhorn Research Institute, Bangkok, Thailand) in the topic of "Isolation and Characterization of Antimicrobial and Anti-nematode Compound(s) from *Streptomyces* sp. DC3**"**

Professional Memberships and Services

2019-present	Golden Key International Honor Society
2017-present	American Industrial Hygiene Association
2017-present	Air & Waste Management Association
2017-2018	American Conference of Governmental Industrial Hygienists
2016-present	American Society of Safety Engineers (Greater Chicago – University of Illinois Chicago)
2015-2019	American Public Health Association