Indoor and Ambient Influences on $PM_{2.5}$ Exposure and Well-being for a Rail Impacted Community and Implications for Personal Protections

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Study Importance

Study findings suggest that land use, building characteristics, and indoor activity all compound to worsen air pollution exposures beyond what is expected for exposures in non-industrialized areas. Findings prompt a call for stronger local, state, or federal regulation, not only for emissions sources that are proximal to residential areas, but also for indoor air quality and zoning standards, specifically for the protection of communities that are impacted by historical and present-day inequities.

Abstract

Background

Higher air pollution emissions can be observed near rail networks, local and highway automobile corridors, and shipyards. Communities near such sources are often disproportionately exposed to emissions from these stationary and mobile sources. One such community is West San Bernardino in California, where households are feet away from the Burlington Northern Santa Fe intermodal facility and are impacted by activities that are estimated to continuously emit air pollutants due to 24/7 operation.

Objective

This study aimed to (1) quantify the impact of personal mobility and housing characteristics on daily $PM_{2.5}$ exposures and well-being for West San Bernardino community members, and (2) develop individualized resilience plans for community collaborators to support future $PM_{2.5}$ exposure reduction.

Methods

Personal $PM_{2.5}$ exposures were measured for each community collaborator for seven consecutive days during three deployment periods: October 2021, January 2022, and March 2022. Indoor and ambient $PM_{2.5}$ levels were also continuously measured for five households over six months using PurpleAir Classic monitors. Demographic and well-being data were collected upon recruitment and after each week of engagement, respectively.

Results

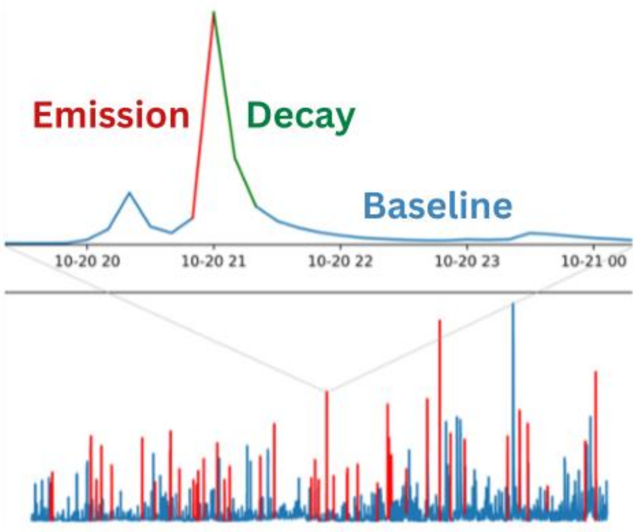
Personal exposures in home microenvironments were highest near the railyard and decreased with distance from the railyard. Home exposures were 40% higher on average compared to non-home microenvironments. Household $PM_{2.5}$ levels had a higher-than-expected average infiltration factor of 0.70, and indoor 98th percentiles across the households far exceeded a healthy level at an average of 61 $\mu g/m^3$. Increasing median personal exposures were linearly correlated with worsening health conditions.

Significance

Results suggest that surrounding land use, household building characteristics, and indoor activity all compound to worsen air pollution exposures beyond what is expected for exposures in non-industrialized

areas. Findings prompt a call for stronger regulation, not only for emissions, but also for indoor air quality and zoning standards that specifically protect disproportionately impacted communities.

Graphic for Table of Contents Only



1. Background

Fine particulate matter (PM) is the term to describe liquid or solid particles with an aerodynamic diameter less than or equal to 2.5 microns ($PM_{2.5}$). Studies have shown that exposure to high levels of $PM_{2.5}$ can adversely affect human health, causing asthma, respiratory disease, and cardiovascular disease.[1–4] In the United States, primary $PM_{2.5}$ is directly emitted from a source into the atmosphere, and sources include construction sites, smokestacks, or wildfires. $PM_{2.5}$ is also generated through complex chemical reactions in the atmosphere, known as secondary PM, which is highly correlated with urban $PM_{2.5}$.[5,6] High concentrations of $PM_{2.5}$ are found in urban areas with a high volume of anthropogenic activities.[7–9] Spatial distributions of $PM_{2.5}$ in the U.S. exhibit significant racial-ethnic disparity.[10,11] Specifically, highly polluted areas are often in low-income and non-white neighborhoods that are surrounded by industrial factories, shipping facilities, warehouses, and railyards.[12–15]

Additionally, people spend over 90% of the time indoors[16,17] and are subsequently exposed to indoor air pollutants that are generated from multiple sources. Indoor activities, such as vacuum cleaning, cooking, dusting, use of consumer products, and smoking are the primary sources of indoor $PM_{2.5}$.[18] These activities can raise indoor $PM_{2.5}$ levels to peak concentrations in a very short period of time, approximately 10 to 30 minutes.[19] An effective range hood can remove a significant amount of $PM_{2.5}$ generated during cooking activities. During high $PM_{2.5}$ episodes, air ventilation also effectively reduces indoor $PM_{2.5}$ levels by diluting with fresh outdoor air.[20,21] Further, baseline indoor $PM_{2.5}$ levels are highly influenced by the penetration of ambient $PM_{2.5}$ into the indoor environment. Although indoor air quality can be improved with proper air exchange and filtration systems, numerous studies have shown a strong relationship between indoor and ambient $PM_{2.5}$ levels.[22–26] In particular, indoor $PM_{2.5}$ concentrations are highly correlated with ambient $PM_{2.5}$ when wildfires occur.[27] Closing the windows and minimizing the air exchange rate can decrease the penetration of ambient particles during such an event. However, closing windows and using central heating or air conditioning is not always an option for lower-income households in California (USA). According to the California Energy Commission's 2019 California Residential Appliance Saturation

Study, less than 50% of households with an income less than \$75,000 will have central air.[28] This implies that lower-income households rely on other methods to cool their homes, including using unfiltered cooling units or opening windows during cooler periods outside. Both approaches make indoor residential environments more susceptible to penetration of ambient air pollution for lower-income households.

This study considers personal exposures and household $PM_{2.5}$ for a lower income, disproportionately impacted community of inland Southern California, which is located near the northern and southern borders of Riverside and San Bernardino Counties, respectively. For reference, this region is historically known for its agricultural economy and more recently for freight shipping activities and a growth of warehouses, creating a significant shift in the region's economy.[14,29] The nationwide shift towards more online shopping in the United States has resulted in further expansion of freight shipping activities in the region. Roughly 45% of products imported from Asia are shipped through inland Southern California each year[30] and distributed across the United States via heavy-duty diesel trucks and railway systems. The Burlington Northern Santa Fe (BNSF) intermodal facility, which is directly adjacent to residential areas within the San Bernardino community (within 200 feet of the fence line), has long been determined as a major air pollution source and health hazard for neighboring communities.[31–34] The facility's emissions are generated from diesel trucks entering and leaving the facility, equipment to load and unload containers, and locomotives.[35]

In this study, we measure $PM_{2.5}$ at the individual and household levels for residents of the West San Bernardino, CA community near the BNSF intermodal facility. We utilize low-cost monitoring technology for both mobile (personal) and stationary (indoor and ambient) measurements. We characterize mobility-influenced microenvironmental exposures using spatial clustering of high-resolution geolocated $PM_{2.5}$ measurements to understand how exposure risk varies near the facility. For households with stationary monitoring, we used a mass balance approach to estimate penetration, indoor emission rate, and air exchange rate, and filtration factors. We compared the findings with previous work that characterized indoor air quality in California homes using crowdsourced data. We also discuss community co-learning, subsequent advocacy activities, and how results could support rail regulation amendments.

2. Materials and Methods

2.1 Study Location

The study was conducted in the West San Bernardino community, located in the southern region of San Bernardino County, California (inland southern California), which is adjacent to the BNSF intermodal facility (Figure 1). Its climate is classified as hot-summer Mediterranean with mild winters and hot, dry summers. Prevailing winds are from the south and west, such that communities directly to the north of the facility are most exposed to its emissions. The West San Bernardino community is bounded by a highway network of U.S. Interstates 10 to the south, 210 to the north, and 215 on the east, which are always in heavy use due to the rapid expansion of freight infrastructure. The Westside San Bernardino neighborhood is a known hot spot for air pollution and high rates of cancer, which is associated with its proximity to the BNSF intermodal facility, the largest concentration of warehouses in the country, air cargo facilities, and multiple freeways.[36,37] In San Bernardino County, CalEnviroScreen 3.0 data highlights 36 census tracts in the 96-100th percentiles for ozone burden, affecting more than 198,000 people (Figure 1).[38]

In this work, efforts are primarily centered on the families living closest to the BNSF intermodal facility and facing the most severe health risks. A 2008 report from the California Air Resources Board (CARB) reports that the facility and railyard occupy 168 acres and operates continuously with nearly 500,000 lift operations occurring annually.[39] It was also reported that the facility was ranked as the leading contributor to excess carcinogenic risk from air pollution, with the highest population exposure to railyard emissions. Diesel PM (a known hazardous air toxin) emissions within one mile of the facility were estimated to be 22 tons annually. Correspondingly, it was found that 3,780 residents had an estimated cancer risk averaging 980 chances per million. As a result of longstanding, disproportionate air pollution and health risks, portions of the impacted San Bernardino community were designated as an Assembly Bill (AB) 617 community in 2018. Under California's AB 617 mandate, the Community Air Protection Program invested resources to form community steering committees and together provide guidance for air monitoring and emissions reductions plans based on community knowledge of local sources.[40]

In our preceding pilot study, it was found that San Bernardino residents were disproportionately exposed to $PM_{2.5}$ even when taking their daily mobility into account.[17] This was largely driven by home exposures. Conversely, higher income residents in other communities were most exposed in non-home microenvironments when accounting for daily mobility. The present study expands the pilot by increasing the number of community collaborators, increasing the length of time of engagement, and incorporating $PM_{2.5}$ indoor monitoring to best understand day-to-day exposure risks and subsequent community well-being.

