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Network of low-cost air quality sensors for monitoring indoor, outdoor, and personal $PM_{2.5}$ exposure in Seattle during the 2020 wildfire season

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HIGHLIGHTS

- Network of the low-cost sensors used to monitor air quality in 7 locations.
- PM reduction up to 70% was observed from the residence with air purifiers.
- Low-cost sensors showed a good agreement with regional monitors.
- Personal $PM_{2.5}$ exposure to wildfire smoke was mapped with a wearable monitor.
- Personal exposure was attributed to the microenvironments based on the GPS data.

ABSTRACT

The increased frequency of wildfires in the Western United States has raised public awareness of the impact of wildfire smoke on air quality and human health. Exposure to wildfire smoke has been linked to an increased risk of cancer and cardiorespiratory morbidity. Evidence-driven interventions can alleviate the adverse health impact of wildfire smoke. During wildfires, public health guidance is based on regional air quality data with limited spatiotemporal resolution. Recently, low-cost air quality sensors have been used in air quality studies, given their ability to capture high-resolution spatiotemporal data. We demonstrate the use of a network of low-cost particulate matter (PM) sensors to gather indoor and outdoor $PM_{2.5}$ data from seven locations in the urban Seattle area, along with a personal exposure monitor worn by a resident living in one of these locations during the 2020 Washington wildfire event. The data were used to determine PM concentration indoor/outdoor (I/O) ratios, PM reduction, and personal exposure levels. The result shows that locations equipped with high-efficiency particulate air (HEPA) filters and HVAC filtration systems had significantly lower I/O ratios (median I/O = 0.43) than those without air filtration (median I/O = 0.82). The median $PM_{2.5}$ reduction for the locations with HEPA is 58% compared to 20% for the locations without HEPA. The outdoor PM sensor showed a high correlation to the nearby regional air quality monitoring stations (pre-calibration $R^2 = 0.92$). The personal monitor showed higher variance in PM measurements as the user moved through different microenvironments and could not be fully characterized by the network of indoor or outdoor monitors. The findings imply that evidence-based interventions can be developed to reduce pollution exposure when combining data from indoor and outdoor sensors. Personal exposure monitoring captured temporal spikes in PM exposure.

1. Introduction

Climate-change-related wildfires have become more frequent and intense in the Western United States. Summer wildfire seasons are 40–80 days longer than they were 30 years ago (Jolly et al., 2015). Evidence suggests that California and other Western states will likely see ever-worsening fires due to climate change and land management practices (Kennedy et al., 2021; Barbero et al., 2015; Spracklen et al., 2009; Burke et al., 2021a). The intensified wildfires will release more smoke into the atmosphere (Yue et al., 2013), traveling significant distances (Tiwari et al., 2017). Fine particulate matter ($PM_{2.5}$), a major pollutant in smoke from wildfires, can travel deep into the respiratory tract (Burke et al., 2021b). The combustion-generated aerosols consist of elemental carbon and organic carbon fraction, which may be more toxic than other $PM_{2.5}$ sources and may have long-lasting impacts on health (Samburova et al., 2017; Aguilera et al., 2021; Magzamen et al., 2021; Landguth et al., 2020). Complex flow structures associated with large-scale flames and low flame temperature in biomass burning lead to low carbonization of organic carbon, thus – high levels of potentially carcinogenic polycyclic aromatic compounds (West et al., 2020;

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Mahamuni et al., 2020; Davis et al., 2019, 2020). Exposure to $PM_{2.5}$, particularly combustion-generated aerosols, has been linked to adverse respiratory and cardiovascular health effects, including ischemic heart disease, stroke, cardiovascular mortality, and exacerbations of asthma and chronic obstructive pulmonary disease (Deflorio-Barker et al., 2019; Liu et al., 2021; Dennekamp and Abramson, 2011; Reid et al., 2016; Matz et al., 2020). More recently the wildfire PM exposures have been linked to higher severity and mortality of SARS-CoV-2 (Meo et al., 2021; Cortes-Ramirez et al., 2021; Kiser et al., 2021; Navarro et al., 2021).

A series of large wildfires impacted air quality in western regions of the United States in 2020. The episode measured in this study (2020 Washington Labor Day fires) began on September 7, 2020, and were 90% contained by September 22. The fires burned over 41,000 acres of the forest (Center, 2020). Due to the SARS-CoV-2 pandemic shelter-in-place order by Washington state in early 2020, people spent a significant amount of time indoors during the 2020 wildfire season. The public health advice for protection from wildfire smoke exposure is to stay indoors, preferably in a “clean room” with filtered air, closed windows and doors, and minimize physical exertion. However, studies have shown that $PM_{2.5}$ could penetrate indoors even with all the windows and doors closed (Xu et al., 2017; Park et al., 2021). With limited access to portable air cleaners during wildfires and increasing awareness of the health impact of wildfire smoke exposure, monitoring indoor $PM_{2.5}$ is critical to estimate household members’ wildfire smoke exposure. Failure to assess the exposure to wildfire smoke could lead to misclassification of exposure in future epidemiology studies and have important public health implications for targeting smoke reduction interventions. The opportunity exists to improve personal exposure assessment and design individualized intervention strategies that would significantly reduce the adverse impact of PM pollution on human health, including the severity and mortality of Covid-19 cases (Laumbach and Cromar, 2021; Rappold et al., 2014).

