Assessing Indoor Versus Outdoor PM_{2.5} Concentrations During the 2025 Los Angeles Fires Using the PurpleAir Sensor Network

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Abstract

In January 2025, a series of fast-moving wildland-urban-interface (WUI) fires swept through the Los Angeles (LA) metropolitan area, causing severe air pollution. While the impacts of WUI fires on outdoor air quality have been extensively studied, indoor exposure remains less understood, despite most people sheltering indoors during WUI fires. This study investigates the spatial and temporal patterns of indoor and outdoor PM_{2.5} concentrations across the South Coast Air Basin, with a focus on LA County during the LA fires. Using high-resolution data from co-located indoor and outdoor PurpleAir (PA) sensors, we analyze hourly PM_{2.5} levels and indoor/outdoor ratios. Outdoor PM_{2.5} concentrations spiked sharply during the fires, reaching unhealthy levels exceeding 130 µg/m³, compared to the mean concentration (12 µg/m³) during non-fire hours. Indoor concentrations also increased, though to a lesser extent, peaking around 60 µg/m³ compared to a mean of 7 µg/m³ during non-fire hours. This reflects the partial shielding that indoor environments provide from outdoor air pollution. The mean (0.42) and median (0.29) indoor/outdoor PM_{2.5} ratios during LA fire hours were lower than the mean (0.93) and median (0.66) ratios during non-fire hours. Indoor/outdoor PM_{2.5} ratios across sensors showed a wide distribution, reflecting differences in building characteristics and occupant behavior, such as indoor activities and the use of air purifiers. These findings emphasize the need for guidance and interventions to reduce indoor PM_{2.5} exposure and protect public health during extreme WUI fire events.

Keywords

PurpleAir data, indoor air quality, wildland-urban-interface (WUI) fire, PM_{2.5}, 2025 Los Angeles Fires, low-cost sensors

Synopsis

Using a low-cost sensor network, we analyzed spatiotemporal patterns of outdoor and indoor PM_{2.5} concentrations during the 2025 Los Angeles fire and quantitatively assessed their differences, providing insights to inform health research and policy interventions.

Introduction

In January 2025, the Los Angeles (LA) metropolitan area experienced one of the most severe wildland-urban interface (WUI) fire events (referred to as *the LA fires* below) in recent history. Starting on January 7, multiple rapidly spreading WUI fires swept across Southern California, fueled by dry vegetation and strong Santa Ana winds. The fires, especially the Palisades and Eaton fires, have caused destructive damage throughout the region; by January 23, these fires had burned more than 50,000 acres and destroyed at least 16,000 structures.

WUI fires produce large volumes of smoke that contain a complex mixture of gases and airborne particles. Among these, fine particulate matter ($PM_{2.5}$) is of particular concern due to its small aerodynamic diameter (less than 2.5 micrometers), which allows it to penetrate deep into the lungs and even enter the bloodstream.^{2,3} These particles emitted from fires can travel hundreds of kilometers to surrounding urban areas, elevating ambient PM₂₋₅ concentrations well beyond health-based air quality standards.^{4,5} Furthermore, these particles can also enter indoor spaces through ventilation systems, open windows, and building leaks. Additionally, people tend to keep their windows closed during smoke, leading to lower natural ventilation rate and the accumulation of indoor pollutants. Therefore, indoor PM_{2.5} concentrations increase during fires, due to both outdoor pollutant penetration and indoor emissions, leading to increased exposure of residents to air pollution in the indoor environments where they spend most of their time. Exposure to air pollution from fire smoke has been consistently associated with increased hospital admissions for asthma, bronchitis, ischemic heart disease, premature mortality, and adverse birth outcomes, with particularly severe effects observed among children, the elderly, and those with pre-existing medical conditions.⁶⁻⁸ LA is uniquely vulnerable to smoke exposure due to its high population density and rapid expansion of wildland-urban interfaces, exposing millions of residents to harmful pollution levels both outdoors and indoors.^{1,9}

Previous studies have used multiple observational data and modeling tools to estimate the impact of fires on air pollution. Specifically, the Air Quality System (AQS), the ground-based regulatory air monitoring network maintained by the U.S. Environmental Protection Agency (EPA), has been used extensively to study the air quality impacts of fires. While AQS offers reliable and accurate criteria pollutant measurements, its sparse spatial coverage limits its ability to capture local-scale pollution spikes during rapidly evolving WUI fire events. To address this shortcoming, some studies have used satellite data, but these approaches still face challenges in predicting ground-level air quality where most human exposures occur. Other studies also combined satellite data with chemical transport models to

estimate ground-level PM concentrations, but were mostly limited to the outdoor environment. Particularly for the January 2025 LA fires, Schollaert et al recently identified January 7-14 as the days impacted by smoke using satellite data, AQS data, and PurpleAir (PA) sensors. However, most of the studies also focused on the impact of outdoor air quality of fires; there has not been a study investigating indoor air quality during the LA fires, which motivates us to investigate this using data from PA sensors.

The PA low-cost sensors provide valuable high-resolution data for both indoor and outdoor air quality, significantly increasing the spatial coverage of air quality monitoring. Their growing adoption in recent years across the Western U.S., particularly in Southern California, presents a unique opportunity to investigate the outdoor and indoor air quality impacts of the LA fires. Previous studies have investigated the spatial and temporal patterns of outdoor PM_{2.5} concentrations in Southern California using PA data combined with machine learning, geostatistical, and chemical transport models.^{18–22} These studies showed that after using appropriate data correction and calibration, the PA network data could complement the regulatory monitors by providing additional temporal and spatial variation details on fire smoke-impacted air quality.²³

Fewer studies have investigated indoor air quality during fire events using low-cost sensors. Krebs et al $(2021)^{24}$ assessed the heterogeneity of PA PM_{2.5} concentrations from indoor and outdoor across a whole year, confirming the validity of comparing and analyzing PA indoor and outdoor PM_{2.5} concentrations. Liang et al $(2021)^{25}$ compared indoor and outdoor PM_{2.5} measurements from PA sensors in California, and found that indoor PM_{2.5} levels increased noticeably during WUI fire events, while the infiltration rate (from outdoor to indoor) during WUI fire days was half of non-fire days. O'Dell et al $(2023)^{26}$ paired indoor and outdoor PA monitors in the western U.S. and found that PM_{2.5} indoor-to-outdoor ratio varies by region, while mean indoor concentrations were 82% higher in fire days compared to non-fire days.

While the PA sensor data is useful for addressing spatial and temporal gaps in $PM_{2.5}$ data, assessing indoor air quality using PA data requires addressing several challenges. First, the metadata specifying whether a sensor is designated for indoor or outdoor use is occasionally inaccurate. To address this issue, we developed a reclassification method based on temperature variability, allowing us to more accurately distinguish between indoor and outdoor sensors. Second, the number of co-located indoor-outdoor sensor pairs is very limited. Meaningful comparison between indoor and outdoor measurements requires careful collocation, ensuring sensors are close to each other. Previous studies typically selected the nearest outdoor counterpart of indoor sensors or set a distance threshold of 1

kilometer for comparison. 26,27 However, it remains unclear whether these distances are sufficiently close to ensure representative comparisons. 25 In our study, we were able to determine 50 pairs of indoor and outdoor sensors located within close spatial proximity (30 meters) in LA to identify differences attributable specifically to indoor versus outdoor PM_{2.5} concentrations, reducing the influence of spatial variability of outdoor PM_{2.5} concentrations.

