

From Outdoor to Indoor: Amplified Inequities in Wildfire PM_{2.5} Exposure across the Contiguous United States

Jing Li, Xinlei Liu, Qiao Yu, and Yifang Zhu*



Cite This: *Environ. Sci. Technol.* 2026, 60, 18733–18744



Read Online

ACCESS |



Metrics & More



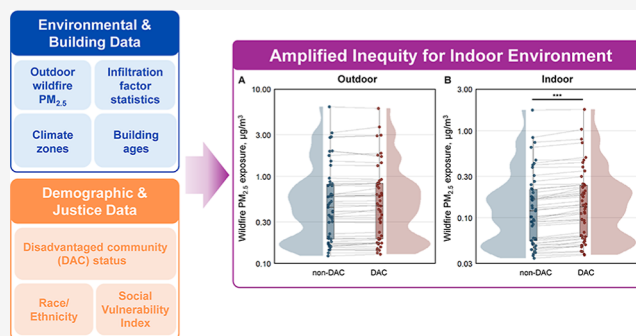
Article Recommendations



Supporting Information

ABSTRACT: Exposure to wildfire smoke is a major public health issue, yet most studies focus on outdoor air, overlooking that people spend most of their time indoors. We estimated 2020 indoor wildfire-related fine particulate matter (PM_{2.5}) concentrations across 72,537 census tracts in the contiguous United States by combining outdoor concentrations with infiltration factors. Annual-average indoor wildfire PM_{2.5} concentrations ranged from 0.02 to 6.2 $\mu\text{g}/\text{m}^3$ across census tracts, with a pronounced west–east gradient and a population-weighted national average of 0.241 $\mu\text{g}/\text{m}^3$. Disparities were modest at the national level but became more pronounced across states. Populations living in disadvantaged communities (DACs) experienced higher outdoor exposures than those in non-DACs in 30 of 49 states and higher indoor exposures in 47 states. Racial–ethnic disparities followed a similar pattern: although Black populations experienced below-average exposure nationally, above-average exposure occurred in 18 states outdoors and 31 states indoors. Inequality analyses further showed that indoor infiltration amplified disparities across several social vulnerability dimensions, including income and disability. These findings demonstrate that indoor infiltration amplified wildfire PM_{2.5} inequities and highlight the need for indoor-focused and location-specific studies.

KEYWORDS: wildfire smoke, particulate matter, indoor environment, infiltration factor, environmental inequity



1. INTRODUCTION

Wildfire-related fine particulate matter (hereafter, wildfire PM_{2.5}) has become a critical environmental and public health issue, particularly due to the intensifying fires in recent years fueled by climate change.^{1–4} In the western United States, wildfires have raised daily PM_{2.5} levels by up to 5 $\mu\text{g}/\text{m}^3$ over the past decade, reversing decades of steady improvements in ambient air quality.^{5,6} Toxicological and epidemiological studies suggest that wildfire PM_{2.5} is more toxic than an equal dose of ambient PM_{2.5}.^{7,8} Exposure to wildfire PM_{2.5} is associated with all-cause mortality,^{9–11} respiratory morbidity including asthma exacerbation and chronic obstructive pulmonary disease (COPD),^{11–15} adverse mental health effects,^{16–19} and negative birth outcomes such as preterm birth and low birth weight^{20–24} and can worsen respiratory infections including influenza and COVID-19.^{25,26}

To date, most studies on wildfire PM_{2.5} have focused on outdoor air. However, people spend most of their time indoors,²⁷ and indoor sheltering is a common response during wildfire events.^{28,29} Yet, wildfire PM_{2.5} can still infiltrate indoor environments, as no building is completely sealed. Studies have shown that in the San Francisco Bay Area, while behavioral responses—such as closing windows—can reduce the infiltration factor of PM_{2.5} from 0.4 on nonwildfire days to

0.2 on wildfire days, indoor PM_{2.5} concentrations still nearly tripled during wildfire events due to elevated outdoor levels.^{28,30} A recent global study estimates that one billion people experience at least one substantial indoor wildfire-pollution day annually.³¹ These findings highlight the critical importance of considering indoor environments when assessing wildfire PM_{2.5} exposure and associated inequities.