Recent advancements in low-cost particulate matter (PM) sensors led to their extensive use in various applications, such as air quality (AQ) monitoring in indoor (Makhsous et al., 2021; Hegde et al., 2020; Li et al., 2018; Kumar et al., 2016) and outdoor (Seto et al., 2014; Liu et al., 2020; Kuhn et al., 2021; Jiao et al., 2016; Gao et al., 2015) environments, including large-scale deployments (Kumar et al., 2015; Li et al., 2020a; Chao et al., 2021; Qiao et al., 2021). Optical PM sensors rely on elastic light scattering providing size-resolved PM concentrations in the 0.3–10.0 μm range. The low-cost sensor measurements may suffer from sensor-to-sensor variability due to a lack of quality control and differences between individual components (Austin et al., 2015; Sousan et al., 2016). The scattering light intensity depends on particle size, morphology, complex index of refraction (CRI), and sensor geometry (Njalsson and Novosselov, 2018). CRI sensitivity can be addressed by optimizing the design to measure scattered light at multiple angles simultaneously or by employing dual-wavelength techniques (Renard et al., 2016; Nagy et al., 2007). However, these solutions are complex and involve expensive components that are not suitable for compact, low-cost devices (Makhsous et al., 2021).

Environmental conditions were reported to affect sensor output, e.g., a non-linear response has been reported with increasing RH (Liu et al., 2019; Jayaratne et al., 2018; Chakrabarti et al., 2004; Sioutas et al., 2000; Malm et al., 2000). High humidity (RH $>$ 75%) creates challenges for particle instruments; e.g., significant variations were observed between different commercially available devices, such as Nova PM sensor (Liu et al., 2019) and personal DataRAM (Chakrabarti et al., 2004). In addition, the RH measurement approach could also affect the sensor output (Liu et al., 2019; Jayaratne et al., 2018), e.g., the RH measurement based on a reference monitoring site rather than inside the sensor enclosure may be different due to the microenvironment and transient effects. The selection of reference instruments with different measuring principles may also influence the calibration of low-cost sensors. For example, the calibration of the Plantower PM sensor in Jayaratne et al., 2018) was based on the tapered element oscillating microbalance (TEOM), while Zusman et al., 2020 calibrated the same sensor against the beta attenuation monitor (BAM) and federal reference method (FRM) measurements (Jayaratne et al., 2018; Zusman et al., 2020). The integrated mass measurements cannot resolve temporal changes in particle size and concentration during the calibration experiment. The instruments that directly measure aerosol size and concentration, such as aerodynamic particle sizer (APS), can be a better fit for sensor calibration (Austin et al., 2015; Manikonda et al., 2016).

As low-cost sensors find applications in pollution monitoring, various studies have evaluated the performance of low-cost PM sensors in laboratory and field settings (Austin et al., 2015; Zusman et al., 2020; Cordero et al., 2018; Feenstra et al., 2019; Kelly et al., 2017; Sayahi et al., 2019; Tryner et al., 2020; Wang et al., 2020). These reports show that low-cost sensors yield useable data when calibrated against research-grade reference instruments (Chao et al., 2021; Huang et al., 2021a; Li et al., 2020b). The low-cost sensor networks have the potential to provide high spatial and temporal resolution, identifying pollution sources and hotspots, which in turn can lead to the development of intervention strategies for exposure assessment and intervention strategies for susceptible individuals. Time-resolved exposure data from wearable monitors can be used to assess individual exposure in near real-time (Duncan et al., 2018).

This study utilized a network of indoor, outdoor, and wearable low-cost air quality sensors to evaluate 1) the effectiveness of intervention strategies used in different households in terms of $PM_{2.5}$ I/O ratios and $PM_{2.5}$ reduction during the 2020 Washington wildfire in seven locations, including residential and office buildings; 2) estimation of personal exposure by (i) wearable sensor and (ii) a combination of indoor and outdoor monitors, where the fraction of personal exposure from different microenvironments is determined based on the Global Positioning System (GPS) and time-resolved PM sensor data.

2. Methods

2.1. PM monitor

The monitor used in this study consists of a PM sensor, a temperature/humidity/pressure sensor, a GPS module (ublox SAM-M8Q), and a display (see Fig. 1a). The PM sensor (Plantower PMS A003, Beijing Plantower Co., Ltd, China; referred to as PMS hereafter) is an optical scattering-based sensor with a photodiode positioned normal to the excitation beam. The scattering light intensity is converted to a voltage signal to estimate PM number concentration and mass concentration using a proprietary calibration algorithm. The PMS provides estimated particle counts in six size bins with the optical diameter in the 0.3–10 μm (#/0.1L) range and mass concentration (μg/m^3) for PM_1, $PM_{2.5}$, and PM_{10}. The mass concentrations can be set to “standard” and “atmospheric”, altering the assumed particle density. The “standard” condition is designed to be used in industrial settings, whereas the “atmospheric” condition best measures particles in the ambient environment. The “ATM” setting for $PM_{2.5}$ concentration was used in this study; the sampling interval was set to 10 s. The same device was also used as the wearable persona monitor. GPS data were used to coordinate the personal data to a specific location and attribute the PM exposures to the user’s microenvironment.