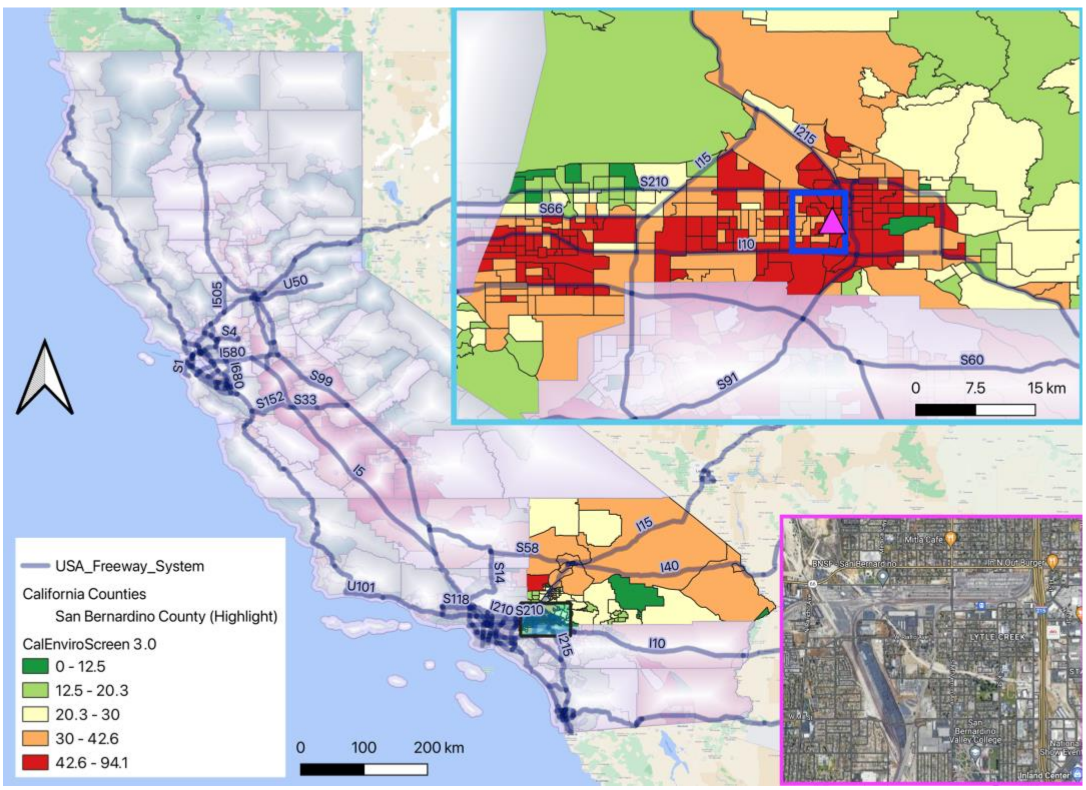


Figure 1: Map of California and the relative extent of community engagement (aqua) within San Bernardino County (highlighted). The larger inset map (upper right) shows a zoomed in extent of southwest San Bernardino County and the West San Bernardino community (blue), lying west of I-215 and bordered to the north and south by I-210 and I-10, respectively. The smaller inset map (lower right) shows the extent of BSNF intermodal facility, which is indicated by the magenta triangle in the larger inset map (Source: Google Maps).

2.2 Community Collaboration

West San Bernardino residents have a history of engaging in research and community monitoring through previous studies[31,32], and most recently through the California Air Resources Board AB Community Air Protection Program.[39] Community collaborators were recruited by organizers from Center for Community Action and Environmental Justice (Jurupa Valley, CA). Specifically, 45 community collaborators were engaged in personal monitoring activities, and 5 households participated in indoor and outdoor PurpleAir monitoring. All community collaborators were invited to attend four educational sessions to gain hand-on training on operating low-cost air pollution monitors and discuss technical and logistical aspects of the community collaboration. One household participated in both the personal and household monitoring activities. All personal monitoring collaborators filled out an intake form to collect demographic and pre-existing health information. This information included age, home rental status, annual income range, education level, occupation, vehicle ownership, smoking status (exclusion from the study if smoker), air conditioning in the home, medical history, and perception of air quality in inland southern California. Details on the intake form questions are provided in the Supplemental Information (Table S1).

2.3 Microenvironmental Exposure Analysis

Personal exposure monitoring for $PM_{2.5}$ took place over three deployment periods for three weeks at a time (October 2021, January 2022, and March 2023) (Table S2). A range of 9-14 community collaborators were engaged for seven consecutive days during each deployment week. Collaborators were asked to carry the monitor with them as they went about their daily activities, and they filled out a dynamic survey to report present-day well-being information at the end of each 7-day engagement period. Details on the dynamic survey questions are provided in the Supplemental Information (Table S3). After concluding all personal monitoring, five community collaborators provided additional context for their data in follow-up interviews at the end of the deployment period. All personal exposure participants received a one-page infographic that summarized their data and listed recommendations for exposure mitigation in high-risk microenvironments.

$PM_{2.5}$ was measured using wearable monitors (Applied Particle Technology, San Mateo, California, USA), and measurements are made every 15 seconds.[17] The monitors also record relative humidity, temperature, and GPS location. Prior to data analysis, measurements were averaged to one hour and then adjusted based on co-located reference measurements from a beta-attenuation monitor (BAM 1020, Met One, Grant Pass, Oregon, USA). Reference comparison data are provided in the Supplemental Information (Tables S4 and S5); R^2 ranged from 0.63 - 0.79. Use of the density-based spatial clustering analysis with noise (DBSCAN) method was shown to be a viable approach in the preceding pilot study.[17] DBSCAN was again used here to aggregate space-time measurements of $PM_{2.5}$ into organized clusters to quantify microenvironmental exposures. For this study, the minimum number of cluster members was 50, and the cluster distance tolerance was 37.5 meters. Google Maps was then used to classify the microenvironment into one of seven categories: home (H), work/university (W), restaurant (R), retail (RE), leisure indoor (LI), leisure outdoor (LO), and transient (T). We then identifed the activity or more place-specific information based on Google Maps. Further, data points that were not clustered, but met the speed criteria, were classified as transient. Clusters are considered "unclassified" if there is not a readily identifiable activity due to unavailable GPS measurements.

2.4 PurpleAir Measurements and Data Processing

Fifteen PurpleAir Classic (Draper, Utah, USA) monitors were deployed in the community in ten households to assess trends in $PM_{2.5}$ over seven months (July 2022 – January 2023). Specifically, five homes were selected for the installation of both indoor and ambient monitors, while the other five homes had only ambient $PM_{2.5}$ monitoring. Here, we focus on the indoor and ambient pairing comparison. The sample size was limited by funding availability and community capacity. Given the sample size and privacy protocols, locations of the five homes will not be specified, however a snapshot of the monitoring setup near the BNSF facility is provided in the Supplemental Information (Figure S1). Ambient PurpleAir monitors were installed in the back yard or front yard, and indoor monitors were installed in the living room (i.e., main room). The sensors were powered continuously by 120V outlets. The monitors provided measurements every 120 seconds for temperature (°F), relative humidity (%), and $PM_{2.5}$ concentration (μg/m^3). We used 10-minute averages to compute indoor emission and decay rates. The data were averaged hourly to remove noise before computing statistical summaries. Hourly averages were used to evaluate data against the National Ambient Air Quality Standards (NAAQS) for 24-hour $PM_{2.5}$. In absence of co-location due to external constraints, we applied a linear correction factor to the raw PurpleAir $PM_{2.5}$ measurements based on recommendations by Barkjohn et al. (Eq. 1), where $PM_{2.5}$ is the corrected concentration, PA is the average raw $PM_{2.5}$ concentration from PurpleAir channels a and b, and RH is relative humidity.[41]

$$PM_{2.5} = 0.524PA - 0.0862RH + 5.75 \tag{1}$$

2.5 Indoor $PM_{2.5}$ Modeling

Simultaneously indoor and ambient $PM_{2.5}$ sampling enabled the derivation of a simple mass balance to estimate the loss rate constant, indoor emission rate constant, and penetration for the homes with paired monitors. The loss rate constant is the combination of the air exchange and filtration rate constant, which are responsible for the decay of indoor $PM_{2.5}$ concentrations. The indoor emission rate constant is the magnitude of indoor emissions, and the penetration rate constant represents the effectiveness of $PM_{2.5}$ transfer from the outside to the indoor environment. The mass balance applied in this study is expressed in Eq. 2:

$$\frac{dC_{in}}{dt} = aPC_{out} - (a+k)C_{in} + \left(\frac{E_{in}}{V}\right) \tag{2}$$

where C_{in} is indoor $PM_{2.5}$, C_{out} is ambient $PM_{2.5}$, a and k are the air exchange rate and filtration constant, P is the penetration factor, V is the volume of the house, and E_{in} is the indoor emissions.

Emission event: To compute indoor emission rates, we assumed the penetration was negligible. When an emission event occurs, the rate of change in C_{in} is steep, and the penetration amount is minimal compared to indoor emissions. The solution to the ODE in Eq 2. is shown in Eq. 3, where E/V is the indoor emission rate per m^3 ($\mu g * hr^{-1} * m^{-3}$):

$$\frac{E}{V} = \frac{C_{in}(t) - C_{in}\left(t = t_{peak}\right)e^{\alpha\Delta t}}{1 - e^{\alpha\Delta t}}\alpha \tag{3}$$

For each home, we computed multiple values for α, which is $(a + k)$, and E/V based on a set of criteria (See SI Note 2).

Decay event: After an indoor emission event, we assumed zero $PM_{2.5}$ generation at the peak of C_{in} (the intersection of the green and red lines, as shown in the top panel of Figure 2). The decay of C_{in} only depends on the loss due to air exchange and filtration rates. At the time of peak C_{in}, the indoor $PM_{2.5}$ concentration is much higher than ambient $PM_{2.5}$. Eq. 4 can be simplified to

$$\frac{dC_{in}}{dt} = -(a + k)C_{in} \tag{4}$$

implying that right after the peak of an emission event, the change in indoor $PM_{2.5}$ depends only on the air exchange and filtration rate constants. The solution to the ODE in Eq. 4 during periods dominated by decay is Eq. 5. $C_{in}(t = peak)$ occurs when indoor $PM_{2.5}$ is maximum at the intersection of the red and green lines, as shown in **Error! Reference source not found.**. Δt is the difference in time t between $C_{in}(t)$ and $C_{in}(t = peak)$.

$$\alpha = -\frac{\ln\left(\frac{C_{in}(t)}{C_{in}(t = peak)}\right)}{\Delta t} \tag{5}$$

Baseline indoor model: We reconstructed the indoor $PM_{2.5}$ to validate the estimated penetration and air exchange constant based on Eq. 6, where C_{model} is the modeled indoor $PM_{2.5}$ concentrations, α is the combination of air exchange rate and filtration constant, and aP is the penetration factor which is equal to C_{in}/C_{out}. Eq. 6 is valid if there are no indoor emissions and when the ambient $PM_{2.5}$ is greater than indoor $PM_{2.5}$ in the absence of indoor emission events. All ODE solution derivations can be found in the Supplemental Information.

$$C_{model}(t) = C_{model}(t-1)e^{\alpha\Delta t} + \frac{aPC_{out}(t)}{\alpha} \tag{6}$$

Overall, the peaks of indoor $PM_{2.5}$ were ten times greater than the indoor average, and the slopes were steep. Typically, indoor emissions were generated in 10 to 20 minutes, and the decay lasted about 10 to 50 minutes. The red lines from the bottom panel in Figure 2 were used to calculate average indoor emissions and decay constants. Derivations of all solutions are provided in Notes 1-3 in the Supplementary Information.