Our study investigates how the disastrous LA fire affects both outdoor and indoor air quality, and for the first time quantitatively compares their difference in $PM_{2.5}$ concentrations. Using hourly-averaged PA data across the South Coast Air Basin (SCAB), we calibrated $PM_{2.5}$ measurements and sensor location types (i.e., indoor and outdoor), identified pollution hotspots, and analyzed $PM_{2.5}$ concentrations of co-located indoor–outdoor sensor pairs before, during, and after the fire. The indoor and outdoor $PM_{2.5}$ concentration levels reported in this study could be further analyzed for public health studies. Furthermore, our study offers insights for individuals seeking to reduce exposure to smoke and suggestions for air quality management agencies aiming to strengthen public health protection.

Methods

PA data description

PA provides real-time monitoring air quality data through wide deployment of low-cost sensors globally. We retrieved data of hourly-averaged PM_{2.5} concentrations along with temperature and relative humidity (RH) for all publicly available and activated sensors located within the South Coast Air Basin from the Purple Air API from January 1 to January 31, 2025.²⁷ Metadata such as GPS coordinates, location type (as labeled by users when first activated), and sensor start date were included for further classification and analysis.

The PA dataset used in this study includes measurements from both PA-I and PA-II sensors. The majority are PA-II sensors, which contain two Plantower PMS5003 laser-scattering particle counters, referred to as channels A and B, that alternate measurements every 10 seconds. By incorporating two sensing channels, the design allows for cross-validation between channels, enhancing data reliability through internal consistency checks. PA-I sensors are primarily designed for indoor use and contain a single particle counter (typically the Plantower PMS1003). These sensors report multiple estimated PM_{2.5} mass concentrations, based on particle counts in different size bins and calibration algorithms

developed by Plantower, known as CF=1, CF=ATM, and ALT-CF3.4. All sensors also include a Bosch BME280 sensor for measuring temperature, RH, and pressure.

For our analysis, we used the "CF=1" data field (referred to as "pm2.5_cf_1" in the PA API), which represents the calibrated $PM_{2.5}$ concentrations by Plantower accounting for particle hygroscopic growth under varying humidity. We further calibrated both indoor and outdoor PA sensor readings based on the US EPA method. We used the same calibration methods for indoor and outdoor $PM_{2.5}$ concentrations to ensure comparability between them, since our analysis is focused on indoor-to-outdoor relationships.

Data cleaning and calibration

We conducted multi-step cleaning and calibration of hourly PA measurements.

First, we removed data from PA sensors that did not report any temperature, RH, and $PM_{2.5}$ data. We also removed sensors that have a data coverage of $PM_{2.5}$ concentrations less than 50% in our study period, January 2025. The data coverage for each sensor was computed as a ratio of the number of available hourly $PM_{2.5}$ observations to the total number of hours in January 2025.

Second, we removed implausible measurements. Specifically, we removed sensors if recorded temperatures were outside the range of -200° F to 1000° F (-129° C to 537° C) or if RH values were outside the 0–100% range. We also removed sensors whose monthly average PM_{2.5} concentration exceeded $500~\mu\text{g/m}^3$, as persistently high values may indicate sensor malfunction.

Third, we assessed the quality and consistency of $PM_{2.5}$ readings from the dual optical particle counters, channels A and B within the Plantower PMS5003 sensor. These two channels operate in alternating 10-second intervals and generate averaged $PM_{2.5}$ values over two-minute periods. Each channel uses a laser-based method that measures 90° light scattering from airborne particles, utilizing a 680 ± 10 nm wavelength. Records were removed when data from both channels was missing or equal to zero. ²⁰ When both channels A and B provided valid and consistent readings, the average of the two was used. Note that, to maintain an adequate number of observations for analysis, we did not remove data from sensors that only have one channel.

Lastly, to correct biases in PA $PM_{2.5}$ measurements, we applied the RH-based calibration method developed by the US EPA, using different equations for typical ambient $PM_{2.5}$ concentrations and high concentrations due to fire smoke [see details in Barkjohn et al.

(2022)].²³ Figure S1 shows the comparison between our calibrated PA $PM_{2.5}$ concentrations and those measured by a nearby EPA air monitoring station.

Indoor and outdoor sensor reclassification

The metadata provided by PA users regarding sensor location type (indoor or outdoor) could be inaccurate. To address this issue, we reclassified each sensor based on its observed temperature variability. Specifically, we calculated the daily temperature range (DTR) for each sensor from January 1 to January 31, 2025. Sensors with low DTR (<5 °C) were likely installed indoors, as indoor climate is more stable, while those with high DTR (>10 °C) were likely outdoors. This temperature threshold for reclassification was determined from historical outdoor records in LA (January 2025), where the average of DTR is ~10 °C and the 5th percentile is ~ 5°C (see Figure S2?? Based on this approach, we identified 35 of the 933 sensors retained after data cleaning as likely misclassified. We reclassified 16 originally labeled as indoor sensors to outdoor, and 19 outdoor sensors to indoor (Figure S3).

Identification of co-located indoor and outdoor sensors

To identify co-located indoor and outdoor PA sensors for analyzing indoor—outdoor air quality relationships, we used sensor metadata containing geographic coordinates. Coordinates were converted to a projected coordinate reference system (EPSG:3857), and a spatial proximity analysis was conducted. For each indoor sensor, we identified all outdoor sensors located within 30 meters and active during the study period (January 1–31, 2025). Sensor pairs (one indoor and at least one outdoor sensor) within this 30-meter buffer were classified as co-located. When multiple outdoor sensors were paired with an indoor sensor, we averaged their outdoor PM_{2.5} concentrations. Figure S4 shows the spatial distribution of these sensor pairs; of the 61 co-located pairs identified in the South Coast Air Basin, 50 pairs are located in LA County, covering the downwind area of smoke plume.

Identification of fire hours

For our further analysis of indoor vs outdoor daily concentrations in LA County, we identified hours when co-located indoor and outdoor PA sensors' air quality readings were impacted and not impacted by smoke from the LA fire. We used the cleaned and calibrated hourly PM_{2.5}

dataset. We classified a sensor-hour as fire-impacted within the fire period (January 7–12, 2025) if its hourly outdoor PM_{2.5} concentration exceeded 15 μ g/m³, the corresponding paired indoor sensor was marked as fire-impacted accordingly. This threshold of 15 μ g/m³ was chosen based on empirical conditions during the study period: the mean outdoor concentration on hours outside the fire period (January 7–12) in LA County in January 2025 was 15.07 μ g/m³. All other hours that were not classified as fire hours were considered as "non-fire hours".

Results and Discussion

Number of available indoor and outdoor PA sensors

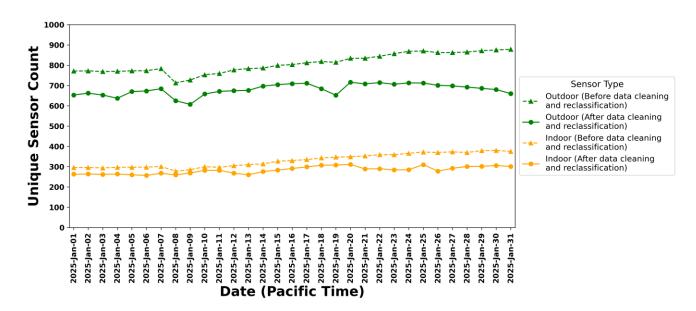


Figure 1. Daily count of unique indoor and outdoor activated PA sensors operating in the South Coast Air Basin (SCAB) during January 2025. Solid lines with circle markers represent sensors retained after data cleaning and reclassification, while dashed lines with triangle markers show counts before data cleaning and reclassification. Daily counts only include sensors recording at least 18 hours of data on a given day in Pacific Standard Time (PST).