2.2. Sampling sites

The monitors were deployed in seven urban Seattle locations (see Figure A1). Each site had one outdoor sensor and at least one indoor sensor. The L2 location had two indoor sensors positioned in different rooms within the residence. One user from the sampling site L2 wore an additional personal monitor for the duration of the study. The study covered the wildfire episode between September 10 and September 21, 2020. The sampling sites included two University of Washington (UW) buildings and five residences in Seattle. Data from the nearby Puget

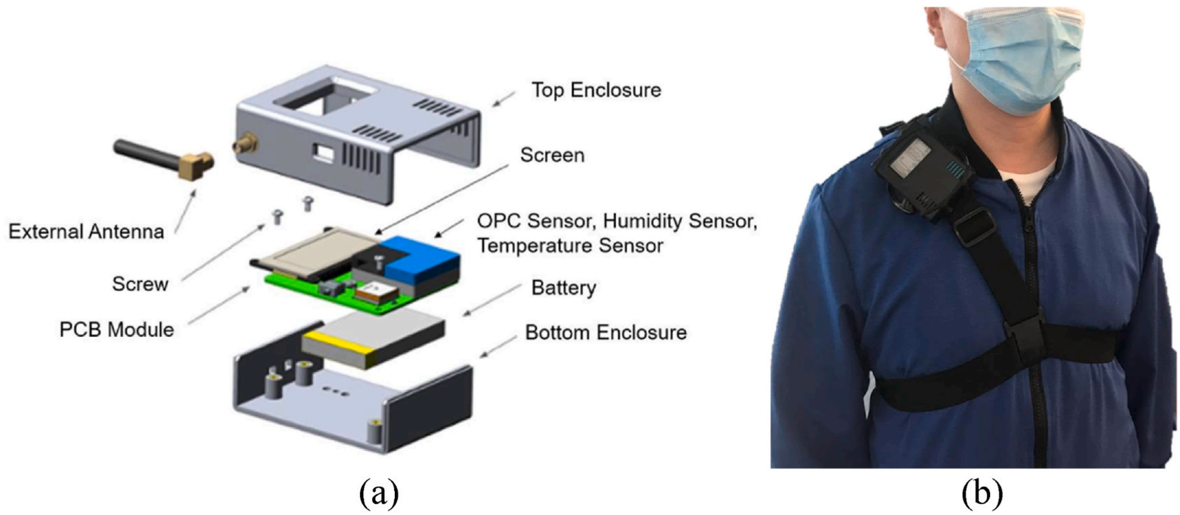

Fig. 1. a) Exploded view of the monitor; b) The wearable monitor.

Sound Clean Air Agency (PSCAA) regional stations were used for the data quality control. Before the study, information about the sites, such as housing type, size, HVAC, primary indoor PM sources, and possible sensor locations, was collected (see Table 1). Three sites (L1-L3) had portable air purifiers or built-in high-efficiency air filtration in HVAC systems. Both UW buildings (L6 and L7) were largely unoccupied due to the shelter-in-place order and were not equipped with HEPA filtration units. The residents at the sampling sites were not given specific instructions on whether to keep the windows and doors open or closed but were asked about this after the sampling was completed. The research staff performed the sampling at the UW buildings, and the windows were kept closed during sampling.

2.3. Data analysis

The low-cost sensor data were corrected against the average of $PM_{2.5}$ from the two nearby PSCAA regional monitors (Lake Forest Park and Seattle 10th & Weller). The correction model was generated using a data subset from the outdoor sensor outside a UW building (L6) during the wildfire event. The L6 building was largely unoccupied during the wildfire and had minimum local activities that would influence $PM_{2.5}$ measurement compared to the other sampling sites. The L6 is located at least 200 m from any major traffic arterials. Before the deployment, PMS sensors were accessed for their data accuracy. Sensor to sensor difference was within 10%, as shown in our previous aerosol chamber experiments (Huang et al., 2021a). Informed by our previous PMS sensor calibration study, a linear model and a quadratic were tested to fit using the outdoor sensor data from L6:

$$\boldsymbol{Ref} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \cdot \boldsymbol{PMS} \tag{1}$$

$$\boldsymbol{Ref} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \cdot \boldsymbol{PMS} + \boldsymbol{\beta}_2 \cdot \boldsymbol{PMS}^2 \tag{2}$$

where β_0, β_1, and β_2 are the regression coefficients, *Ref* is the hourly reference $PM_{2.5}$ concentrations from the nearby PSCAA monitoring stations, and *PMS* and PMS^2 are the linear and quadratic coefficients of the raw $PM_{2.5}$ data from the sensor, respectively. The fits with zero intercept ($\beta_0 = 0$) and non-zero intercept ($\beta_0 \neq 0$) were tested. The Bayesian Information Criterion (BIC) informed the optimal calibration model.