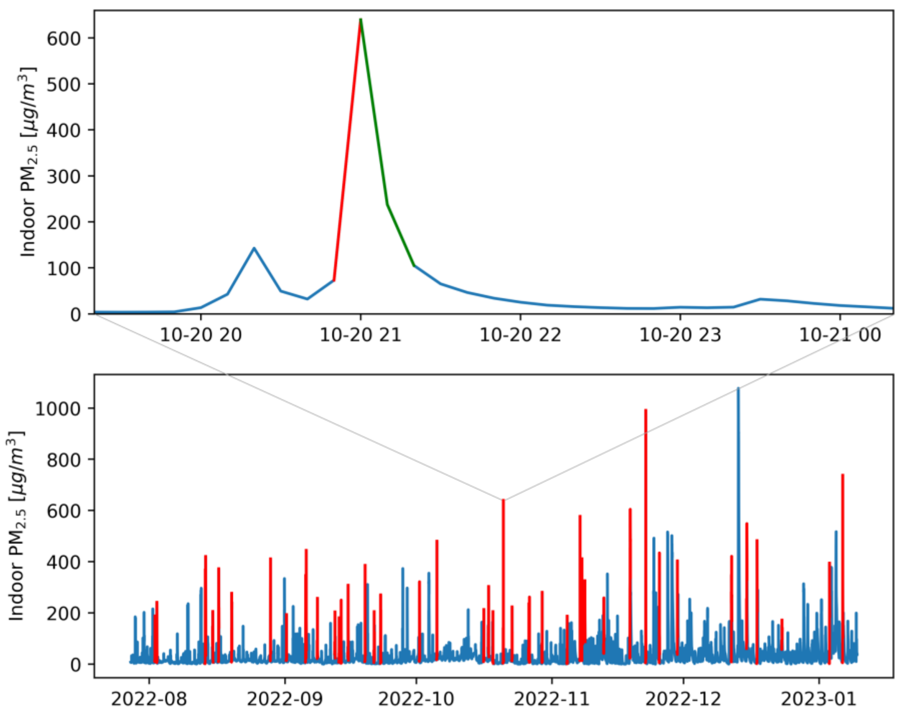


Figure 2: Sample time series for one home from 2022 Aug to 2023 Jan (bottom); the red lines are the data used to compute average indoor emissions. Zoom-in on the time series (top); the red line is used to calculate the indoor emissions (E/V) and green line is used to calculate the decay constant (α) based on Eqs. 3 and 5, respectively.

3. Results

3.1 Personal Monitoring and Microenvironmental Exposures

DBSCAN clustering resolved a total of 573 clusters for the entire engagement period, and this total excludes data classified as transient or data within unclassified microenvironments. Taking seven days (168 hours) as the maximum possible measurement period for each collaborator's seven-day engagement period (103 unique engagement periods), there were a maximum of 17,304 possible measurement hours. Of those possible measurement hours, data were collected during 69, 80, and 67% of the possible measurement hours in October, January, and March, respectively (12,440 total hours) (Table S6). Of the data collected, only 5.1, 4.3, and 4.9% of measurements were labeled as "unclassified (U)" microenvironments. Details that follow describe $PM_{2.5}$ averages for classified microenvironment clusters: home, work/university, restaurant, retail, leisure indoor, leisure outdoor, and transient (in motion). Home microenvironments had the highest percentages of measurements collected, 86, 85, and 86% in October, January, and March, respectively.

Microenvironments were clustered and classified, and the viable (GPS available) $PM_{2.5}$ measurements were averaged for each unique engagement period and for each community collaborator (Figure 3). Larger cluster symbols indicate higher average exposures. On average, home exposures were 40% higher than non-home microenvironments, where the largest differences were seen in during the January deployment – 60% higher in October, 30% higher in January, and 40% higher in March. Home average $PM_{2.5}$ was 22, 54, and 9.8 $\mu g/m^3$ for the October, January, and March deployments, respectively. Non-home average $PM_{2.5}$ was 14, 41, and 7.2 $\mu g/m^3$ for the October, January, and March deployments, respectively. Generally, microenvironmental exposures were highest near the railyard, decreasing with distance from the railyard as seen in the heat map in SI Figure S2.

Upon examination of high-risk non-home/non-transient microenvironments, where high risk is considered here to be an average $PM_{2.5}$ concentration greater than the 24-hour NAAQS (35 $\mu g/m^3$), Chick-fil-A, AutoZone, and a friend's home had high-risk average exposures of 69, 91, and 269 $\mu g/m^3$. It is worth noting that time spent in each location was approximately one hour or less. Other locations with similarly short-term, high-risk exposures include a dermatology center, Pinoy restaurant, shopping mall, hotel, bowling club, church, and swim complex with average concentrations of 35, 45, 46, 71, 154, 270, 1062 $\mu g/m^3$, respectively. Regarding transient or in-motion exposures, some measurements averages exceeded

1000 μg/m^3. It should be noted that the optimal range of measurements for Plantower 5003 sensors (within the wearable monitor) is 0-500 μg/m^3.

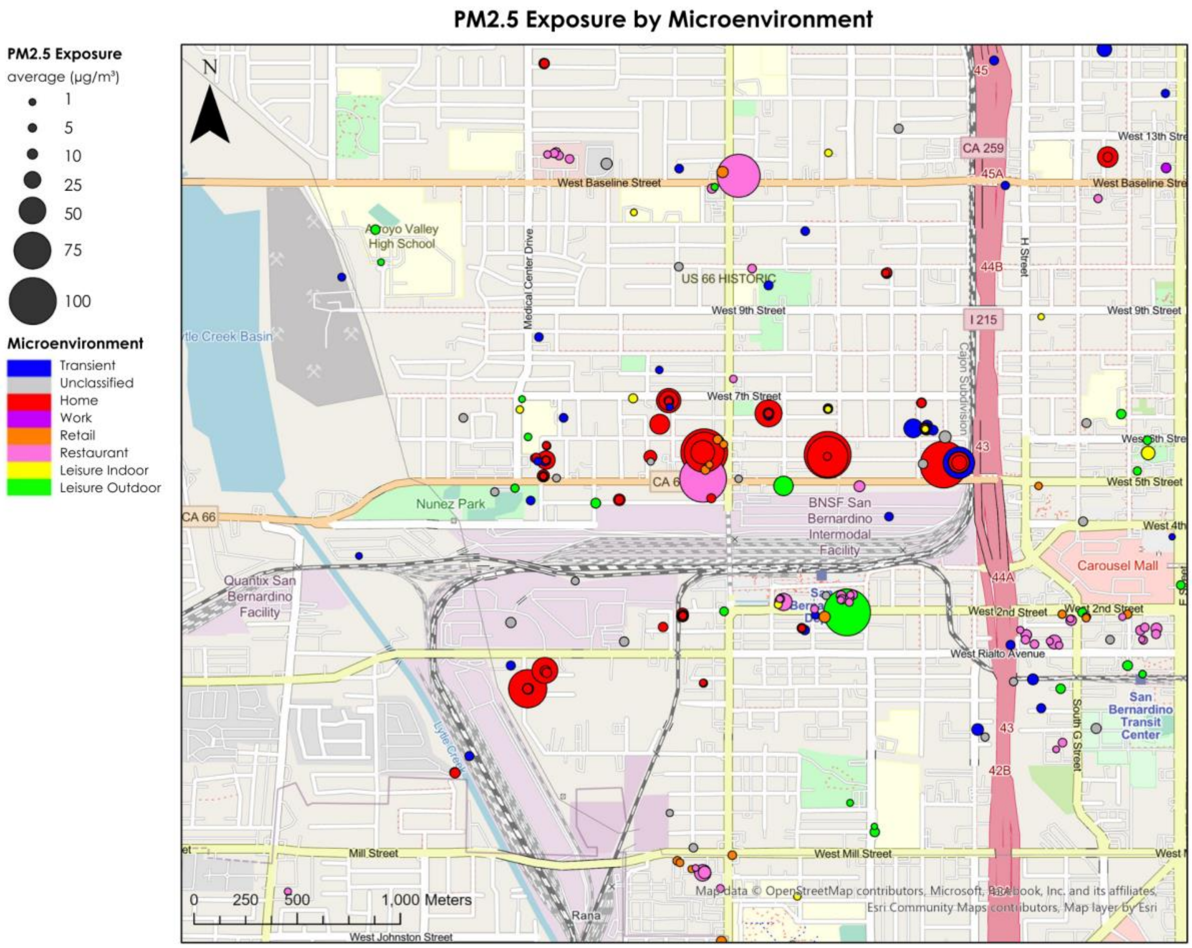


Figure 3: Personal PM$_{2.5}$ exposure clusters with quantified averages and classified microenvironments. Each cluster represents one participant's data in one deployment period.

3.2 Indoor and Ambient PurpleAir Analysis

We present the analysis of indoor PM$_{2.5}$ for the five homes where indoor and ambient pairs of PurpleAir were installed. Based on an evaluation indoor and ambient temperature (and verified by household data collected at the start of community engagement), house 3 did not use an air conditioning unit as its indoor temperature was approximately greater than the ambient temperature during summertime (Figure S3). The histograms in Figure S4 show the ratio of indoor and ambient PM$_{2.5}$ (I/O ratio); indoor and outdoor histograms and time series are also provided for reference (Figures S5 and S6). The peaks of the

I/O histogram distributions are centered around the value of one. For homes 1, 3, and 5, the mode for I/O ratio (most frequent occurrence) occurs when the indoor $PM_{2.5}$ is nearly the same as ambient $PM_{2.5}$, which contradicts previous studies, for which the distribution modes were approximately 0.62 using crowdsourced information.[27] The I/O ratios from crowdsourced data generally reflect a higher socioeconomic status population with high accessibility to indoor air quality monitoring. Further, population-based studies will likely not reflect the lived experiences of disproportionately impacted communities that have more limited access to indoor monitoring equipment. Historically, racial-ethnic minority groups are the most sensitive and highly affected by the poor ambient air quality.[10,11,42]

Our findings also suggest that elevated ambient $PM_{2.5}$ levels directly influence indoor air quality in West San Bernardino homes (Table S7), which is further evidenced by the seasonal statistics (Tables S7-S8). The consistent values across all PurpleAir monitors for the corrected 25th, 50th, and 98th percentile ambient $PM_{2.5}$ reflect good performance for ambient measurements in the West San Bernardino area. For the 50th percentile across all months, indoor $PM_{2.5}$ was less than ambient for all homes except for house 3 (no air conditioning or filtration), where indoor $PM_{2.5}$ levels were higher than ambient levels for all quartiles. Indoor mean and 98th percentile were significantly higher than corresponding ambient levels for all five houses, reflecting the influence of indoor emissions.

Seasonal variations between summer (Jul – Sep 2022) and fall (Oct 2022– Jan 2023) are provided in the Supplemental Information (Tables S8 and S9). Summer temperatures were high, with an average of 82°F and exceeding 100°F around 5% of the time. During high-temperature periods, four out of five houses used air conditioning to regulate indoor temperatures resulting in their indoor $PM_{2.5}$ being less than ambient $PM_{2.5}$ levels (Table S8). This indicated that filtration systems from air conditioning units effectively reduced concentrations. The average temperature was 60 °F in the fall/winter, allowing open-window ventilation to regulate indoor environments and increasing air exchange rate and penetration. Due to increased penetration, indoor $PM_{2.5}$ baseline levels rose, leading to indoor levels exceeding ambient $PM_{2.5}$ across all quartiles (Table S9).