Most evidence on inequity in wildfire PM_{2.5} exposure comes from outdoor air. A nationwide analysis in the United States found that Hispanic populations experienced higher outdoor wildfire PM_{2.5} exposure than White populations,⁵ while a California-specific study reported higher-than-average exposure among White populations and lower-than-average exposures among Hispanic populations.³² These contrasting findings suggest exposure disparities may vary by regional context. Additionally, indoor inequity patterns may differ because the infiltration of outdoor air pollutants is largely affected by

Received: December 13, 2025

Revised: June 10, 2026

Accepted: June 11, 2026

Published: June 25, 2026



ACS Publications

© 2026 American Chemical Society

18733

<https://doi.org/10.1021/acs.est.5c18065>
Environ. Sci. Technol. 2026, 60, 18733–18744

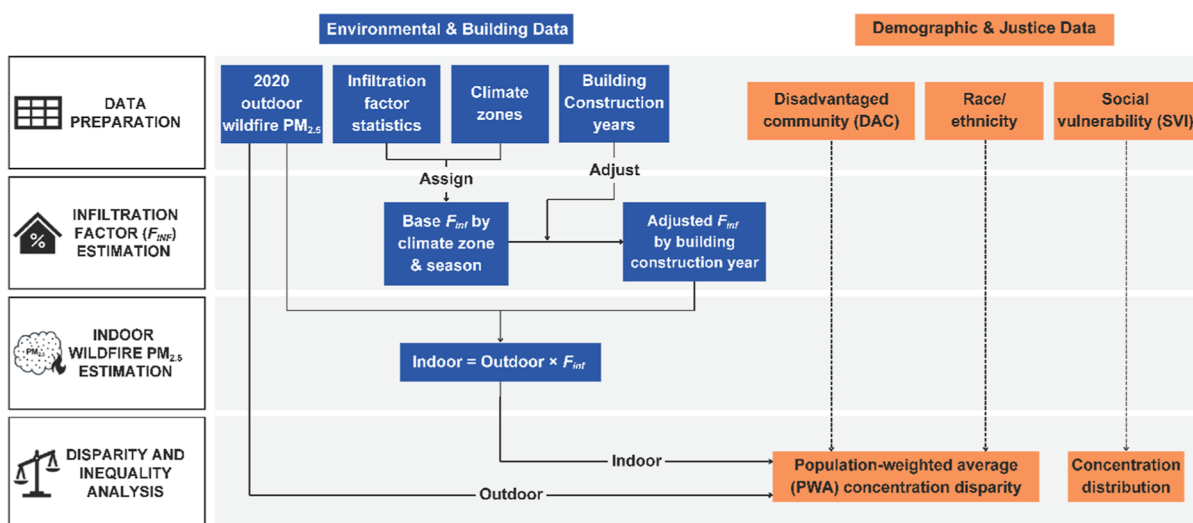


Figure 1. Workflow for data preparation and analysis.

building characteristics, such as construction age and ventilation. Older buildings typically have higher infiltration factors than newer constructions.³³ Mechanical ventilation with high-efficiency air filters can significantly reduce infiltration.³⁴ Socioeconomic disadvantage may limit access to newer housing, home renovations, or the ability to purchase and maintain air filtration systems. Previous research found that Google searches for “air filter” were substantially more frequent in wealthier counties.²⁹ Together, these findings highlight a critical knowledge gap: whether—and how—indoor wildfire PM_{2.5} exposure, shaped by outdoor levels and infiltration, alters inequities observed in outdoor air. Ignoring indoor conditions risks underestimating the full extent of wildfire smoke disparities and their impact on vulnerable populations.

To address these knowledge gaps, we aim to answer three research questions: (1) What are the levels of indoor wildfire PM_{2.5} concentrations across the contiguous United States (CONUS)? (2) To what extent does indoor infiltration affect inequities observed in outdoor air? (3) How do inequities differ at the national level compared with those at the state level? Here, we generated nationwide estimates of indoor wildfire PM_{2.5} concentrations across 72,537 census tracts and examined the associated inequities from three different layers:¹ disadvantaged community (DAC) and non-DAC population exposure disparity,² racial–ethnic exposure disparity, and³ concentration distribution across socially vulnerable populations. Together, these analyses offer the comprehensive national assessment of indoor wildfire PM_{2.5} exposure inequities, revealing how indoor environments reshape inequities beyond what outdoor data alone can show.