The time-resolved PM concentration I/O ratio was calculated to assess the smoke infiltration. We conducted the Wilcoxon signed-rank tests (for paired comparison) to compare the I/O ratio during the wildfire to the I/O ratio post the wildfire. To assess the reduction in PM levels, we compared indoor and outdoor time-resolved PM concentrations. We calculated $PM_{2.5}$ reduction for each site and the personal exposure as:

$$PM_{2.5}\text{Reduction} = \frac{\boldsymbol{O} - \boldsymbol{I}}{\boldsymbol{O}}\% \tag{3}$$

where *O* is the average outdoor $PM_{2.5}$ concentration (μg/m^3) during the wildfire and *I* is the average indoor or personal $PM_{2.5}$ concentration (μg/m^3).

To understand the contribution of each microenvironment to personal exposure, we attributed the user's daily $PM_{2.5}$ exposures in each location using GPS data with a 2.5m horizontal accuracy from the wearable monitor. The personal exposure attribution was done using Python 3.7.1. The raw $PM_{2.5}$ data were first aggregated into 10-min averages to reduce the data size without losing significant spatial resolution. The geocoordinates, recorded in conjunction with the $PM_{2.5}$ concentration, were grouped into three categories where the user spent most of the time: home, office, and other. We defined the buffer zones encircling the residence and the office locations with a 10-m clearance to minimize misclassification caused by the GPS drift. The home and office geolocation data were visually confirmed on a map for each occurrence when the user with the wearable monitor was at the location. Records collected outside these two buffer zones were classified as "other locations". Then the $PM_{2.5}$ exposures attributed to each microenvironment for each day were calculated as:

Table 1
General characteristics of the sampling sites.

Location ID	Building Type	Size (sq. ft)	HVAC	HEPA	Window Opening[a]	Indoor PM Sources[a]
L1	1-story SFH	1600	N	Y	Sometimes	Occasional cooking
L2-a L2-b	1-story SFH	1500	N	Y	No	Occasional cooking
L3	2-story SFH	3500	Y[b]	N	No	Occasional cooking
L4	2-story SFH	3000	N	N	Always	Frequent cooking
L5	Apartment	800	N	N	Sometimes	Occasional cooking
L6	Office	135	Y	N	No	N/A
L7	Office	144	Y	N	No	N/A

Definition of abbreviation: SFH = single-family home; Y = Yes; N= No; sq.ft = square feet.
[a] Self-reported information.
[b] Electrostatic precipitator built in the HVAC.

Table 2
Summary of the indoor and outdoor $PM_{2.5}$ levels (μg/m^3) and I/O ratios for each sampling site.

Location ID	Indoor		Outdoor		I/O ratios				$PM_{2.5}$ Reduction (%)[a]
	Mean	Max	Mean	Max	Min	Median	Mean	Max	
L1	20.9	42.2	102.0	174.2	0.1	0.21	0.23	0.74	79.6%
L2-a	58.7	147.4	114.5	206.3	0.18	0.52	0.54	1.41	48.7%
L2-b	42.4	100.1	114.5	206.3	0.04	0.40	0.41	1.09	63.0%
L3	48.9	124.7	104.5	185.3	0.10	0.46	0.54	5.23	53.2%
L4	104.3	396.2	123.8	215.7	0.73	0.86	0.88	1.44	15.7%
L5	79.7	154.9	112.2	205.5	0.51	0.69	0.73	1.93	29.0%
L6	90.9	150.9	110.1	208.6	0.57	0.84	0.86	3.62	17.5%
L7	82.5	170.7	105.5	196.7	0.44	0.80	0.80	1.71	21.8%

[a] Comparison between indoor and outdoor $PM_{2.5}$ levels during the wildfire as calculated using equation (3).

$$AC_{k_j} = \frac{C_{k_j} \times F_{k_j}}{\sum_{k=1}^{n} F_{k_j}} \quad (4)$$

where AC_{k_j} represents the attributable exposures of microenvironment k to the total personal exposure on day j; C_{k_j} is the hourly average $PM_{2.5}$ concentrations (μg/m^3) of microenvironment k on day j ; and F_{k_j} is the fraction of time spent in microenvironment k on day j.