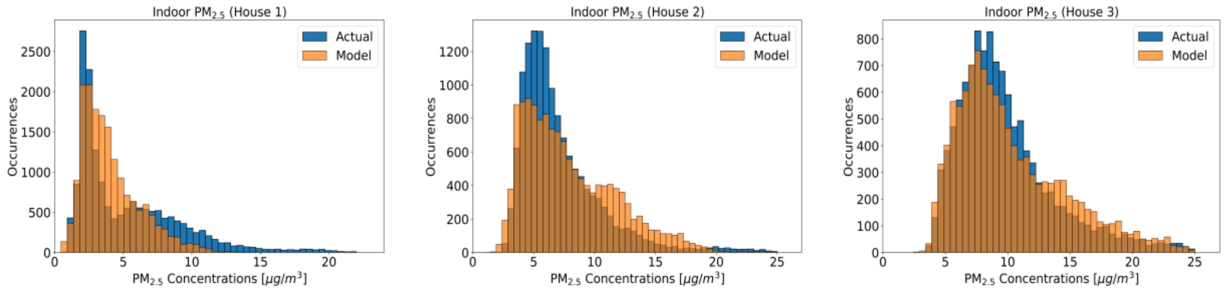
Estimated indoor emissions: Four out of five homes had an indoor 98th percentile that exceeded the 24-hour $PM_{2.5}$ NAAQS level (35 $\mu g/m^3$). High 98th percentiles resulted from high indoor emissions and poor ventilation, which can be explained by the average decay constants (Homes 1 and 5 in Table 1). Houses with low decay constant suffered from prolonged periods of high $PM_{2.5}$ episodes after indoor emission events (Homes 2, 3, and 4 in Table 1). An indoor emission event is defined as when indoor $PM_{2.5}$ levels are significantly higher than ambient $PM_{2.5}$ levels. The frequencies of indoor emissions were also estimated for the homes, considering the instances where indoor $PM_{2.5}$ concentrations peaked at levels five times higher than the average indoor $PM_{2.5}$ concentrations. Indoor emission rates per m^3 were estimated to be a minimum of 619 $\mu g * h^{-1} * m^{-3}$ and a maximum of 1190 $\mu g * h^{-1} * m^{-3}$ for houses 2 and 1, respectively.

Table 1. Summary of calculated average decay constants, average indoor emissions per m^3, and infiltration factors for all five participant houses. Indoor peaks account for values greater than five times the indoor average $PM_{2.5}$.

	House 1	House 2	House 3	House 4	House 5
Indoor 98th Percentile ($\mu g/m^3$)	26	49	100	94	35
Exceed Ambient $PM_{2.5}$ %	20	27	45	36	35
Indoor Emission Peaks (frequency, f)	263	417	533	719	160
Infiltration ($F_{in} = C_{in}/C_{out}$)	0.57	0.65	0.84	0.67	0.78
Avg Decay Constant, α (hr^{-1})	4.8	2.7	2.7	3.2	3.3
Avg Indoor Emissions, E/V ($\mu g * hr^{-1} * m^{-3}$)	1190	619	663	863	779

Estimated decay and infiltration constants: The average decay constants, average indoor emissions per m^3, and infiltration factors for all five homes were calculated based on the mass balance (Eq. 2) and the set assumptions discussed in the Data and Methods section. Indoor activities, air exchange rates, and filtration rates were highly variable, resulting in different infiltrations values across the study period. The average infiltration values for each house also represent family habits during the community engagement period. Infiltration value ranges from zero to one, where zero represents no penetration, and one indicates the indoor $PM_{2.5}$ and ambient $PM_{2.5}$ levels. In our study, the lowest infiltration value is 0.57 the highest is 0.84 for houses 1 and 4, respectively, implying the vulnerability of indoor environments to the changes in ambient conditions (Table 1). The infiltration values of this study are significantly higher than those in the previous studies that rely on crowdsourced data or a test house. Stephens et al. used a mass balance, and the calculated infiltration factor was 0.34 for a test house (Utest House).[19] Liang et al. used a similar approach and utilized the PurpleAir sensor network in California that monitored more than 1400 buildings to assess the impact of wildfire smoke on indoor air quality, and the derived average infiltration factor was 0.45.[27] The average infiltration factor in this study across the five homes is 0.70, which is relatively higher compared to previous studies, indicating a more significant impact of ambient air quality on the indoor environments of this rail-impacted community.

Baseline indoor $PM_{2.5}$ model: To evaluate the calculated infiltration and decay constant, we reconstructed indoor $PM_{2.5}$ concentrations using the mass balance. Here, we did not consider emissions in the baseline model. Therefore, the model is only a function of decay constant, penetration, and ambient $PM_{2.5}$, as described in Eq. 6. The model gave good predictions and captured the trend of occurrences (Figure 4). Although the model successfully reconstructed the distribution of indoor $PM_{2.5}$ for homes 3, 4, and 5, it did not capture the peak for house 2 and high concentrations in homes 1 and 4. The errors were caused by indoor minor emission events, which were not accounted for as long as the indoor $PM_{2.5}$ was still less than ambient $PM_{2.5}$. Minor emissions are difficult to trace with the time series without additional activity information from home occupants. Uncertainties in participants' habits, such as opening the windows, turning on the fume hood, and using air conditioning, largely contributed to the model's errors.



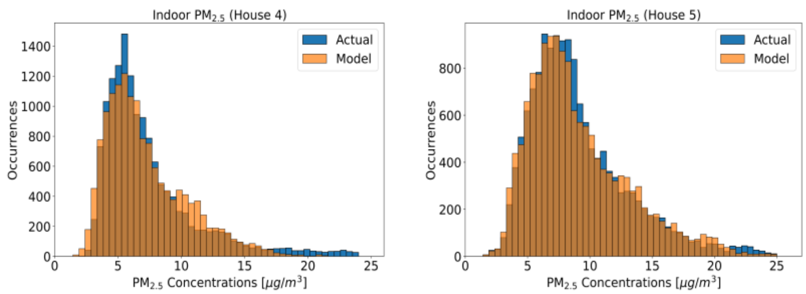


Figure 4: Actual indoor $PM_{2.5}$ (blue) and model $PM_{2.5}$ (orange) based on Eq. 6 based 10 minute average data. The distribution only shows the data when indoor $PM_{2.5}$ levels were less than ambient $PM_{2.5}$ levels.

98th percentile regression model: Intuitively, indoor $PM_{2.5}$ levels are managed by the decay constant, $(\alpha = a + k)$ and the frequency, f. We performed linear regression with the two dependent variables to predict the indoor 98th percentiles, for which $Indoor\ 98^{th}\ \%ile = c_1\alpha + c_2 f + c_3$, where $c_1$and c_2 are the coefficients for decay constant and frequency, respectively, and c_3 is the bias. The values for c_1, c_2, and c_3 are listed in Eq. 7, and the R^2 for the regression model is 0.84. The scatter plot for the prediction and actual indoor 98th percentile is provided in the Supplemental Information (Figure S7). The regression model shows that the indoor 98th percentile has a negative correlation with the decay constant and a positive correlation with indoor emission frequency.

$$Indoor\ 98^{th}\ \%ile = -11.1\alpha + 0.12f + 49 \tag{7}$$

where α is the decay constant $(\alpha = a + k)$, and f is the frequency accounting for the $PM_{2.5}$ peaks, which are identified when indoor $PM_{2.5}$ is greater than five times the indoor average. Interestingly, the computed average indoor emission rates (E/V) had relatively little impact on the modeled indoor 98th percentile, for which house 1 with the highest average emission rate still had the lowest indoor 98th percentile $PM_{2.5}$.

3.3 Community Well-being

Results from the static survey responses for history and severity of allergies, wheezing, rhinitis, couching, shortness of breath, nocturnal wheezing, nose bleeds, or headaches were assigned numerical values: 1 (none), 2 (light), 3 (moderate), and 4 (severe). A minimum score of 8 reflects excellent health condition, and a maximum score of 32 reflects poor health condition. Mean and median personal exposures across all microenvironments were combined for each unique health score (Figure 5). There was no observable trend when comparing health scores across age or across mean personal exposures. However, two positively correlated clusters were observed for median exposures. This finding suggests that more frequent exposures to higher $PM_{2.5}$ levels were associated with worse self-reported health history. Findings also underscore community anecdotes and state agency studies that report that disproportionately higher air pollution exposures in Westside San Bernardino are linked to overall worsening of community health.

Community collaborators self-reported their dynamic well-being at the end of each seven-day deployment period, and rankings included excellent, good, fair, and poor. Distributions of cluster averaged $PM_{2.5}$ were grouped based on these dynamic well-being rankings for each deployment period (Figure 5). Outliers (indicated by red crosses) for good, fair, and poor were higher than those for excellent for each deployment period. Although not reported in January, the 75th percentile for poor rankings exceeded that of the other rankings for the October and March periods. Median $PM_{2.5}$ associated with fair scores was lower than the median $PM_{2.5}$ for good scores for the October and January periods. Regarding self-reported income, median $PM_{2.5}$ averages decreased as income increased, and this trend is strongest for the January and March periods. The higher income levels (>$20,000) experienced higher outlier $PM_{2.5}$ compared to the lowest income group.