2. MATERIALS AND METHODS

2.1. Overall Study Workflow

Figure 1 illustrates the overall workflow of this analysis. All analyses were conducted at the census tract level. Census tracts are small statistical subdivisions defined by the U.S. Census Bureau that typically contain about 4,000 residents (approximately 1,500 housing units), although individual tracts may range from about 2,500 to 8,000 residents (roughly 1,000–3,000 housing units).³⁵ In total, 72,537 census tracts across the contiguous United States (CONUS) were included in the analysis.

We estimated annual-average indoor wildfire PM_{2.5} concentrations for 2020, a year marked by severe wildfire activity in the United States.^{26,36} This estimation combined previously reported outdoor wildfire PM_{2.5} concentrations with building infiltration factors estimated in this study. Infiltration factors were assigned to each census tract based on climate zone-specific values and then adjusted according to building construction year, using distributions reported in prior studies.³³

To examine inequities associated with wildfire PM_{2.5}, we linked both the estimated indoor concentrations and reported outdoor concentrations with demographic data sets at the census tract level. Disparities were assessed using population-weighted average (PWA) concentrations (hereafter also referred to as “exposure”), while inequalities were assessed using distributional metrics including concentration curves (CCs) and concentration indices (CIs). Uncertainty and sensitivity analyses were conducted to evaluate the robustness of the results. Details are provided below.

2.2. Data Preparation

We compiled two categories of published data: (i) environmental and building data and (ii) demographic and environmental justice data sets.

2.2.1. Outdoor Wildfire PM_{2.5} Concentrations. Daily outdoor wildfire PM_{2.5} concentrations for 2020 were obtained from Childs et al. (2022), who developed machine learning-based estimates across 72,537 census tracts in the contiguous United States (CONUS).⁵ This data set has been widely applied in studies of wildfire-related exposure, inequality, and health impacts.^{36–40} A limitation of this data set is the lack of uncertainty estimates,^{5,36} which we addressed by assuming a 20% coefficient of variation (CV) (see 2.6 Uncertainty analysis).

2.2.2. Infiltration Factor Summary Statistics. Data used to estimate infiltration factors were derived from Lunderberg et al. (2023), which utilized crowdsourced sensor data and a random component superposition method to quantify infiltration across national climate zones and building age categories, providing a framework that aligns closely with our census tract–level analysis.³³ Specifically, it provides: (i) summary statistics of infiltration factors across four climate zones (Marine, Hot–Dry, Cold, and “Other,” which includes Mixed–Humid, Mixed–Dry, Hot–Humid, and Very Cold) and four seasons (spring: March, April, May; summer: June, July, August; fall: September, October, November; and winter: December, January, February) and (ii) summary statistics for eight decadal construction-year subgroups (1935–1945, 1945–1955, 1955–1965, 1965–1975, 1975–1985, 1985–1995, 1995–2005, and 2005–2015).

2.2.3. Climate Zone Classification. Climate zone data were obtained from the U.S. Department of Energy's Building America Program,⁴¹ which provides climate zone classifications at the county level.

2.2.4. Building Construction Year. Census tract-level building construction year information was derived from the National Structure Inventory (NSI), which provides median construction year estimates at the census block level.⁴² We aggregated these values to derive a single median construction year for each census tract based on the spatial relationships between blocks and tracts. The number of census blocks within a tract varies substantially with settlement density, typically ranging from a few dozen blocks in rural areas to several hundred in dense urban areas.

2.2.5. Climate and Economic Justice Screening Tool (CEJST). The CEJST identifies disadvantaged communities (DACs) that have historically faced social marginalization, elevated pollution burdens, and limited access to infrastructure and services.⁴³

2.2.6. Racial–Ethnic Population Data. Racial and ethnic composition was obtained from the U.S. Census 2019 American Community Survey (ACS) estimates at the census tract level⁴⁴ and categorized based on self-identification at the census tract level. We examined six groups: Hispanic (Hispanic or Latino of any race, 18%), White (non-Hispanic or Latino, White alone, 61%), Asian (Asian alone, 5%), Black (Black or African American alone, 12%), AIAN/NHPI (including American Indian, Alaska Native, Native Hawaiian, and Other Pacific Islander; combined in this study due to relatively small population sizes at the tract level and referred to as "AIAN/NHPI" in the figures and text, 1%), and Other (including some other race and people identifying with two or more races, 3%).