3. Results and discussion

3.1. PMS sensor correction

The data from the L6 outdoor sensor shows a good agreement with the regional monitors with the pre-calibration $R^2 = 0.92$. The linear model shows the lower root-mean-square-error (RMSE) and BIC, with the overall RMSE improved from 18.47 μg/m^3 to 14.35 μg/m^3 against the regional monitors with the post-calibration $R^2 = 0.94$ (see Figure A2). The quadratic model was also tested and did not result in a significant improvement; thus, the data from all the other sensors were corrected with the linear model. After the correction, the correlation between the average outdoor PM concentration from the sensor network and the average of the reference monitors is 0.97. The high correlation suggests that a wildfire is a regional event with low spatial variance. Both OEM and the custom calibrations for the wildfire smoke performed well in the high PM level study. The correlation is higher than the R^2 value from California's low-cost sensor calibration study in 2020 (Bi et al., 2020). Other researchers reported similar values for the $PM_{2.5}$ index in their field calibrations of PMS sensors (Kelly et al., 2017; Levy Zamora et al., 2018; Zamora et al., 2019). In the Siberian wildfire monitoring study, Lin et al. reported agreement with the BAM reference instruments of $R^2 = 0.94$ (Lin et al., 2020), similar to our results. Liang et al. analyzed the data from the PurpleAir sensors during the California wildfire season and reported good agreement with the EPA measurements ($R^2 = 0.87$) (Liang et al., 2021). The recent EPA challenge has also demonstrated that PM type-specific calibrations improved the PM sensor accuracies to ~75–83% for conditions typical to wildfire events (Landis et al., 2021). These studies and our results suggest that a high correlation of PMS to reference instrument for $PM_{2.5}$ index can be attributed to specific correction for wildfire smoke and the dominance of these PM in the airshed during the wildfire. Note that PMS A003 performed well when tested against several different aerosols if the mass index for $PM_{2.5}$ was used. Our earlier study showed that the addition of PM-specific terms (such as complex index of refraction and density) improves the accuracy of the PMS sensor for both number density and mass concentration. However, the RH term did not improve calibration in the RH = 17–80% range (Huang et al., 2021a). During this study, the RH was lower than 80%. Thus, the RH term was not included in the correction model used in this analysis.

There are some additional considerations for stationary and wearable sensor selection specific to wildfire smoke monitoring. Kelleher et al. reported that the Sharp GP2Y1023AU0F sensor suffered from temperature dependence, drift, and imprecision during the wildfire smoke tests (Kelleher et al., 2018). The same sensor had difficulty tracking high PM concentrations in monitoring high woodsmoke concentrations from residential combustion sources (Bjornsson, 2014). Thus, the saturation limit of the sensor must be considered in the plume tracking and wildfire studies. In this study, the stationary and wearable PMS sensors did not exhibit significant drift over one-week deployment, and the correlation to PSCAA reference stations was consistent throughout the study for outdoor network sensors (see Fig. 2).

3.2. Time-resolved PM concentrations

Fig. 2 shows 1-h averages of $PM_{2.5}$ concentrations measured by the sensor network and the regional monitors during the wildfire. The data are divided into indoor and outdoor categories. The indoor data are further divided into HEPA (L1-L3) and Non-HEPA (L4-L7) subsets. The shaded areas represent one standard deviation (1σ) of the measurements. The data from the outdoor monitors closely match the reference monitors. The locations with active air filtration had a significantly lower PM concentration, while locations without HEPA filters had only slightly lower PM levels. Occasional spikes in PM concentration, above the already high baseline, were observed due to cooking activities. Note that even with the active PM control strategies implemented in several households, the average indoor $PM_{2.5}$ is still much higher than the typical (non-wildfire season) outdoor $PM_{2.5}$ levels (<10 μg/m^3) in this region (Xiang et al., 2020; Huang et al., 2021b).

3.3. Detailed PM concentrations and analysis

We present a case-by-case analysis to provide insight into the effectiveness of aerosol mitigation strategies and the significance of the

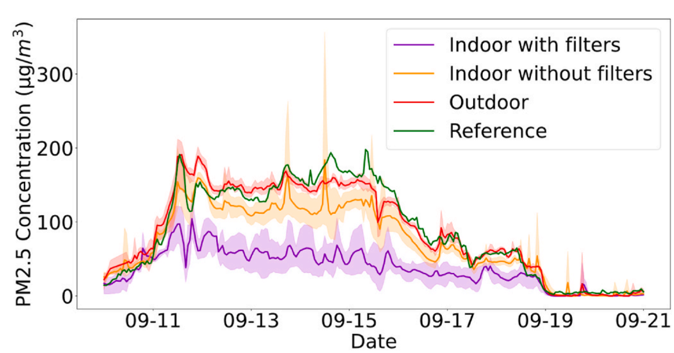

Fig. 2. Corrected average indoor and outdoor $PM_{2.5}$ concentrations across the seven sampling sites compared to the reference monitors during the wildfire. The purple and orange lines illustrate the average indoor $PM_{2.5}$ concentrations at the sampling sites with and without HEPA filtration, respectively. The shading around each line shows the one standard deviation (1σ) of the measurement. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

quantity and placement of sensors within the residences. Fig. 3 shows the 1-h average indoor and outdoor data for all sites with the averaged $PM_{2.5}$ from the two reference monitors in green color for comparison.

Overall, the outdoor sensors are in close agreement with PSCAA data. In some cases, the outdoor sensors reported spikes in PM concentration likely due to the local activities near monitoring sites, which the PSCAA monitors could not detect (see Fig. 3). Similar spikes were reported in several previous studies using low-cost sensors for local AQ monitoring (Hegde et al., 2020; Mousavi and Wu, 2021; Gupta et al., 2018). These differences can be explained by (i) spikes in the local PM concentration or (ii) mismatch in sensor sampling rate as the network sensors sampling interval was set to ~ 10 s, while the reference monitors' reporting interval was 1 h. Though both scenarios are possible, the PM levels difference between the locations suggests that some differences in outdoor $PM_{2.5}$ concentration were driven by local events that the regional monitors could not capture.