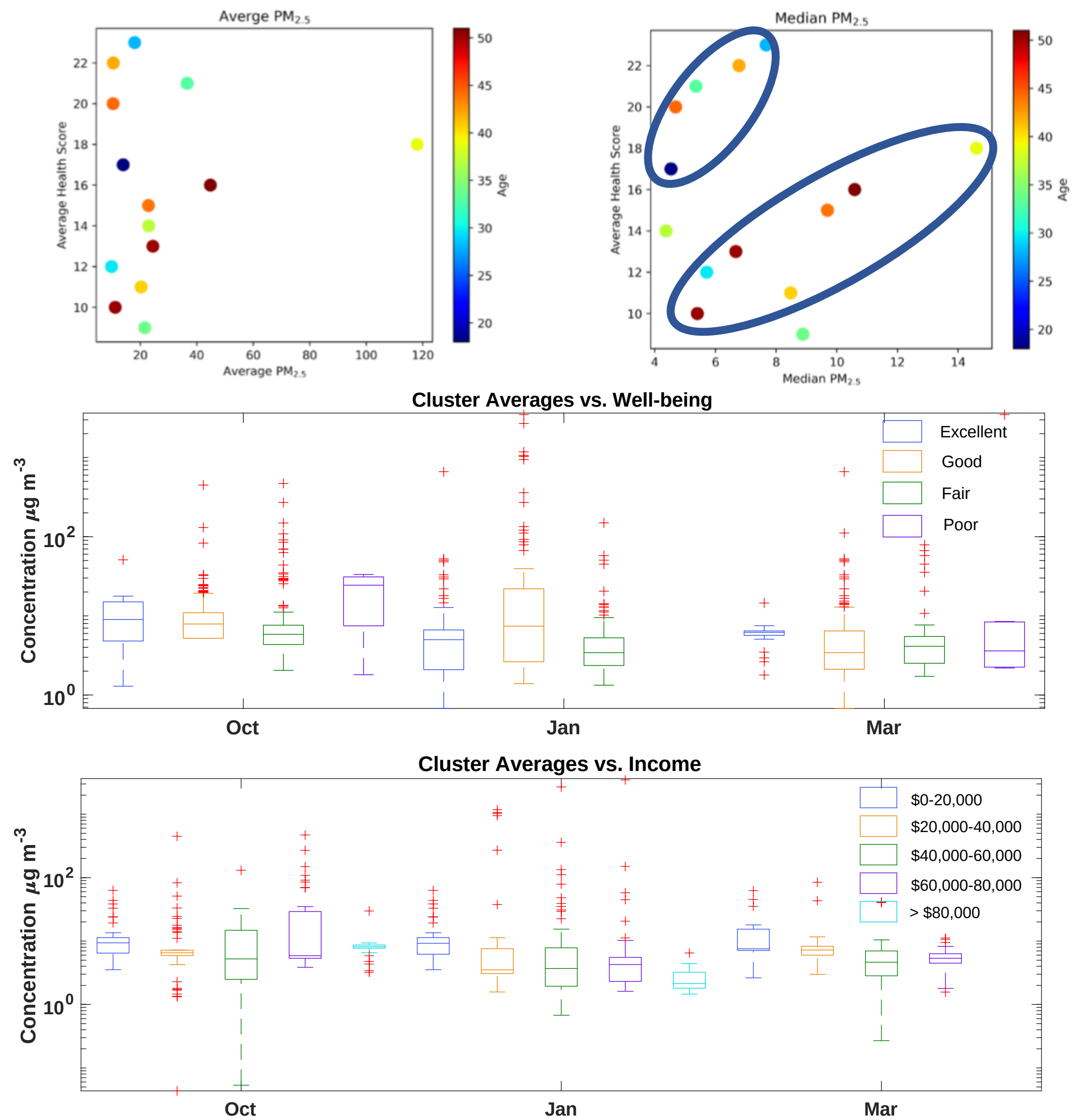


Figure 5: *Top-left*: Average weekly $PM_{2.5}$ exposure vs. average static health score colored by age. *Top-right*: Median weekly $PM_{2.5}$ exposure vs. average static health score colored by age. Two clusters appear to have linear correlations for median $PM_{2.5}$ exposures. *Middle*: Cluster $PM_{2.5}$ averages corresponding to self-reported, dynamic well-being. There were no poor rankings in January. *Bottom*: Cluster $PM_{2.5}$ averages corresponding to self-reported income. There were no >$80,000 clusters in March.

3.4 Community Co-learning and Personal Protection

The research team engaged with community collaborators on four occasions for group co-learning sessions. In summer of 2021, a virtual interest meeting was held to discuss the objectives, motivation, and timeline of the study, and to provide an overview of the CARB Community Air Protection Program. A second in-person meeting was held before monitoring began to discuss study logistics and schedule participation. Two additional community meetings were held in-person during and after personal monitoring concluded to discuss preliminary findings, as well as other concerns surrounding air, water, and soil pollution in and around San Bernardino. Each meeting provided an opportunity to receive community feedback on study logistics and purpose, and prioritizing this intimate exchange of critical information reduced communication barriers and logistical challenges. In-person meetings were held at the local community center to reduce accessibility challenges for community collaborators.

A critical goal of the community collaboration was the dissemination of individualized resilience plans, which were one-page text and graphical summaries of the personalized monitoring data and the team's subsequent recommendations for reducing personal $PM_{2.5}$ exposure. Generalized tips were provided across all exposure resilience plans that addressed air pollution basics, respective health impacts, and relevant indoor and outdoor pollution sources. High-risk microenvironments were relayed to community collaborators, along with daily average exposures throughout each engagement week. Tailored recommendations were based on microenvironment(s) with highest exposures. Recommendations included, but were not limited to:

- Use an air filter to clean indoor air
- Wear a fitted mask (N-95) to reduce your pollution exposure
- Avoid outdoor activity when the air quality is poor
- Reduce open flames/smoke from potential sources indoors
- Open windows if there is an open flame, and turn on the exhaust fan when cooking
- Breathe through your nose to filter out larger particles
- Check local air pollution and daily Air Quality Index

Five follow-up interviews were conducted to better understand community collaborator concerns and feedback regarding their tailored resilience plans. Collaborators also provided additional context for the personal exposure data collected, including the identification of indoor pollution generating activities and the frequency of those activities. In the weeks that followed, collaborators were able to reference their resilience plans during community advocacy meetings, providing quantitative evidence that reflected their individual lived experiences around air pollution exposure. The resilience plans featuring data-driven $PM_{2.5}$ exposures and the community microenvironmental exposure maps have also been used by community members most recently in regional, state, and federal efforts to reform rail emissions policy.

4. Discussion

4.1 Microenvironmental Analysis and Uncertainties

Personal $PM_{2.5}$ was highest in winter (January), which correlates with the peak $PM_{2.5}$ period in inland Southern California. Higher relative humidity and lower temperatures during winter promote aerosol formation through heterogenous chemistry and condensation.[43,44] It is well-known that relative humidity may influence low-cost sensor readings[45–47], and therefore the reference-based adjustments were carried out for personal measurements, improving overall correlations of hourly averages. As such, the personal exposure results presented in this study are precise across all wearable sensors. We also temper interpretation of measurements greater than 500 μg m^{-3} given the effective range (0-500 μg m^{-3}) of the PMS5003 sensor within the wearable monitor.[48,49]

Given that approximately 70% of all possible measurements were collected, there is the possibility of missing personal exposures. Community collaborators reported intermittent loss of connectivity and battery power, which explains data missingness. Further, the visual classification of microenvironments could possibly be influenced by human error in Google Maps interpretation. However, the microenvironment classification results are of high confidence due to the majority of measurements being made in home microenvironments, where collaborators spent most of their time and had ready access to electricity to charge the monitors. We find that the wearable sensor choice promoted more inclusive community collaboration given the lower barrier for access and use of the sensor, as well as its ability to resolve high-resolution, mobility-influenced exposure disparities.[17]

While most microenvironments were recorded within several blocks of the BNSF intermodal facility, there was still a strong correlation with income, suggesting that additional exposure prevention interventions should be directed towards the lowest income community members within the impacted area. Further, although home microenvironments posed the greatest chronic risk for higher $PM_{2.5}$ exposures, elective time spent in non-home microenvironments also posed high exposure risks. Such non-home locations may be good candidates for continuous monitoring to protect sensitive populations (e.g., children and people with asthma).

4.2 Indoor Analysis and Uncertainties

Our analyses show a strong effect of ambient $PM_{2.5}$ on the indoor levels for five community homes that are near the BNSF facility with an average infiltration of 0.7, a value higher than that previously published using crowdsourced data. The 98th percentile regression model implies 98th percentile concentrations are linearly correlated with the air exchange rate, filtration, and indoor emission frequency. Indoor $PM_{2.5}$ concentrations can be regulated by increasing ventilation during indoor emission events or minimizing the air exchange rate when outdoor $PM_{2.5}$ concentrations are high (during daytime peaks in fall/winter). We strongly recommend that impacted homes near the BNSF facility have adequate air filter to minimize penetration and indoor levels. We also recommend that open access fenceline monitoring data for the BNSF facility be made available for $PM_{2.5}$, its species, and other criteria pollutants given the current study's findings and the historical environmental health challenges for downwind areas. We suggest that PurpleAir sensors be permanently installed in impacted homes near the BNSF facility (or any large industrial source) to continuously monitor home indoor air quality and provide real-time feedback for mitigating indoor pollution. For instance, occupants should increase filtration and ventilation during indoor emission events when ambient $PM_{2.5}$ levels are low.

The uncertainties of estimated constants arose from the assumption that there were no emissions at the peaks (inflection points) and no penetration when indoor $PM_{2.5}$ levels were high. Infiltration uncertainty is derived from omitting minor indoor emissions from consideration, causing a slight overestimation of infiltration factors. Despite these uncertainties, our analysis of household infiltration is critical for the protection of disproportionately impacted households due to the influence of outdoor sources on indoor $PM_{2.5}$.[50]

4.3 Recommendations for Future Studies

In future studies, the team will provide additional information on how to rank dynamic health status as there wasn't clarity on the category definitions. This may have led to the unexpected trends in good and fair well-being rankings. In ongoing work, the team seeks to to understand the drivers of public action toward personal $PM_{2.5}$ exposure protections.[51] Overall, the greatest strength of the study is the creation of resilience plans for community collaborators, supporting community data sovereignty and making efforts towards exposure reduction. This step is oftentimes missing in air pollution studies that seek to address the environmental injustices faced by historically impacted communities. Future efforts will mirror this study, where community collaborations will be centered in data collection and subsequent solution building. Findings support ongoing efforts to reduce direct and indirect emissions from industrial sources that are near disparately impacted communities.

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Conflict of Interest

Authors declare no conflicts of interest.

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Supplemental Information for:

Indoor and Ambient Influences on $PM_{2.5}$ Exposure and Well-being for a Rail Impacted Community and Implications for Personal Protections

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9 Tables, 7 Figures, and 3 Notes with equation derivations. All material is listed in order that it is referenced in the main text.

Table S1. Intake form questions for community collaboration for personal monitoring. Intake survey was also available in Spanish.

Question	Response Options	Question	Response Options
Age	≥ 18	Describe your experiences with poor air quality	Open answers
Language(s) spoken	English; Español; Tagalog; 中国人; Indigenous/Native; Language; Other	History of smoking	Never smoker; previous smoker; current smoker; household member smokes
Rental status	Rent, own	Average outdoor activity (hours per week)	0-1; 1-5; 5-10; Other
Household income	\$0 - \$20,000; \$20,000 - \$40,000; \$40,000 - \$60,000; \$60,000 - \$80,000; \$80,000 - \$100,000; \$100,000+; Other	Current use of medications	Open answers
Education level	Less than high school; high school; some college; bachelor's degree; graduate degree; Other	History of hospitalization	Yes; No; Other
Occupation	Open answers	Cardiovascular or respiratory hospitalization	Yes; No
Vehicle ownership	Yes; No	History of respiratory illness (e.g., asthma, lung cancer)	Open answers
Mode of transportation to work	Personal vehicle; motorcycle; public transportation; walk; not applicable; Other	Severity of respiratory symptoms: asthma, wheeze, rhinitis, cough, phlegm, shortness of breath, nocturnal wheeze, nose bleeds, headaches	None; light; moderate; severe
Commute to work everyday	Yes; No	Previous asthma diagnosis	Yes, plus inhaler use; Yes, no inhaler; No, but inhaler use; No
Daily length of commute (in minutes)	≥ 0 minutes	COVID-19 diagnosis in the last year	Yes; No; Decline to answer
Describe current state of air quality in the Inland Empire	Poor; fair; moderate; excellent	Household air conditioning	Yes; No; Other

Table S2: Date range and number of participants for each engagement period.

	October 2021	January 2022	March 2022
Week 1	Oct 2-9 (11)	Jan 22-29 (12)	Mar 6-12 (13)
Week 2	Oct 9-16 (9)	Jan 29-5 (11)	Mar 12-19 (10)
Week 3	Oct 16-23 (14)	Feb 5-12 (11)	Mar 19-26 (12)

Table S3: Dynamic survey questions during community collaboration for personal monitoring. Dynamic survey was also available in Spanish.