2.2.7. Social Vulnerability Index (SVI). The SVI developed by the U.S. Centers for Disease Control and Prevention (CDC) was used to characterize community vulnerability.⁴⁵ It is structured hierarchically, comprising an overall index (referred to as "the overall SVI"), four thematic dimensions (socioeconomic status, household composition and disability, minority status and language, and housing type and transportation), and 15 component indicators (e.g., unemployment, minority status, disability), and is widely used to assess a community's capacity to respond to hazardous events and identify populations most in need of support.

2.3. Estimation of Infiltration Factors

Infiltration factors represent the fraction of outdoor PM_{2.5} that penetrates indoors and remains suspended. We estimated infiltration factor for each census tract by integrating climate zone-specific and building age-dependent information based on previously reported statistics (33; see 2.2 Data Preparation). First, each census tract was assigned a base infiltration factor corresponding to its climate zone and season. The base infiltration factor was then adjusted based on the median construction year of buildings within each census tract. The adjustment was implemented using the relative difference in infiltration factors among decadal construction-year subgroups. Specifically, the adjustment factor $P_{yy,c}$ represents the percentage difference in infiltration factor between the construction-year subgroup corresponding to the median construction year of census tract c and the overall median infiltration factor across all construction-year subgroups. The adjusted infiltration factor was calculated as

$$F_{\text{inf},c} = F_{\text{inf},z,s} \times (1 + P_{yy,c}) \quad (1)$$

where $F_{\text{inf},c}$ denotes the final infiltration factor estimated for census tract c , $F_{\text{inf},z,s}$ indicates the climate-zone- and season-specific infiltration factor assigned to census tract c before accounting for building age, where z represents climate zone for census tract c and s represents season, and the adjustment factor $P_{yy,c}$ is defined as

$$P_{yy,c} = \frac{F_{\text{inf},yy,c} - F_{\text{inf},m}}{F_{\text{inf},m}} \quad (2)$$

where $F_{\text{inf},yy,c}$ represents the infiltration factor associated with the construction-year subgroup (yy) corresponding to the median

construction year of the census tract c and $F_{\text{inf},m}$ is the median infiltration factor across all decadal construction-year subgroups, which serves as a reference value for calculating the relative adjustment. The parameter $P_{yy,c}$, therefore, represents the percentage increase or decrease in infiltration factor associated with the construction-year subgroup relative to this reference value. A limitation of our infiltration factor estimates is the lack of national data on behavioral determinants, such as window opening, heating, ventilation, air conditioning (HVAC) operation, and air purifier use, which prevents us from capturing how these behaviors influence the distribution of infiltration factors. However, this limitation does not preclude the assessment of disparities. In fact, our approach likely yields conservative estimates, thereby making our findings more robust (see Section 4. Discussion for more details).

2.4. Estimation of Indoor Wildfire PM_{2.5} Concentrations

Indoor wildfire PM_{2.5} concentrations were estimated by combining the outdoor concentrations with infiltration factors. For each census tract and season, indoor concentrations were calculated as the product of the outdoor wildfire PM_{2.5} concentration and the corresponding seasonal infiltration factor. Annual average indoor wildfire PM_{2.5} concentrations were then determined by averaging the four seasonal estimates.

2.5. Inequity Analysis

2.5.1. Exposure Disparity Analysis. Wildfire PM_{2.5} exposure between DACs and non-DACs and among racial–ethnic groups were quantified using population-weighted average (PWA) concentrations. This metric accounts for population size by assigning greater weight to larger population groups, thereby more accurately reflecting exposure across the total population. Exposures were calculated separately for indoor and outdoor concentrations using the same equation for different groups across the CONUS and within each state, as shown below:

$$PWA_{g/d,n/s} = \frac{\sum_c (P_{g/d,c} \times E_c)}{\sum_c P_{g/d,c}} \quad (3)$$

where g/d denotes the subgroup of interest, representing either a racial–ethnic group (g) or DAC status (d , i.e., DACs or non-DACs), n/s indicates the spatial scale of analysis (national or state level), and c refers to a specific census tract; therefore, $PWA_{g/d,n/s}$ is the population-weighted average wildfire PM_{2.5} concentration for subgroup g/d at specified spatial scale, E_c represents the wildfire PM_{2.5} concentration in census tract c (indoor or outdoor, depending on the analysis), and $P_{g/d,c}$ denotes the population of subgroup g/d in census tract c . Relative disparities for each racial–ethnic group were calculated as the difference between group-specific exposure and the overall population exposure, normalized by the overall population exposure.