Figure 1 shows the changes in the number of activated sensors in our study period. The change in count of activated sensors throughout January 2025 in the South Coast Air Basin, reflects both fire-related disruptions and human responses to WUI fire events. Both indoor and outdoor sensor activity dropped on January 8, likely due to power outages or connectivity loss caused by WUI fires. However, after January 10, the number of sensors began to increase steadily. This upward trend might be attributed to increased public interest

in local air quality, as more individuals activated existing PA sensors or installed new PA Sensors in response to fire events. From January 8 to January 31, 2025, the total number of activated indoor sensors increased from 278 to 375, while the number of activated outdoor sensors increased from 713 to 878. These trends may reflect public interest in understanding and responding to air quality challenges following extreme air pollution events like WUI fires.

Figure 1 also compares the number of available sensors before and after data cleaning and reclassification of indoor/outdoor sensor types. Following these procedures, the number of sensors included in our analysis (solid lines) is slightly lower than the total number of available sensors (dashed lines). Their difference reflects our removal of data with dual-channel inconsistencies, temperature and humidity-related anomalies, and low data coverage. In particular, the difference was much higher after mid-January, because many newly activated sensors had less than 50% data coverage in January and were excluded from our analysis. Nonetheless, the cleaned dataset still provided a substantial number of high-quality observations, with more than 250 indoor sensors and more than 650 outdoor sensors, providing both strong data quality and sufficient spatial coverage for subsequent analysis.

Hotspots of Indoor and Outdoor PM_{2.5} Concentrations

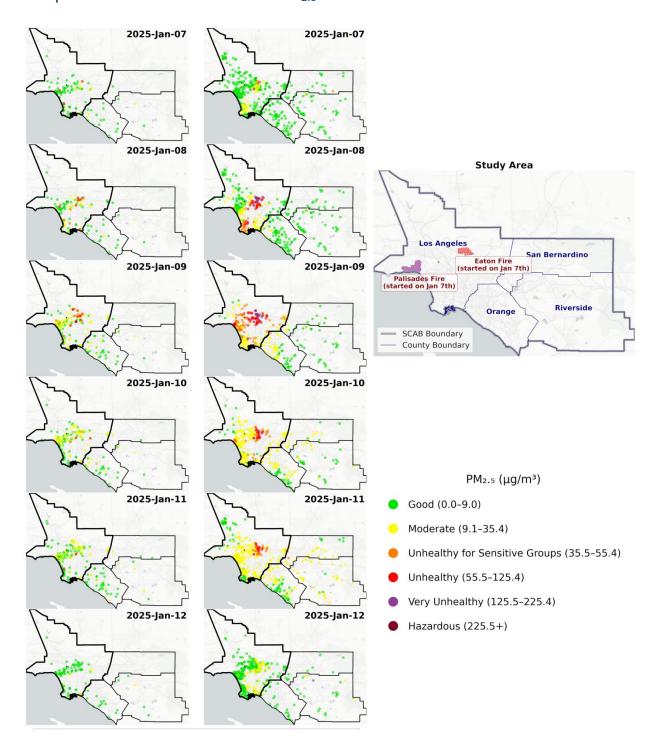


Figure 2. Daily maps showing the spatial distribution of indoor and outdoor average PM_{2.5} concentrations across the South Coast Air Basin (SCAB) from January 7-12, 2025 (Pacific Time). Each dot represents a PA sensor, and its color represents daily average PM_{2.5} concentration, categorized into six concentration bins according to the U.S. EPA Air Quality

Index (AQI) thresholds: Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous. For each day, only sensors with at least 18 valid hourly readings are included. SCAB and county boundaries are shown in black, with the boundary of the intersection of LA County and SCAB highlighted in bold.

The high density of indoor and outdoor PA sensors in the South Coast Air Basin (especially LA County) enables us to investigate the spatial and temporal variability of PM_{2.5} concentrations during the LA fire period (Figure 2). Figure 2 shows drastic increases in outdoor PM_{2.5} concentrations between January 7 and January 11, peaking on January 9. Outdoor sensors in LA County recorded elevated PM_{2.5} concentrations in the unhealthy range, reaching the very unhealthy and hazardous Air Quality Index (AQI) levels. In the center of LA County, some sensors recorded extremely high outdoor PM_{2.5} concentrations above 125.5 µg/m³. In contrast, San Bernardino, Riverside, and Orange Counties had fewer sensors and experienced much milder PM_{2.5} pollution during the same period, with most outdoor PM_{2.5} concentrations remaining in Good or Moderate AQI levels. The spatial pattern of elevated PM_{2.5} concentrations during the LA fire is likely driven by prevailing Santa Ana winds and the location of fires, which blew Palisades Fire smoke offshore and constrained Eaton Fire smoke largely within the LA basin.^{29,30} As a result, the LA fires predominantly affected PM_{2.5} levels in LA County, ¹³ with limited impact on neighboring counties during this time period.

Indoor sensors also recorded increases in PM_{2.5} concentrations during this period, though levels remained considerably lower than outdoor concentrations. Most indoor sensors showed concentrations in the 9–55.4 μ g/m³ range during January 8–9 (yellow to orange dots on the maps), with a few in central LA exceeding 55.4 μ g/m³, reaching unhealthy AQI levels. Note that AQI is designed for outdoor air quality assessment, but we also describe it for indoor air quality just to put numbers into perspective.

Both outdoor and indoor PM_{2.5} concentrations started to decline after January 9 with the spatial range and intensity of hotspots (red and purple dots) visibly shrinking on the map. PM_{2.5} concentrations returned to Good and Moderate AQI levels on January 12. This rapid decrease may reflect both reduced fire intensity and favorable meteorological conditions for dispersion outdoors, reduced infiltration indoors, and potentially greater air cleaning and filtration indoors. Additionally, daily maximum PM_{2.5} concentrations from indoor and outdoor sensors that represent peak exposure levels are reported in Figure S8. These values highlight peak exposure levels during the fire episode, showing that while average concentrations were moderately elevated, some locations experienced short-term extreme conditions far exceeding the AQI thresholds. This distinction between mean and maximum values underscores the potential for acute exposure risks.

Comparison of PM_{2.5} Concentrations between Indoor and Outdoor Sensors

As shown in Figure 2, the LA fires led to much higher increases of outdoor $PM_{2.5}$ levels in LA County, compared to other counties within the South Coast Air Basin. To better understand and compare indoor and outdoor exposure trends during the fire period, we focused our temporal analysis of $PM_{2.5}$ concentrations on sensor data aggregated across LA County to capture fluctuations in both indoor and outdoor air quality (Figure 3).

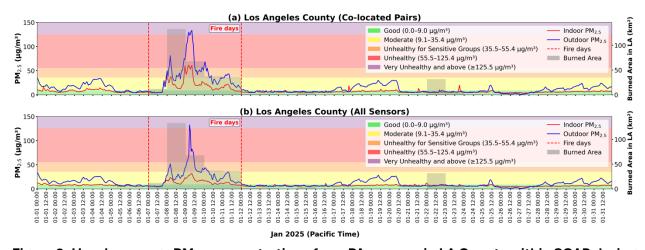


Figure 3. Hourly average PM_{2.5} concentrations from PA sensors in LA County within SCAB during January 2025. Panel (a) shows co-located indoor and outdoor sensor pairs in LA County; panel (b) includes all available indoor and outdoor sensors in LA County. Indoor and outdoor PM2.5 concentrations are plotted as solid red and blue lines, respectively. Shaded background colors represent updated U.S. EPA AQI thresholds: green (Good $\leq 9.0~\mu g/m^3$), yellow (Moderate $\leq 35.4~\mu g/m^3$), orange (Unhealthy for Sensitive Groups $\leq 55.4~\mu g/m^3$), red (Unhealthy $\leq 125.4~\mu g/m^3$), and purple (Very Unhealthy and Above $\geq 125.5~\mu g/m^3$). Daily burned area in LA County (km²) is overlaid as gray bars. All data is shown in Pacific Time.