Question	**Response Options**
Date	Month, day, year
Time of Day	HH:MM AM/PM
Zone	1; 2; 3
APT Device Number	Open answers (##)
COVID-19 diagnosis in the last seven days	Yes; No; Decline to answer
Respiratory/cardiovascular symptoms in the past seven days; If so, please list them	Open answers
Health rating for the past week	Poor; Fair; Good; Excellent

Table S4: Regression statistics for hourly averaged co-location data collected in December 2021 (23 days) and February 2022 (15 days). Co-location of wearable sensors was carried out with a BAM 1020 (Met One, Grant Pass, OR, USA). These data were used to adjust October and January deployment data.

Sensor	Before Adjustment			After Adjustment		
	Slope	Int.	R^2	Slope	Int.	R^2
39	0.87	0.48	0.72	0.95	0.24	0.75
44	0.79	-0.07	0.79	0.97	0.15	0.79
47	1.08	-1.10	0.78	0.96	0.27	0.79
50	1.08	0.12	0.78	0.95	0.29	0.78
52	1.04	0.21	0.78	0.96	0.26	0.78
61	0.98	-0.15	0.79	0.96	0.20	0.79
62	0.94	-0.12	0.79	0.95	0.26	0.78
63	1.01	-0.15	0.79	0.96	0.24	0.79
65	0.77	-0.25	0.79	0.97	0.19	0.79
67	0.85	-0.08	0.79	0.98	0.21	0.78
68	1.16	0.24	0.78	0.96	0.18	0.78
71	1.01	-1.21	0.77	0.96	0.30	0.78
74	-	-	-	-	-	-
78	0.88	-0.14	0.78	0.92	0.50	0.75
79	0.97	0.04	0.78	0.96	0.22	0.78
80	0.85	-0.22	0.78	0.96	0.24	0.78
81	0.82	-0.17	0.78	0.96	0.21	0.78
89	-	-	-	-	-	-

Table S5: Regression statistics for hourly averaged co-location data collected in February 2022 (15 days) and June 2022 (26 days). Co-location of wearable sensors was carried out with a BAM 1020 (Met One, Grant Pass, OR, USA). These data were used to adjust March deployment data.

Sensor	Before Adjustment			After Adjustment		
	Slope	Int.	R^2	Slope	Int.	R^2
39	3.12	-0.15	0.52	0.94	0.50	0.63
44	0.48	0.92	0.47	0.97	0.23	0.66
47	-	-	-	-	-	-
50	0.61	1.35	0.42	0.93	0.59	0.64
52	1.01	32.02	0.41	0.94	0.47	0.63
61	0.52	1.06	0.44	0.95	0.44	0.64
62	0.56	1.07	0.44	0.94	0.55	0.64
63	0.54	1.16	0.42	0.94	0.53	0.64
65	0.46	0.74	0.46	0.94	0.53	0.64
67	0.47	0.97	0.44	0.94	0.54	0.65
68	-	-	-	-	-	-
71	-	-	-	-	-	-
74	0.56	0.57	0.51	0.96	0.36	0.67
78	2.93	-0.36	0.48	0.94	0.45	0.64
79	0.58	1.15	0.44	0.96	0.34	0.64
80	2.47	-0.21	0.51	0.95	0.44	0.65
81	0.51	0.84	0.47	0.96	0.38	0.64
89	0.54	0.51	0.52	0.96	0.31	0.65

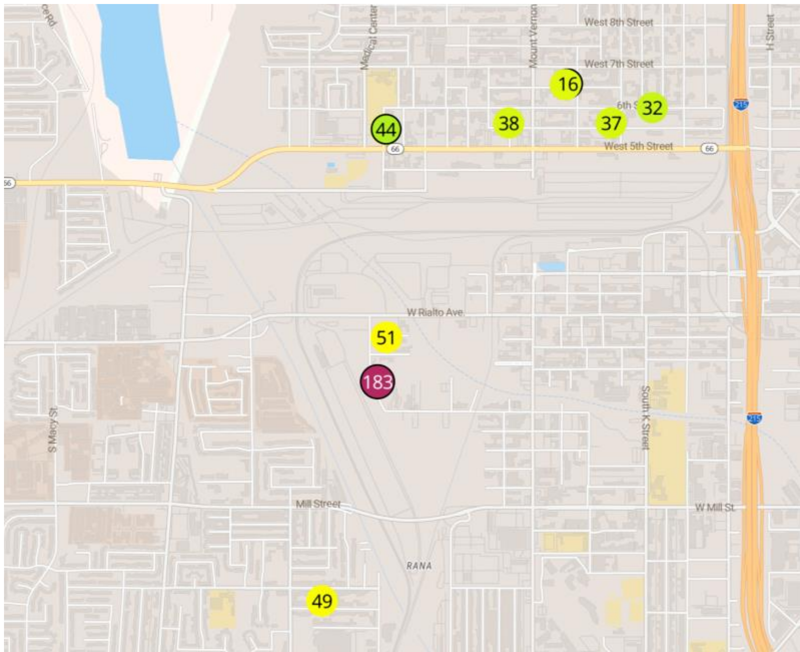

Figure S1: BNSF facility and household sampling locations. Source: map.purpleair.com

Note 1: Average decay constant $\boldsymbol{\alpha}$, where $\boldsymbol{\alpha} = \boldsymbol{a} + \boldsymbol{k}$

$$\frac{dC_{in}}{dt} = aPC_{out} - (a+k)C_{in} + \left(\frac{E_{in}}{V}\right) \tag{1}$$

Right after an indoor emission event, we assume penetration and emission rate are zero.

$$\frac{dC_{in}}{dt} = -(a+k)C_{in} \tag{2}$$

Solving (2)

$$\ln(C_{in}) = -\alpha t + C_1$$

Initial condition (IC) is at $t = t_o$ => $C_{in} = C_{in\ at\ peak}$

$$C_{in} = e^{-\alpha(t_0 - t)} C_{in\ at\ peak}$$

$$\alpha = -\frac{\ln\left(\frac{C_{in}(t)}{C_{in}(t = peak)}\right)}{\Delta t} \tag{3}$$

Note 2: Average indoor emission rate $\boldsymbol{E_{in}/V}$

During an indoor emission event, we assume penetration is zero.

$$\frac{dC_{in}}{dt} = -\alpha C_{in} + \left(\frac{E_{in}}{V}\right)$$

Using integrating factor $e^{\int \alpha dt}$ to obtain the solution for C_{in}

$$C_{in} = \frac{E_{in}}{\alpha V} + C_1 e^{-\alpha t} \tag{4}$$

IC at $t = t_{peak}$ => $C_{in} = C_{in\ at\ peak}$

$$C_1 = \left(C_{in\ at\ peak} - \frac{E_{in}}{\alpha V}\right) e^{\alpha t_{peak}}$$

Substituting C_1 into Equation 4 to solve for the average emission rate.

$$\frac{E_{in}}{V} = \frac{\left(C_{in} - C_{in\ at\ peak} e^{\alpha \Delta t}\right)\alpha}{1 - e^{\alpha \Delta t}} \tag{5}$$

Note 3: Full solution for Equation 1

Using integrating factor $e^{\int \alpha dt}$ to obtain the solution for C_{in}

The solution for Equation 1 is:

$$C_{in} = \frac{aPC_{out} - \left(\frac{E_{in}}{V}\right)}{\alpha} + C_1 e^{-\alpha t} \tag{6}$$

IC at $t = t_o \Rightarrow C_{in} = C_o$

$$C_1 = C_o e^{\alpha t_o} + \frac{\alpha P C_{out}}{\alpha} + \frac{E}{\alpha V}$$

The solution for Equation 6 assuming there are not indoor emissions and $C_{in} < C_{out}$ at a given time is:

$$C_{in\ at\ t} = C_{in\ at\ t-1} e^{\alpha \Delta t} + \frac{aPC_{out\ at\ t}}{\alpha}$$

Table S6: Time spent in each microenvironment as a percentage of total hours of data collected (total = 12,440 hours).

Percent time spent	**Oct**	**Jan**	**Mar**
Home (H)	86%	85%	86%
Work or university (W)	0.5%	2.0%	0.5%
Restaurant (R)	0.5%	0.3%	0.5%
Retail (RE)	1.5%	2.4%	1.5%
Leisure indoor (LI)	3.8%	3.4%	3.8%
Leisure outdoor (LO)	0.9%	0.8%	1.2%
Transient (T)	1.9%	1.9%	1.9%
Unclassified (U)	5.1%	4.3%	4.9%

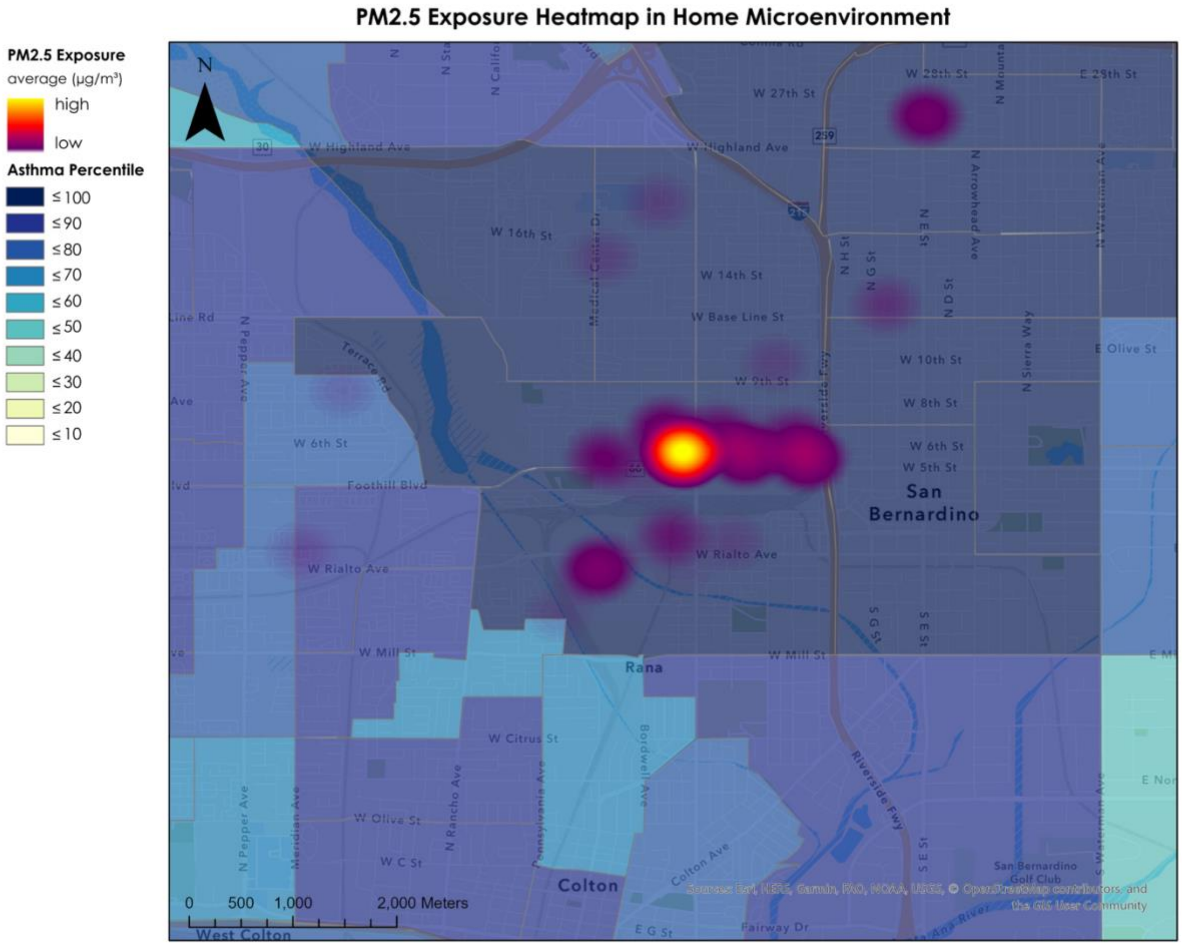

Figure S2: Personal $PM_{2.5}$ exposure clusters presented qualitatively as low to high, relative to the maximum observed cluster averages. The polygon data represent the severity of asthma according to CalEnviroScreen 4.0 for Census tracts near the intermodal facility.[1,2]