HEPA filters and electrostatic air purifiers reduced indoor $PM_{2.5}$ concentration by 48–80% at L1-3. A similar $PM_{2.5}$ reduction level was also observed in other studies summarized in Kelly and Fussell's review of air purification technologies in pollution reduction in indoor environments (Kelly and Fussell, 2019). Only a moderate PM reduction (16–29%) was observed when no PM filers were used at L4 - L7. Xiang et al. reported that portable HEPA filter units led to a 48%–78% decrease in indoor $PM_{2.5}$ during the same wildfire episode (Xiang et al., 2021a). Stauffer et al. compared the $PM_{2.5}$ concentrations in the office to those recorded at the nearest Air Quality monitoring station during the wildfire episode. The portable air cleaner reduced PM in the office by 73%–92% (Stauffer et al., 2020), similar to the smaller home office setting (L1) in our study. Table 2 lists the mean and maximum of $PM_{2.5}$ and hourly $PM_{2.5}$ indoor/outdoor (I/O) ratio for each sampling site. $PM_{2.5}$ reduction levels were calculated for each sampling location to indicate the effectiveness of mitigation strategies for households.

Location L1 had the indoor monitor placed in a relatively small room (home-office ~ 150 ft^2) with a high-volume HEPA filter for the entire wildfire episode. This relatively small "clean room" environment strategy resulted in the study's lowest median I/O ~0.2 (see Table A1). However, data for other locations (e.g., bedrooms, living room) within the residence are not available, which is problematic for assessing personal exposure.

The residents of the L2 residence had the two monitors in separate rooms: L2a was placed in a larger living room (~350 ft^2) and L2b - in the adjacent home office (120 ft^2). Two portable HEPA filtration units were used: one in the living room, and the other was moved from the office to the bedroom at nighttime. The data from the living room has relatively low variance; however, the larger room was not cleaned as effectively as the smaller home office or bedroom, I/O ratio stayed relatively constant at ~0.5. When the filtration unit was positioned in the office, the I/O ratios dropped to ~0.4. When the filter was moved from the home office to the bedroom, the PM level in the office increased to the level of the adjacent living room. The bedroom was not monitored by a fixed sensor; however, the resident's wearable sensor recorded a significant PM reduction in the bedroom during the night, with the I/O ratio close to 0.1 (see Fig. 4).

The L3 site had an electrostatic precipitator installed in the HVAC system. The HVAC system was controlled by a thermostat, which

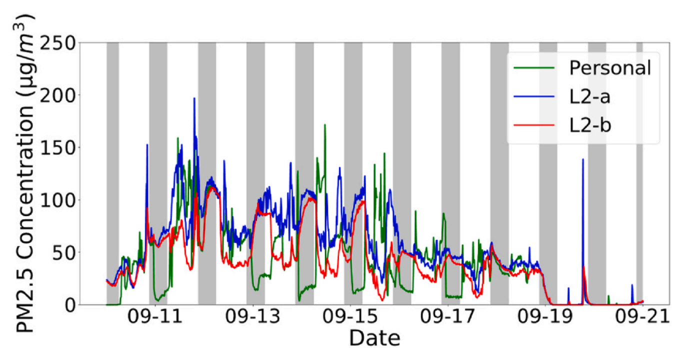

Fig. 4. Profile of 10-min averaged $PM_{2.5}$ concentrations by the personal monitor (green line) and the bedroom monitors (the blue and purple line) during the wildfire. The shaded areas mark the nighttime (10:00 p.m. - 6:00 a.m.). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