From January 1 to 7, $PM_{2.5}$ concentrations were consistently low. Outdoor levels typically ranged from 10–35 μ g/m³, while indoor $PM_{2.5}$ levels were below 12 μ g/m³ in most cases. Average outdoor PM levels were within the Good and Moderate AQI levels, suggesting relatively clean air quality conditions.

The Eaton and Palisades fires, which began on January 7, triggered drastic $PM_{2.5}$ concentration increases across the LA County (and SCAB). Data from co-located sensors shown in Figure 3(a) is especially useful for comparing indoor versus outdoor concentrations, because each indoor sensor is positioned within 30 meters of corresponding outdoor sensors. The mean outdoor concentrations surged rapidly and peaked in the morning of

January 9 at ~133 μ g/m³, reaching the Very Unhealthy AQI level. Indoor PM_{2.5} concentrations from co-located sensors also rose substantially, peaking at ~60 μ g/m³ in the morning of January 9. During the peak smoke period (January 8–11), indoor and outdoor PM_{2.5} concentrations exhibited similar temporal patterns. Overall, the indoor PM_{2.5} concentrations were lower than outdoors, suggesting that indoor environments offer a degree of protection from WUI fire smoke. However, the concentrations still exceeded the "Unhealthy for Sensitive Groups" AQI threshold, indicating notable indoor exposure when outdoor PM_{2.5} is heavily impacted by smoke.

Following the peak PM_{2.5} concentrations in the morning of January 9, both indoor and outdoor PM_{2.5} declined rapidly, returning to pre-fire levels by the end of January 12. In the absence of new WUI fire activity, outdoor PM_{2.5} still had fluctuations, possibly due to the influence of other emission sources and meteorological factors such as vehicle exhaust, atmospheric stagnation, or residential wood burning. During this same period, indoor PM_{2.5} concentrations remained relatively stable, suggesting the role of indoor environments in buffering occupants from ambient air pollution. Figure 3(b) includes the mean concentrations of all available ~700 outdoor and ~300 indoor sensors across LA County. The overall temporal trends are similar to those of the 50 co-located sensor pairs in Figure 3(a). Figures 3(a) and 3(b) both show clear peaks of outdoor PM_{2.5} concentrations on January 9 at ~133 μ g/m³ for outdoor sensors of co-located pairs and ~132 μ g/m³ for all outdoor sensors.

Figure 3 also presents the daily burned area data to provide context for the fire burning situation. We obtained the daily burned area data from Near-Real-Time (NRT) product of Fire INventory from NCAR (FINN) version 2.5.1. The data is based on fire detections from Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellites.31 The temporal alignment between periods of burned area and PM_{2.5} peaks confirms WUI fire smoke as the primary pollution driver during early January. In contrast, PM2.5 fluctuations in mid-to-late January occurred without significant burning, suggesting other emission sources (e.g., traffic and local burning) and meteorological factors (e.g., stagnation events). It is also worth noting that an increase in burned area may not necessarily result in measured increases in concentrations. This could be partially due to limited or no sensor coverage in the downwind area of fires (e.g., the ocean). This could explain the lack of observed elevated $PM_{2.5}$ concentrations correlated with the burned area in late January (mainly from the Hughes Fire in North of SCAB). While Figures 3(a) and 3(b) focus on mean concentrations, variability across the large number of sensors is also important. Figure S9 in Supplementary Information presents shaded standard deviations around the mean PM_{2.5} concentration. During the fire period, the shaded

standard deviations broaden substantially, particularly for outdoor sensors. Indoor sensors also show increased variability, though to a lesser extent. In contrast, non-fire hours exhibit narrow variability bands, reflecting relatively uniform and low $PM_{2\cdot5}$ levels. Figure S10 further shows the 10^{th} – 90^{th} percentile PA data ranges around the mean $PM_{2\cdot5}$ concentrations. The relatively wide percentile bands during fire hours highlight the larger variability across sensors.

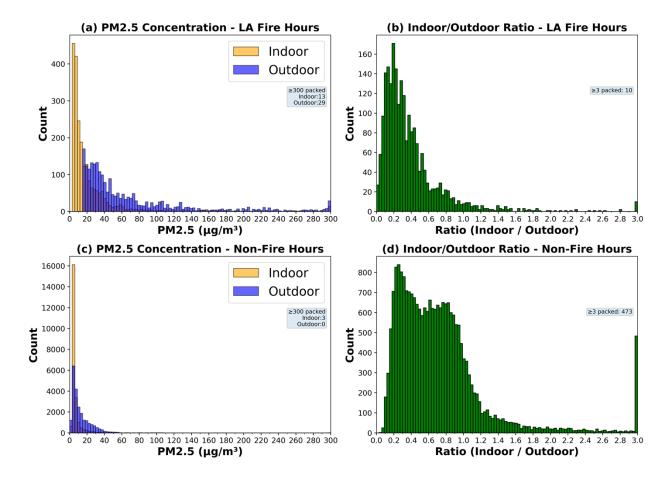


Figure 4. Histograms of hourly PM_{2.5} concentrations and indoor/outdoor PM_{2.5} ratios from colocated PA sensor pairs in LA County during LA fire hours and non-fire hours in January 2025. Panels (a) and (b) show histograms of hourly indoor (yellow bars) and outdoor (blue bars) PM_{2.5} concentrations and indoor/outdoor PM_{2.5} ratios during fire-impacted hours, while panels (c) and (d) display the corresponding distributions for non-impacted hours. Indoor/outdoor ratios (panels b and d) are calculated as the indoor concentration divided by the outdoor concentration, measured by each co-located sensor pair. "Count" on the y-axis indicates the number of hourly observations in each bin. The rightmost bin in each panel aggregates all

values at or above the axis cap ($\geq 300 \ \mu g/m^3$ for PM_{2·5}; ≥ 3.0 for Indoor/Outdoor ratios). The number of data points exceed the cap and are stacked into that final bin were also reported.

We further classified the $PM_{2.5}$ concentration data of co-located sensors into sensor-hours impacted by LA fire and non-fire hours, and presented the distribution of hourly $PM_{2.5}$ concentrations for hours impacted and not impacted by the LA fire. During the LA fire hours (Figure 4a), outdoor $PM_{2.5}$ levels had a wide variability with half of readings exceeding 40 $\mu g/m^3$ and some surpassing 150 $\mu g/m^3$ (the 95th percentile reaching 214.9 $\mu g/m^3$). In contrast, during non-fire hours (Figure 4c), the vast majority of outdoor $PM_{2.5}$ concentrations remained below 40 $\mu g/m^3$, with a 95th percentile at 31.2 $\mu g/m^3$, much lower than the concentrations during fire hours.

Indoor $PM_{2.5}$ concentrations remained comparatively lower and more stable. For both LA fire hours and non-fire hours, indoor $PM_{2.5}$ distribution were heavily skewed to the right (Figures 4a and 4c). Despite the increases in indoor $PM_{2.5}$ concentrations, they generally remained within the "Good" and "Moderate" AQI categories.