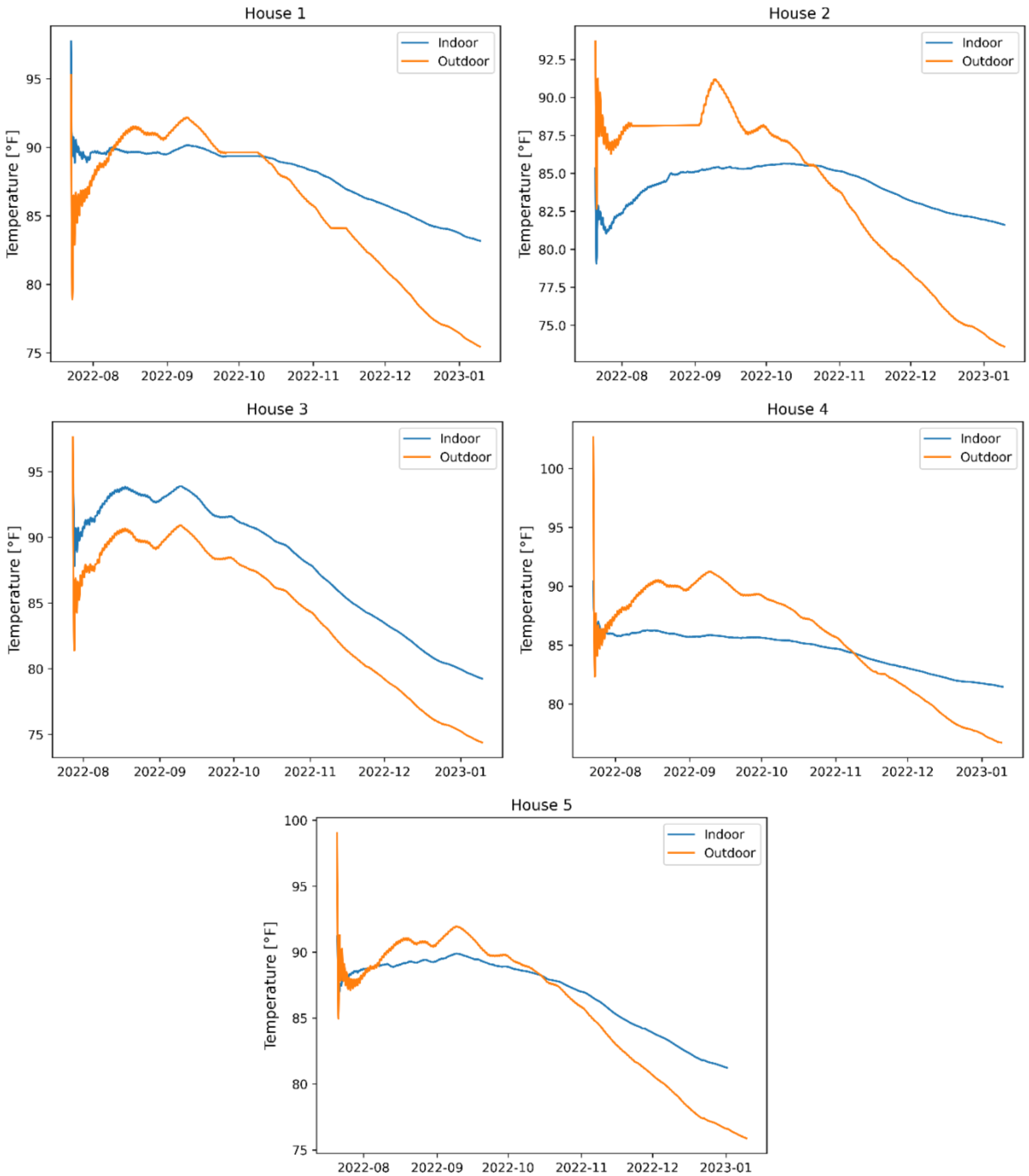

Figure S3: Hourly average time series plots for indoor (blue) and outdoor temperature (orange) for five participant houses. During the summertime, there were active air conditioning units to regulate indoor temperature for house 1, 2, 4, and 5. However, the indoor temperature in house 3 consistently exceeded the ambient temperature indicating there was no active air conditioning in the house.

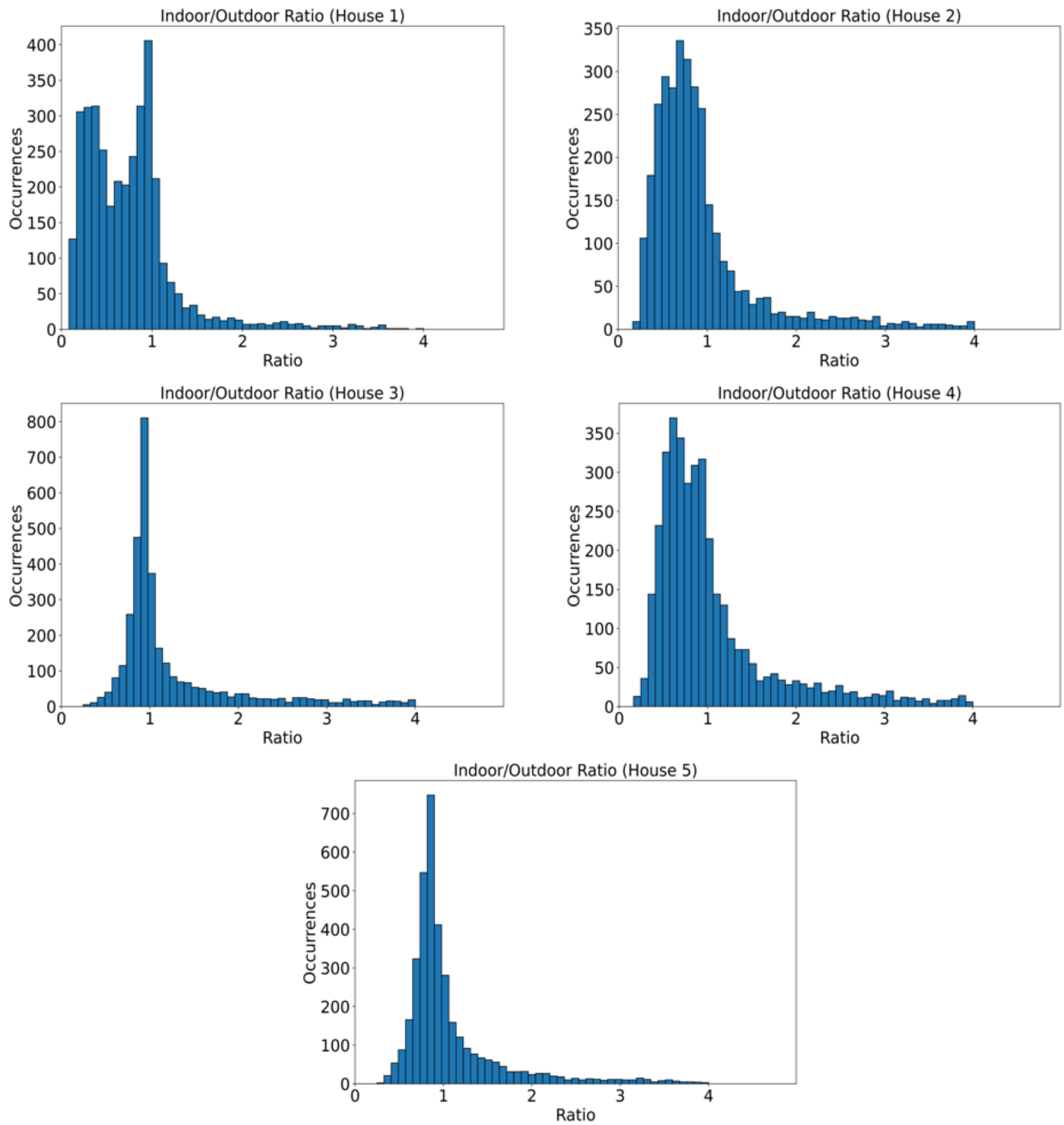

Figure S4: Indoor/outdoor $PM_{2.5}$ ratios for the five participant houses. The histogram was limted to 4 due to the high values when ambient concentrations were very small. Ratios are based on 10 minute average.