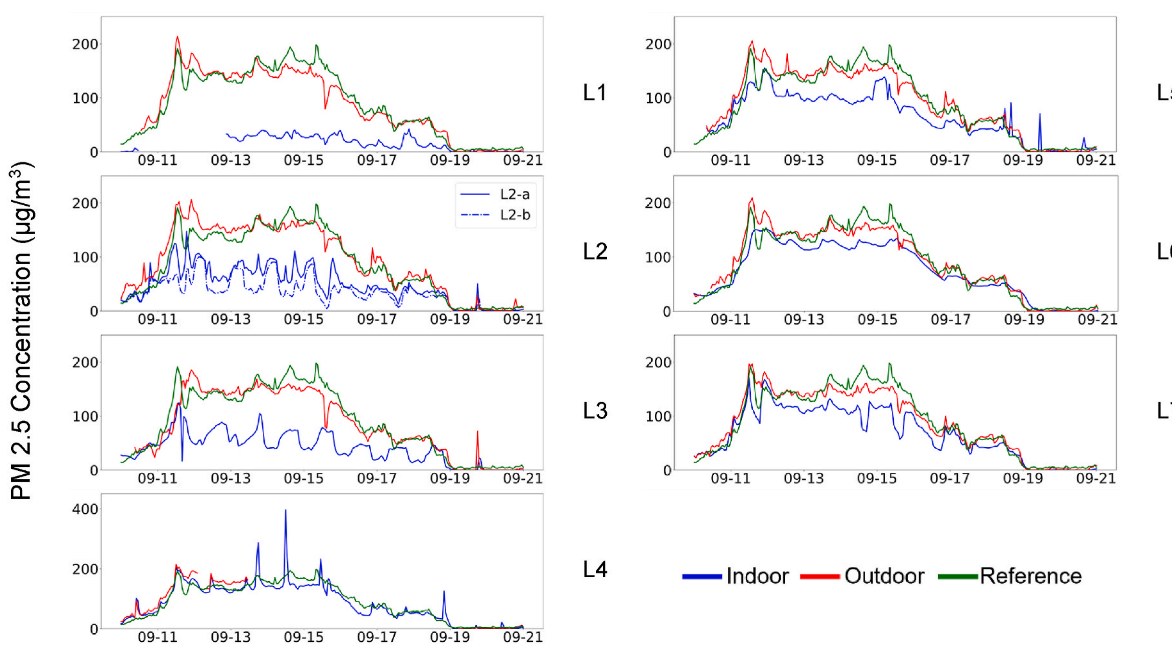

Fig. 3. Time-series plots of indoor and outdoor $PM_{2.5}$ concentrations are compared to the reference monitors for each sampling site during the wildfire. The blue and red lines represent the indoor and outdoor $PM_{2.5}$ measured by the sensors, and the green line represents the averaged $PM_{2.5}$ concentrations from the two nearby regional monitoring sites. Note that L4 has the Y-axis range of 0–400 μg/m^3 to show the spikes of the indoor $PM_{2.5}$. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

explains the periodic pattern of the PM concentration. The PM concentration (measured in the bedroom) dipped during the daytime when the forced air HVAC system was ON and went up during the nighttime when the HVAC was OFF.

L4 indoor monitor was placed in the kitchen, where it detected the spikes from cooking activities in addition to the high background level from wildfire smoke intrusion. L4 residents kept their kitchen windows open during the wildfires, which explains the highest background indoor PM level among all the sampling sites. L4 outdoor sensor stopped working three days after the deployment because it was accidently unplugged from the AC outlet. I/O ratio for L4 was calculated using the data collected before September 13. The sampling site L4 without air filtration and closed windows had only a 13% indoor-outdoor difference.

The L5 residence did not have a central HVAC system. A portable AC unit (AeonAir Model #RPAC08EE) with a low-grade PM filter was used by the residents during the wildfire. The window in the residence was closed for the entire duration of sampling (self-reported). L5 monitor was placed in the apartment's kitchen/living room area (200 ft2). PM concentration was lower than the outdoor level during the wildfire but higher than in other residences with air filtration units. L6 and L7 are two UW buildings with HVAC systems but low-grade filtration units. The data is similar to the L5 residential site. The buildings were largely unoccupied during the wildfire due to COVID lockdown, and the windows were closed. The indoor $PM_{2.5}$ at L6 and L7 are lower than outdoor. The I/O ratios were similar to L5 (~0.7–0.8).

Interestingly, sites L3 and L7 with central filtration units show similar trends. PM concentration dipped rapidly when the HVAC was turned ON (controlled by a thermostat). As the central HVAC unit was OFF, the PM concentration climbed up due to the infiltration of smoke. Though the analysis of HVAC performance is beyond the scope of this manuscript, these data can be used to design and optimize HVAC performance, such as the use of economizers, sensor-based controls, filter upgrades, etc.

The average I/O ratio across all seven sites was 0.62. The sites with HEPA filters (L1, L2-a, L2-b, and L3) and the sites without HEPA filters (L4- L7) had an average I/O ratio of 0.43 and 0.82, respectively. Lower I/O ratios were found in the study conducted in the same region during the same wildfire episode (I/O = 0.19 for the households with air cleaners; I/O = 0.56 for the households without air cleaners) (Xiang et al., 2021b). May et al. evaluated $PM_{2.5}$ infiltration in the western US during the 2020 wildfire and found I/O ratios for the school (0.7) and residential (0.4) buildings (Mae et al., 2021). Similar to our results, the authors noted that using multiple filter units in residences was associated with substantially lower I/O values.

3.4. Personal exposure measurement - A case study

To assess personal exposure as a function of the microenvironment, we compared the personal data measured by the wearable monitor with the wearer's home-based monitor data. Fig. 4 shows the 10-min average of $PM_{2.5}$ concentration measured by the user's personal and home-based monitors for reference. The wearable sensor $PM_{2.5}$ data showed a 68% $PM_{2.5}$ reduction, which is lower than the $PM_{2.5}$ reduction estimated using the wearer's indoor monitors. The shaded areas mark the nighttime (10:00 p.m. - 6:00 a.m.). The personal monitor recorded significantly lower $PM_{2.5}$ concentration at night compared to the other two home-based monitors located in the living room and the home office, which can be explained by the colocation of the HEPA air cleaner and wearable monitor. The user is an aerosol researcher who monitored his exposure during the wildfire. The difference in the personal exposures, measured by the wearable and the home-based monitor, indicates that access to special hyperlocal resolution (Indoor - room level, Outdoor – 2.5 m, Wearable sensor level – 2.5m with 10 m buffer) for PM data can enhance the efficacy of PM exposure interventions.