Distribution of both indoor and outdoor $PM_{2.5}$ concentrations shifted towards higher concentrations during the LA fire hours, as compared to LA non-fire hours. During LA fire-impacted hours, the median hourly outdoor and indoor $PM_{2.5}$ concentrations were 11.8 $\mu g/m^3$ and 41.8 $\mu g/m^3$, respectively. The median hourly outdoor and indoor concentrations were 4.9 $\mu g/m^3$ and 8.0 $\mu g/m^3$ during non-fire hours, respectively. Overall, we found that indoor concentrations were lower than those outdoors.

Indoor/outdoor PM_{2.5} ratios during LA fire hours and non-fire hours

Despite the increases in PM_{2.5} concentrations for both indoor and outdoor sensors during LA fire hours, Figure 4 b shows that hourly indoor/outdoor PM_{2.5} ratios were significantly lower during LA fire hours, where most ratios fell within 0.1 to 1, with a peak between 0.2 and 0.3 and median ratio of 0.29. In contrast, as shown in Figure 4d, during non-fire hours, the distribution had a higher median ratio of 0.66 and double modes with peaks observed at \sim 0.25 and \sim 0.8. Notably, during LA fire hours, a much smaller portion of ratios exceeded 1.0 compared to non-fire hours, indicating less frequent instances where indoor PM_{2.5} concentrations surpassed outdoor levels during LA fire hours.

The indoor/outdoor $PM_{2.5}$ ratios also exhibit a wide range. For LA fire hours, their interquartile range (IQR) is 0.32, with Q1 at 0.17 and Q3 at 0.49. Their IQR for non-fire hours (0.55) is even

higher, with Q1 at 0.39 and Q3 at 0.94. The high variability in indoor/outdoor $PM_{2.5}$ ratios (Figures 4b and 4d) suggests that the protective role of indoor environments in reducing $PM_{2.5}$ exposure varies.

Table 1. Summary statistics of daily $PM_{2.5}$ concentrations from co-located indoor and outdoor PA sensors in the area of LA County that is within the South Coast Air Basin during January 2025. The table reports the mean \pm standard deviation of outdoor $PM_{2.5}$, indoor $PM_{2.5}$, indoor/outdoor ratios, and differences of indoor minus outdoor concentrations for days impacted and not impacted by the LA fire. N indicates the number of sensor-day pairs used in each calculation, with each pair representing one day of data from co-located indoor and outdoor sensors.

	Met	rics	Fire hours (N=2,206)	Non-fire hours (N=22,960)
Indoor	Mean (µg/m³)		24.6	7.0
	SD (µg/m³)		48.5	14.2
	Percentile	5%	4.3	3.2
		25%	6.6	4.2
		50%	11.8	4.9
		75%	24.5	6.2
		95%	75.9	16.0
	Mean (µg/m³)		65.8	11.8
	SD (µg/m ³)		66.3	9.5
		5%	16.7	2.8
Outdoor	Percentile	25%	26.2	5.3
		50%	41.8	8.0
		75%	76.7	15.8
		95%	214.9	31.2
	Mean		0.42	0.93
	SD		0.46	2.95
In dee (0. stdees		5%	0.07	0.20
Indoor/Outdoor ratio	Percentile	25%	0.17	0.39
		50%	0.29	0.66
		75%	0.49	0.94
		95%	1.17	1.84
	Mean (µg/m³)		-41.2	-4.9
Indoor-Outdoor difference	SD (µg/m ³)		63.8	16.0
	Percentile	5%	-155.5	-22.9
		25%	-54.3	-8.8
		50%	-25.1	-2.5
		75%	-12.6	-0.3
		95%	5.6	2.7

Table 1 shows a summary of mean and standard deviation for PA hourly indoor and outdoor PM_{2.5} concentrations. Outdoor mean PM_{2.5} concentrations reached 65.8 μ g/m³ during the LA fire hours, a factor of six times higher than the mean PM_{2.5} concentrations during non-fire hours (11.8 μ g/m³). Indoor mean concentration was 24.6 μ g/m³ during fire-impacted hours, a factor of 3.5 higher than the concentration during non-fire hours (7.0 μ g/m³). The increases in indoor concentrations we observed during the LA fires are comparable to findings by Liang et al. (2021),²⁵ which concluded that indoor mean concentrations tripled during fire-impacted days in Northern California.

Table 1 also compares the indoor versus outdoor $PM_{2.5}$ concentrations. The mean indoor/outdoor ratio decreased from 0.93 during non-fire hours to 0.42 during LA fire hours. The absolute difference between mean indoor $PM_{2.5}$ concentrations and outdoor $PM_{2.5}$ concentrations during LA fire hours reached 41.2 μ g/m³, which is significantly larger than 4.9 μ g/m³ on non-fire hours. These differences, together with the pattern shown by Figures 4a and 4b, reflect the protective role of indoor environments in mitigating exposure to WUI fire-related $PM_{2.5}$. They may also reflect actions taken by residents during high pollution events, such as the active use of air filters.

Discussion

Our analysis of PA sensor data provides a comprehensive comparison between indoor and outdoor $PM_{2.5}$ and for LA fire and non-fire hours, providing valuable insights into the extent to which indoor environments may buffer residents from elevated outdoor pollution levels during WUI fire events. We found that both indoor and outdoor $PM_{2.5}$ concentrations experienced large increases during LA fire days in LA County and had similar temporal and spatial patterns. Across most co-located indoor–outdoor sensor pairs, indoor $PM_{2.5}$ concentrations were consistently lower than outdoor levels, reflected by an average indoor/outdoor ratio of 0.93 during non-fire hours. This ratio declined further during the LA fire period to 0.42.

The broad range of indoor/outdoor ratios may reflect variations in building characteristics (e.g., filter efficiency indicated by Minimum Efficiency Reporting Values [MERV] in central air conditioning systems), indoor and outdoor air quality, and occupant behaviors such as the use of air purifiers, consistent with previous studies on infiltration rate variability. ^{32,33} Xiang et al. (2021)³⁴ similarly reported that outdoor-to-indoor infiltration factors during wildfire

hours varied substantially across buildings (0.33–0.76) and that high-efficiency particulate air (HEPA) purifiers operating in auto mode reduced indoor $PM_{2\cdot5}$ concentrations by 48%–78%.

The distribution of indoor/outdoor ratios was unimodal during the fire period (Figure 4b) but bimodal on non-fire hours (Figure 4d). We hypothesize that the two modes observed on non-fire hours may be driven by indoor activities, which exert a stronger influence on indoor $PM_{2\cdot5}$ in the absence of wildfire-related outdoor pollution. Additionally, interquartile range (IQR = 0.55) of indoor/outdoor ratios is greater on non-fire hours, reflecting greater variability from indoor sources such as cooking, cleaning, or other household activities. In contrast, the narrower interquartile range (IQR = 0.32) during the fire period likely reflects the stronger influence of elevated outdoor $PM_{2\cdot5}$ concentrations, combined with more consistent protective behaviors (e.g., closing windows, reducing ventilation, or using air cleaners). Spatial heterogeneity in housing type and socioeconomic conditions may also contribute to the observed distributions of indoor/outdoor ratios during the LA fire. However, we did not identify clear spatial patterns in indoor/outdoor ratios during fire or non-fire periods (Figure S11).