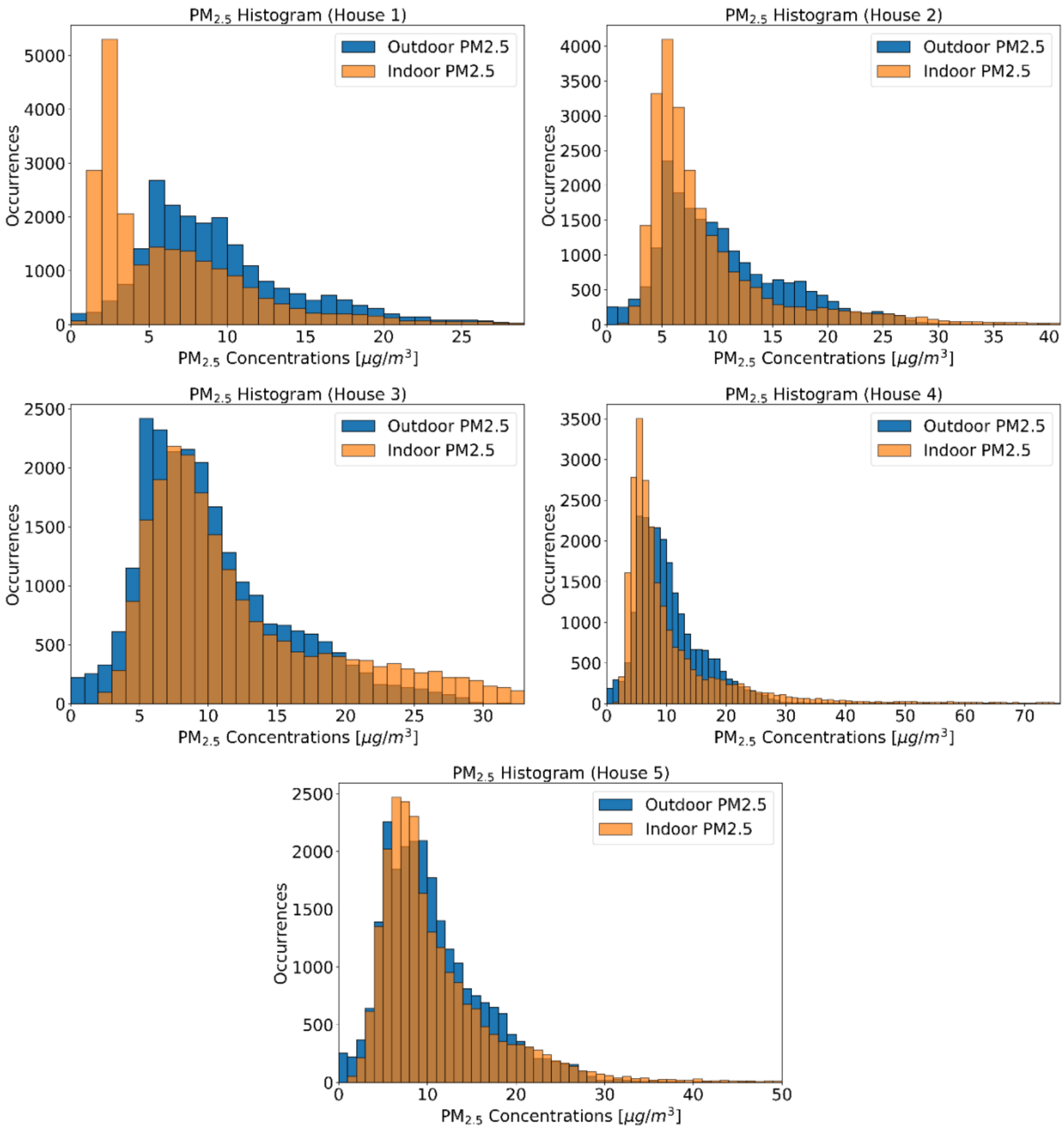

Figure S5: Histograms of indoor (orange) and outdoor (blue) for five participant houses based on 10-minute average. House 3 and 5 have a similar distribution between indoor and outdoor $PM_{2.5}$ while house 1, 2, and 4 have higher frequency of $PM_{2.5}$ levels at lower values.

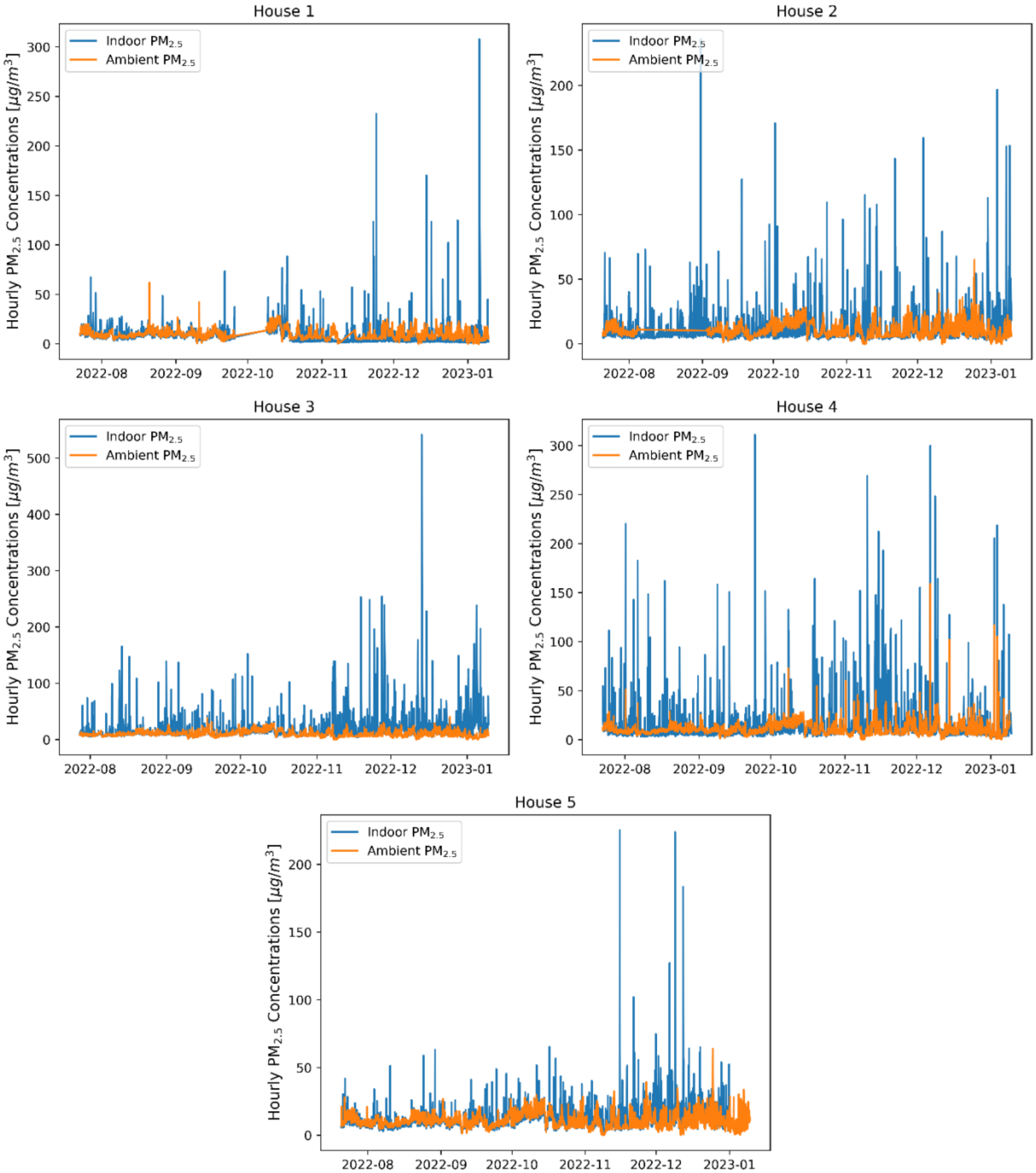

Figure S6: Hourly average time series plots for indoor (blue) and ambient $PM_{2.5}$ (orange) concentrations for five participant houses. Peaks of indoor $PM_{2.5}$ exceeded the ambient levels due to indoor emissions.

Table S7: Statistics based on hourly averaged indoor (In) and ambient (Out) $PM_{2.5}$ concentrations (in $\mu g/m^3$) for five homes. The sampling duration is seven months (July 2022 to January 2023) spanning the summer and winter periods. The table includes the 25th, 50th, 75th, and 98th percentiles, mean, and standard deviation (STD).

	25th %ile		50th %ile		75th %ile		98th %ile		Mean		STD	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
House 1	2.4	5.9	5.1	8.5	9.2	11.7	26.2	22.6	7.4	9.5	10.8	5.1
House 2	5.3	6.2	7.1	9.2	11.3	13.7	49.3	25.3	11.0	10.5	13.5	6.0
House 3	7.7	6.5	11.1	9.1	20.7	13.0	100	24.0	19.2	10.2	26.7	5.3
House 4	5.6	6.7	7.8	9.3	14.0	13.1	93.7	25.9	14.9	10.8	23.1	7.0
House 5	6.8	6.8	9.3	9.7	14.0	13.5	34.9	25.4	11.9	10.8	10.0	5.7

Table S8: Statistical summary of indoor and outdoor sensors for five houses. Sampling duration is three months from Jul 2022 to Sep 2023 spanning over the summer period. Based on 10-minute average.

Summer	25%ile		50%ile		75%ile		98%ile		Mean		STD	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
House 1	6.2	7.1	8.1	9.1	10.7	11.2	23.9	18.9	9.3	9.6	6.0	4.2
House 2	5.4	7.1	6.9	9.1	10.2	11.2	34.5	18.0	9.9	9.4	11.7	3.3
House 3	7.3	7.3	8.9	9.1	11.7	11.3	65.9	19.1	13.1	9.7	17.0	3.8
House 4	5.0	7.4	6.7	9.2	10.5	11.2	62.4	18.5	11.8	9.7	20.7	4.1
House 5	6.4	7.6	8.1	9.6	10.1	11.8	25.0	19.3	9.3	10.1	6.8	3.8

Table S9: Statistical summary of indoor and outdoor sensors for five houses. Sampling duration is four months from Oct 2022 to Jan 2023 spanning over the winter period. Based on 10 minute average.

Fall	25%ile		50%ile		75%ile		98%ile		Mean		STD	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
House 1	2.0	5.2	2.6	7.3	4.2	12.6	31.7	24.7	6.1	9.4	16.6	5.9
House 2	5.1	5.7	7.1	9.2	11.5	15.6	61.5	26.3	11.8	11.0	16.8	7.0
House 3	8.1	5.7	13.5	8.9	24.6	14.9	120.3	25.6	23.0	10.6	33.2	6.3
House 4	5.7	5.8	8.3	9.3	15.3	15.8	113.3	27.8	17.0	11.6	29.3	10.7
House 5	6.8	5.5	11.1	9.4	16.9	15.8	43.2	27.3	13.8	11.2	14.0	7.4

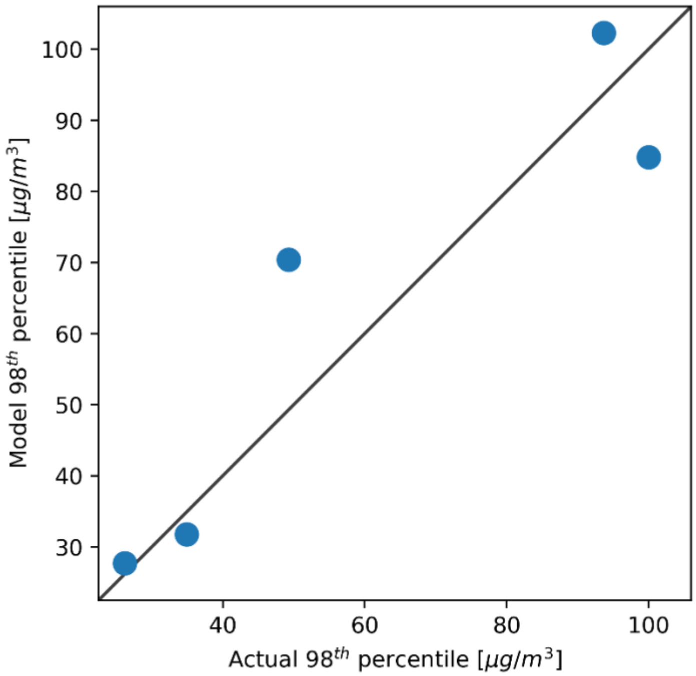

Figure S7: Model vs actual 98th percentile of indoor $PM_{2.5}$ in five homes

References

(1) Faust, J.; August, L.; Bangia, K.; Galaviz, V.; Leichty, J.; Prasad, S.; Schmitz, R.; Slocombe, A.; Welling, R.; Wieland, W.; Zeise, L. Update to the California Communities Environmental Health Screening Tool, CalEnviroScreen 3.0. **2017**, No. January, 166.

(2) Zeise, L.; Blumenfeld, J. *CalEnviroScreen 4.0*; Office of Environmental Health Hazard Assessment, 2021. https://oehha.ca.gov/media/downloads/calenviroscreen/report/calenviroscreen40reportf2021.pdf.