We also apportioned the user's exposure based on the GPS data. Fig. 5a shows the 10-min average of $PM_{2.5}$ concentration measured by the personal sensor color-coded based on the microenvironment. The user spent the most time at home, 15% of the time in the office, and 9% in other locations. Exposure outside the home and the office was categorized into other locations. The wearable monitor recorded higher $PM_{2.5}$ levels in the user's workplace and other locations than at the residence. Fig. 5b shows the weighted daily average personal exposure in different microenvironments. The personal exposure contribution from the office and other locations was 36% of the total smoke exposure during the wildfire, while the time spent in these environments was 24% (see Figure A3). Attributing personal exposure to specific microenvironments can help plan personal activities during wildfire events.

Personal exposure assessment studies used stationary monitoring of microenvironments (Gulliver and Briggs, 2004; Steinle et al., 2015) and wearable monitors. Utilizing the former, Steinle et al. reported substantial variability across microenvironments and noted that it is essential to measure near-complete exposure pathways. (Steinle et al., 2015). Morawska et al., in their review, pointed out a strong dependence on resident activities, source events, and site-specificity on personal exposure. The authors assessed that 10–30% of the total PM exposure was from indoor-generated particles (Morawska et al., 2013). In our work, elevated PM levels due to cooking activities were observed (L4, L5); however, using a portable HEPA filter significantly reduced the exposure during the wildfire if the windows were closed (L1-L3). Han et al. reported that the average daily personal exposure to $PM_{2.5}$ in Beijing was consistently lower than using corresponding ambient concentrations (Han et al., 2021).

4. Conclusions

This study demonstrates the application of a low-cost sensor network for air quality monitoring during the 2020 Washington wildfire event. The outdoor $PM_{2.5}$ data from the sensor network had an excellent agreement with the nearby PSCAA regional monitors. The spatial

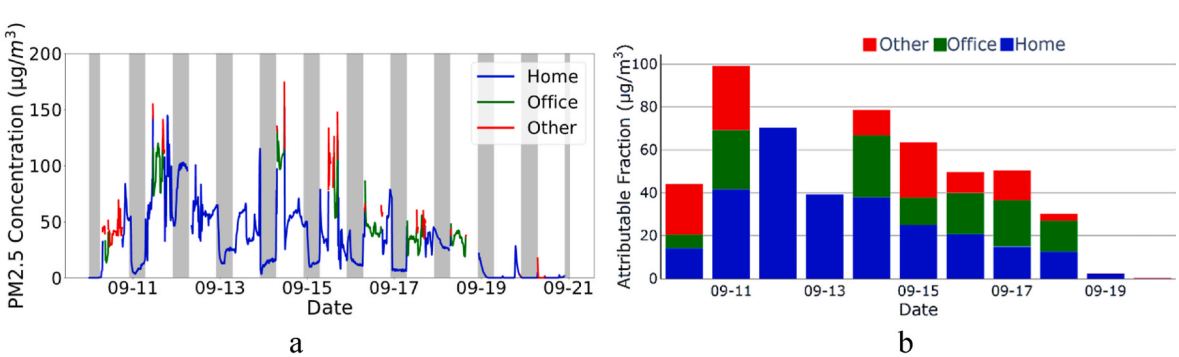

Fig. 5. a) Time series plots of the personal $PM_{2.5}$ exposure color-coded based on the microenvironment the user was in; b) Weighted daily average personal exposure in different microenvironments. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

variance for $PM_{2.5}$ in the urban area was low during the wildfire event. Our results showed that during the 2020 Washington wildfire, the outdoor $PM_{2.5}$ level was as high as > 200 μg/m^3 in the Seattle area. Using a portable HEPA air cleaner was associated with lower indoor $PM_{2.5}$ levels during the wildfire episode, with a $PM_{2.5}$ reduction of 50–77% among the sampling sites. However, the observed levels were still higher than the typical Seattle outdoor PM levels (<10 μg/m^3). The I/O ratio was driven by the smoke infiltration and the quality of air filtration. The personal monitoring results highlighted the influence of microenvironments on an individual's exposure to $PM_{2.5}$. Although this study had a relatively small sample size, it demonstrated that personal action, such as staying indoors and using HEPA air cleaner, can reduce personal exposure to wildfire smoke. The personal exposure analysis suggests that knowledge about personal PM levels can lead to a reduction in exposure. More extensive studies and a collection of time-activity information are warranted to investigate the source of $PM_{2.5}$ exposure and the health impact of PM exposure.

Author contributions statement

Jiayang He: Conceptualization, Methodology, Project administration, Validation, Investigation, Writing - original draft, Writing – review & editing.

Ching-Hsuan Huang: Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Nanhsun Yuan: Software, Data curation, Formal analysis, Visualization, Writing – original draft.

Elena Austin: Supervision, Writing - Review & Editing.

Edmund Seto: Supervision, Writing - Review & Editing.

Igor Novosselov: Conceptualization, Methodology, Supervision, Funding acquisition, Writing - Review & Editing.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2022.119244.

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