We acknowledge several limitations of this study, some of which could be addressed by future studies. First, most households only have a single sensor, which may not adequately capture the spatial variability of PM_{2.5} within indoor environments. Second, our analysis did not attempt to remove PM_{2·5} peaks from indoor sources (e.g., cooking, cleaning, smoking). Our focus of this study is on quantifying indoor and outdoor PM_{2·5} exposures during fire impacted and non-fire impacted periods, rather than estimating the precise fraction of outdoor PM_{2.5} that infiltrates indoors.^{35,36} Future studies that combine activity information (e.g., cooking, burning) and sensor data would be valuable for identifying and excluding short-term indoor emissions to better isolate wildfire-related impacts. Moreover, quantifying infiltrated PM_{2.5}, which is the fraction of indoor PM_{2.5} originating from outdoor sources, may help to more.²³ Thirdly, while AQI categories are included to provide readers with a familiar reference framework for comparing indoor and outdoor concentrations in this paper, it is important to note that they were developed for ambient outdoor air and should not be directly interpreted as indicators of indoor exposure risk. Lastly, the PA sensor network could also be further expanded to enhance its spatial coverage and enable a more comprehensive assessment of PM_{2.5} exposure patterns. Consistent with prior work (Mikati et al., 2023; Bi et al., 2021), we found that PA sensor network is not evenly distributed across socioeconomic groups in outdoor environments, and tends to be more prevalent in affluent neighborhoods. As shown in Figure 2, LA County has a much higher density of both indoor and outdoor

sensors compared to the surrounding counties (San Bernardino, Riverside, and Orange) in SCAB. This higher adoption of PA sensors in LA County may be due to its denser population and greater public awareness. However, within LA County itself, there is also a data gap in Assembly Bill 617 and Senate Bill 535 disadvantaged communities (Figure S12 and Figure S13), especially in the South and Southeast LA. Although the PA network is disproportionately located in more affluent areas and has limited coverage within disadvantaged communities, other monitoring initiatives provide important complementary data. For example, the Los Angeles Unified School District (LAUSD) has deployed Clarity sensors in AB 617 communities, and the South Coast Air Quality Management District (SCAQMD) has expanded monitoring under the AB 617 program.³⁷

Our findings are important for conducting future exposure analysis and guiding effective public health interventions. Analyses of co-located PA sensors could provide information of exposure estimates in future epidemiological studies targeting WUI fire health effects. Expanding such sensor networks across LA communities would provide further data support for both scientific research and public risk communication. With indoor levels still tripling despite reduced infiltration during WUI fire days, residents are advised to stay indoors with enhanced filtration systems to reduce high-level PM_{2.5} exposure.³⁸ Public messaging during WUI fire events has also been shown to effectively prompt protective behaviors.³⁹ We encourage policymakers in LA (e.g., SCAQMD) continue supporting public outreach initiatives regarding the air quality impact of WUI fires and offer subsidies for HEPA purifiers and air quality monitors in disadvantaged and high-risk communities.

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by the South Coast Air Quality Management District. The views expressed in this document are solely those of the authors and do not necessarily reflect those of the South Coast Air Quality Management District. South Coast Air Quality Management District does not endorse any products or commercial services mentioned in this publication.

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Supporting Information

Data cleaning and sensor type reclassification

Table S1. Number of indoor and outdoor PurpleAir sensors remaining after each data cleaning and reclassification step.

Number of Sensors after Each Steps							
Data Cleaning Steps	Indoor Sensors	Outdoor Sensors	Indoor Sensor Removed	Outdoor Sensor Removed			
Data before QC	418	960	0	0			
Step1: Basic Filtering	326	798	92	162			
Step2: Temperature & Humidity Check	324	768	2	30			
Step3: A/B Channel Check	322	735	2	33			
Step4: Reclassify Location	323	734	Outdoor→Indoor: 17	Indoor→Outdoor: 16			

This table shows the number of indoor and outdoor sensors retained after each data cleaning step. "Data before QC" shows the initial sensor count, followed by the number of sensors after

each step: (1) basic filtering for missing values and negative values, (2) removal of implausible temperature and humidity records, (3) A/B channel consistency check, (4) reclassification of sensor locations. The number of sensors removed at each step is listed, and the final row summarizes sensors reclassified between indoor and outdoor categories.

Compare PM_{2.5}_CF_1 at Co-located PurpleAir Sensor-EPA Air Quality Monitoring Stations

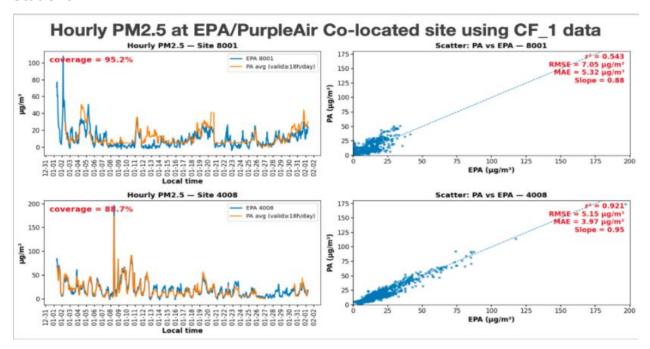


Figure S1. Hourly PM₂. $_5$ comparisons between PurpleAir (PA, CF_1 data) and EPA regulatory monitors at two co-located sites (8001 and 4008) in the South Coast Air Basin. Left two panels show time series of hourly PM₂. $_5$ concentrations measured by PA (orange) and EPA monitors (blue), with data coverage rates of 95.2% (site 8001) and 86.7% (site 4008). Right panels show scatterplots of PA versus EPA concentrations. Site 8001 had RMSE = 7.05 μ g/m³, MAE = 5.32 μ g/m³, and R² = 0.54, site 4008 had RMSE = 5.15 μ g/m³, MAE = 3.97 μ g/m³, and R² = 0.92.

Daily Temperature Range (DTR) in January 2025

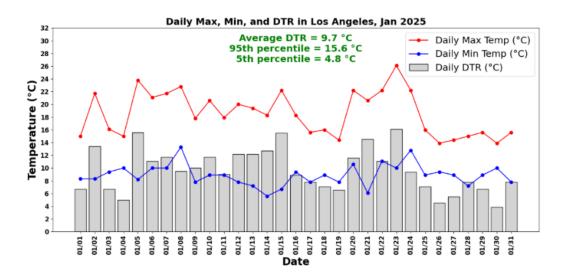


Figure S2. Daily maximum, minimum, and DTR in Los Angeles, January 2025. Red lines represent daily maximum temperatures, blue lines represent daily minimum temperatures, and gray bars indicate the diurnal temperature range (DTR, difference between daily maximum and minimum). Across January 2025, the average DTR was 9.7 °C, with a 95th percentile of 15.6 °C and a 5th percentile of 4.8 °C.

Reclassifying PurpleAir Sensor Location Type

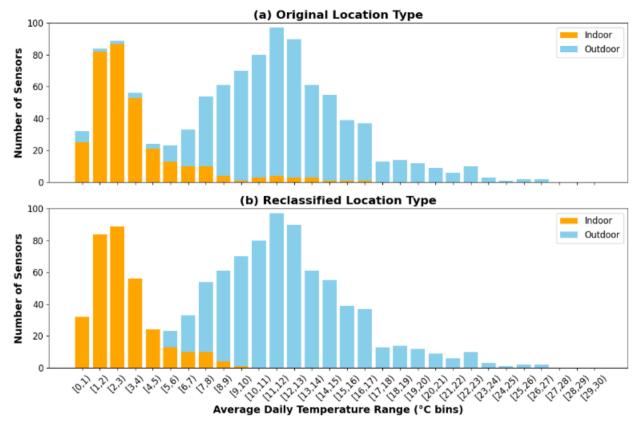


Figure S3. Comparison before and after location reclassification using daily average temperature range as a criteria. Panel (a) shows the distribution of sensors using the original location labels provided by PurpleAir, while panel (b) uses labels after reclassification based on temperature variability. Each bar represents the number of indoor (orange) and outdoor (blue) sensors falling within a specific 1°C-wide bin of average daily temperature range.

Co-located PurpleAir Sensor-EPA Air Quality Monitoring Stations in SCAB

Table S2. Co-Located EPA Air Quality Monitoring Stations and Purple Air Outdoor Sensors

Co-Located EPA Sites and PurpleAir Outdoor Sensors						
Station Name	Matched EPA Air Monitoring Station	Matched PurpleAir Sensors	ID of matched PurpleAir Sensors			
Rubidoux	06-065-0001	8	6806, 3537, 1854, 180081, 5280, 5284, 4748, 2612			
Long Beach Route 710 Near Road	06-037-4008	1	104940			

Based on Euclidean distances calculated in projected coordinates, PurpleAir sensors reclassified as outdoor were matched to EPA air monitoring stations (AMS) if located within 30 meters. This table lists EPA AMS and the AQS site number and IDs of nearby matched sensors, serving as

reference for sensor comparison analyses. EPA AMS 060374008 had one matched sensors, while EPA AMS 060658001 had eight.

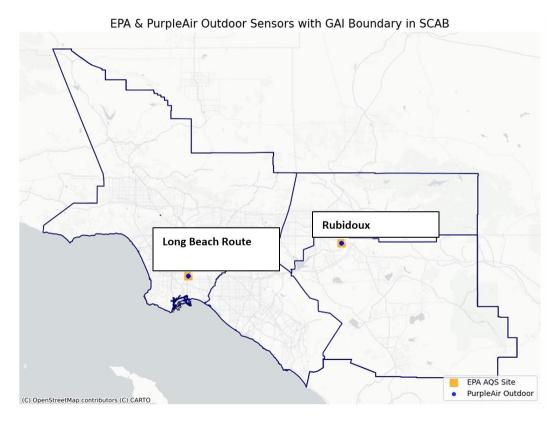


Figure S4. Co-located EPA AMS and PurpleAir outdoor sensors in SCAB. Orange squares indicate EPA monitoring sites, and blue circles represent matched PurpleAir outdoor sensors.

Number and Location of Co-located Indoor-Outdoor PurpleAir Sensor in SCAB

Table S3. The number of co-located indoor-outdoor pairs in each county in SCAB

County Name	Number of Pairs	
Los Angeles	50	
Orange	7	
Riverside	3	
San Bernadino	1	

Table S3.

shows the number of co-located indoor—outdoor PurpleAir sensor pairs in each county within the South Coast Air Basin (SCAB). A sensor pair was defined as an indoor—outdoor sensor combination located within 30 meters of each other. Los Angeles County hosts the vast majority

of sensor pairs (50), while Orange, Riverside, and San Bernardino Counties contain fewer pairs, reflecting differences in sensor network density and urban data availability.

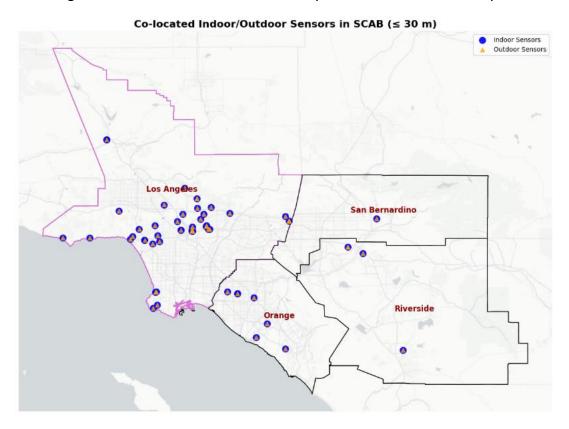


Figure S5. Map of 61 co-located indoor—outdoor PurpleAir sensor pairs identified across SCAB. Each pair consists of one indoor sensor (blue circle) and at least one outdoor sensor (orange triangle) located within 30 meters of each other. Sensor locations were assigned to counties using geographical area index (the intersection of county and air basin boundaries) within SCAB, and co-located pairs were primarily concentrated in urbanized areas of Los Angeles County.

Number of available PurpleAir Co-located Indoor and Outdoor Sensor Pairs in SCAB



Figure S6 Hourly time series showing the number of valid indoor—outdoor PurpleAir sensor pairs across the South Coast Air Basin (SCAB) from January 1 to February 1, 2025. A sensor pair is considered valid for a given hour if the indoor sensor and at least one corresponding outdoor

sensor recorded non-missing PM_{2.5} measurements during that hour. We identified over 60 matched pairs across the region, with hourly valid counts typically ranging from 30 to 50. The figure highlights the high density and temporal resolution of the PurpleAir network in this region, with consistent coverage across most days. Notable dips in availability (e.g., around Jan 7) may reflect sensor power loss or data interruptions during wildfire events.

Number of available PurpleAir Sensor in SCAB

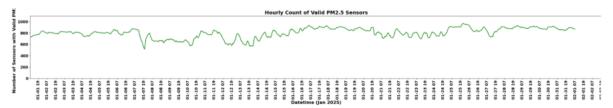


Figure S7. Hourly time series showing the number of PurpleAir sensors with valid $PM_{2.5}$ data across the South Coast Air Basin (SCAB) from January 1 to February 1, 2025. A sensor was considered valid for a given hour if it reported a non-missing $PM_{2.5}$ _cf_1_a measurement.

In January 2025, over 800 sensors reported data hourly, with a peak approaching 1000 active sensors. The slight dips observed on January 7–10 and January 24–25 may reflect sensor outages, network transmission issues, or environmental interferences such as power instability during the wildfire period. The return to stable levels thereafter highlights the resilience of the distributed low-cost monitoring network.

Daily maps showing the spatial distribution of indoor and outdoor Max PM 2.5

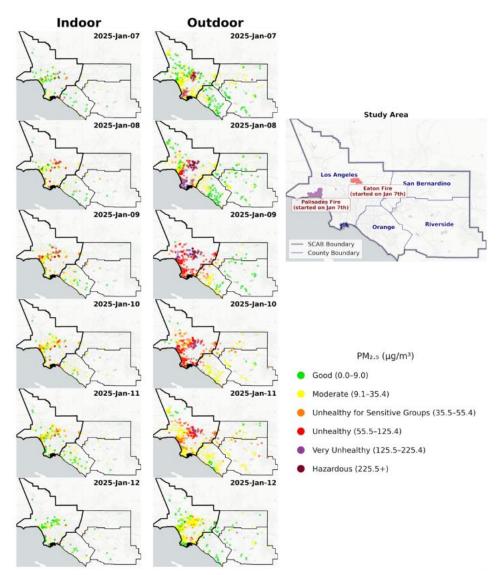


Figure S8. Daily maximum PM_{2.5} concentrations from indoor and outdoor PurpleAir sensors in Los Angeles County during January 7–12, 2025 (Pacific Time). Each dot represents the daily maximum PM_{2.5} concentration recorded by an individual sensor, categorized by the U.S. EPA AQI thresholds (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous). Compared to the daily averages shown in Figure 2, these maximum values highlight short-duration peak exposures that were substantially higher, especially during January 8–9. Outdoor sensors frequently recorded maximum concentrations exceeding 5.5 μ g/m³ (Very Unhealthy AQI level), with some reaching the Hazardous range (>225.5 μ g/m³). Indoor sensors

also exhibited elevated PM_{2.5} concentration, though generally lower than outdoors, with most falling in the Moderate to Unhealthy for Sensitive Groups range.

Comparison of PM_{2.5} Concentrations between Indoor and Outdoor Sensors

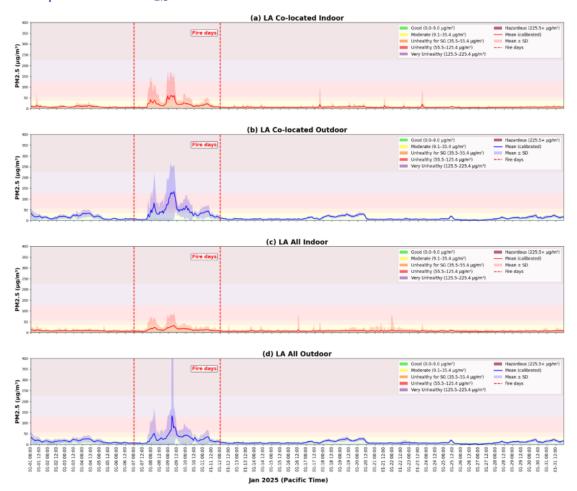


Figure S9. Hourly average PM_{2.5} concentrations for (a) LA co-located indoor, (b) LA co-located outdoor, (c) LA all indoor, and (d) LA all outdoor sensors during January 2025. Solid lines indicate mean values, and shaded areas represent ± 1 standard deviation across sensors, reflecting the variability and representativeness of the reported averages. Background colors represent updated U.S. EPA AQI thresholds: green (Good $\leq 9.0~\mu g/m^3$), yellow (Moderate $\leq 35.4~\mu g/m^3$), orange (Unhealthy for Sensitive Groups $\leq 55.4~\mu g/m^3$), red (Unhealthy $\leq 125.4~\mu g/m^3$), purple (Very Unhealthy $\leq 225.4~\mu g/m^3$), and maroon (Hazardous $\geq 225.5~\mu g/m^3$). Vertical dashed lines indicate the fire period (Jan 7–12).

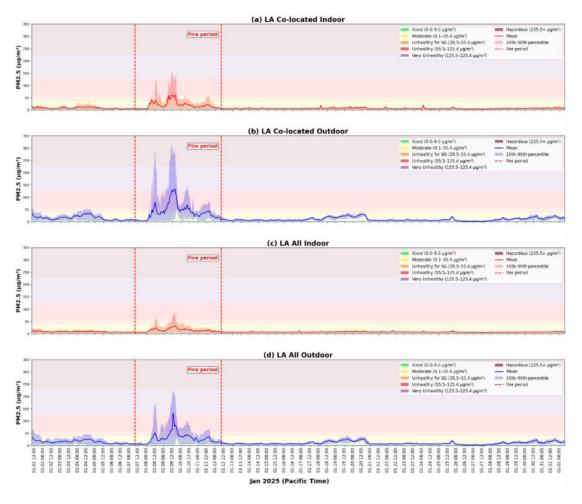


Figure S10. Hourly average PM_{2.5} concentrations for (a) LA co-located indoor, (b) LA co-located outdoor, (c) LA all indoor, and (d) LA all outdoor sensors during January 2025. Solid lines indicate mean values, and shaded areas represent the 10^{th} – 90^{th} percentile range across sensors, capturing the variability in hourly concentrations. Background colors denote updated U.S. EPA AQI thresholds: green (Good $\leq 9.0~\mu g/m^3$), yellow (Moderate $\leq 35.4~\mu g/m^3$), orange (Unhealthy for Sensitive Groups $\leq 55.4~\mu g/m^3$), red (Unhealthy $\leq 125.4~\mu g/m^3$), purple (Very Unhealthy $\leq 225.4~\mu g/m^3$), and maroon (Hazardous $\geq 225.5~\mu g/m^3$). Vertical dashed lines indicate the fire period (Jan 7–12).

Spatial Distribution of Indoor/Outdoor ratio

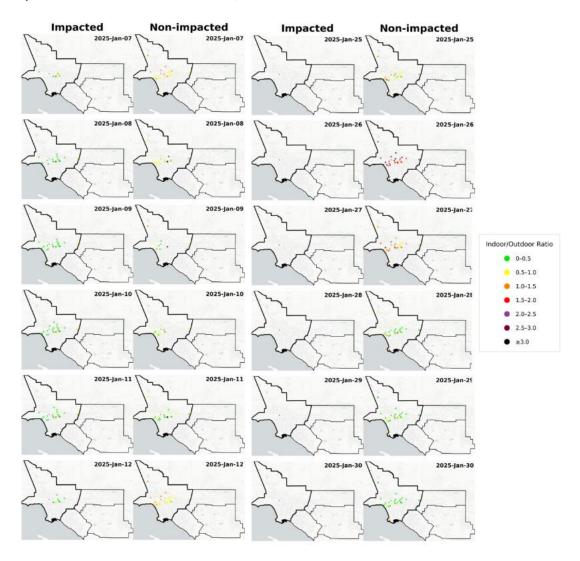


Figure S11. Spatial distribution of median indoor/outdoor (I/O) PM_{2.5} ratios across Los Angeles County during fire-impacted and non-impacted hours of each day during January 7–12 and January 25–30, 2025 (Pacific Time). Each dot represents a co-located sensor pair, with color indicating the daily average I/O ratio binned into seven categories (0–0.5, 0.5–1.0, 1.0–1.5, 1.5–2.0, 2.0–2.5, 2.5–3.0, and \geq 3.0). During fire days, most I/O ratios clustered below 1.0, while non-fire days exhibited greater variability and included sites with ratios above 1.5. Note that there are no dots on figures in the third column because all the hours during January 25–30, 2025 are considered non-fire hours.

Disadvantaged communities in SCAB

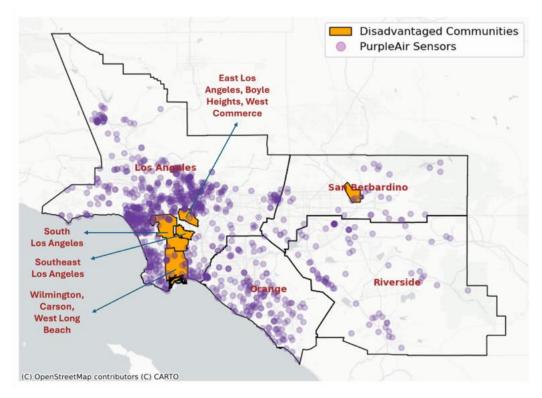


Figure S12. Map of Assembly Bill 617 disadvantaged communities (orange polygons) and PurpleAir sensors (purple dots) across SCAB.

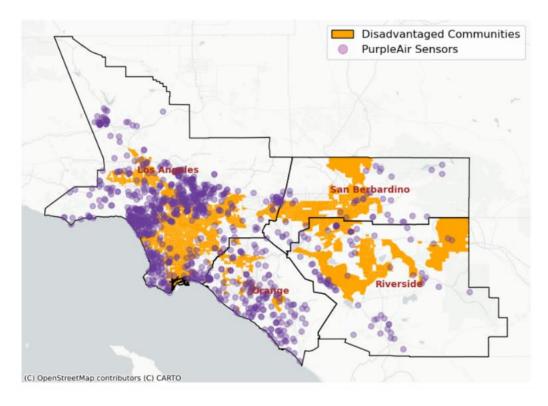


Figure S13. Map of Senate Bill 535 (SB 535) disadvantaged communities (orange polygons) and PurpleAir sensors (purple dots) across SCAB. The disadvantaged communities within LA County (especially in South Los Angeles and Southeast Los Angeles) have sparser PurpleAir sensors coverage.