2.5.2. Concentration Curve (CC) and Concentration Index (CI). Inequality in wildfire PM_{2.5} with respect to social vulnerability was assessed using the CC and CI, adapted from the Lorenz curve and Gini coefficient. These measures are commonly used to quantify how environmental exposures are distributed across populations with different social characteristics.^{46–48} The CC and CI were calculated following the methodology recommended by the World Bank.⁴⁹ To construct the CC and CI, census tracts were first ranked according to the demographic or vulnerability indicator of interest (e.g., the proportion of racial–ethnic minorities) from lowest to highest using the SVI. The cumulative proportion of the population was then plotted against the cumulative share of wildfire PM_{2.5} concentrations to generate the CC:

$$CC(p) = \frac{\int_0^p E(q) dq}{\int_0^1 E(q) dq} \quad (4)$$

where $E(q)$ represents wildfire PM_{2.5} concentration associated with population quantile q , and p denotes the cumulative population

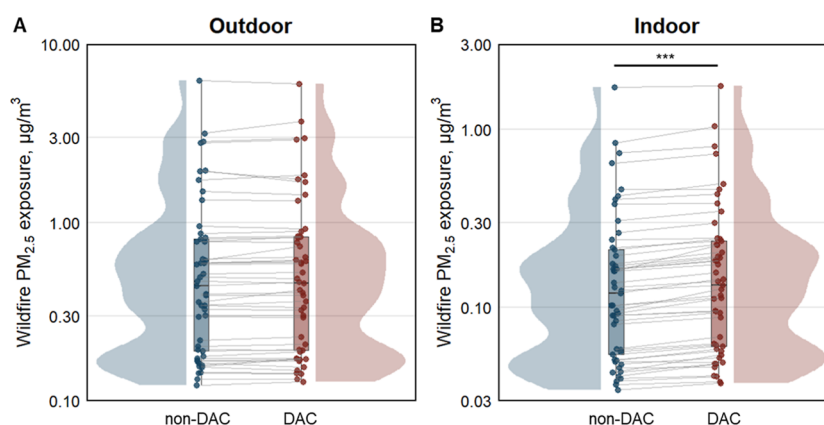


Figure 2. State-level disparities in outdoor and indoor wildfire $\text{PM}_{2.5}$ exposure between disadvantaged community (DAC) and non-DAC populations across 49 contiguous United States (CONUS) states. Raincloud plots show outdoor (A) and indoor (B) exposure for each state, comparing DACs and non-DACs. Each plot includes an unmirrored violin plot (showing the probability density), a boxplot (median and interquartile range), whiskers (5th and 95th percentiles), and individual state-level data points (horizontally jittered for clarity). Paired lines connect each state's DAC and non-DAC data points to highlight within-state disparities. The y-axis is displayed on a log₁₀ scale, with decade anchors (0.1, 1, 10) and $\sqrt{10}$ intermediates (0.3, 3) to visualize data spread consistently. Note that the y-axis scales differ between panels. Paired difference was tested using the Wilcoxon signed-rank test, as the data were not normally distributed. Asterisks (***) denote significance at $p < 0.001$.

proportion (ranging from 0 to 1) after ranking census tracts by the selected vulnerability indicator. The CI was then calculated as

$$\text{CI} = 1 - 2 \int_0^1 \text{CC}(p) dp \quad (5)$$

where $\text{CC}(p)$ denotes the concentration curve and p is the cumulative population proportion. In this formulation, the integral represents the area under the concentration curve. Because the area under the equality line equals 0.5, the CI is defined as twice the difference between the quality line and the concentration curve, which normalizes the index to range from -1 to 1 . CIs were calculated for the overall SVI, its four themes, and all 15 component indicators at both national and state levels.

2.6. Uncertainty Analysis

We quantified uncertainty using 1,000 Monte Carlo simulations for all key outputs, including indoor wildfire $\text{PM}_{2.5}$ concentrations, exposures, and CIs. Uncertainty was propagated from three primary input data sets: (i) outdoor wildfire $\text{PM}_{2.5}$ concentrations, (ii) infiltration factors, and (iii) population data. Each data set was represented by a probability distribution derived from its mean or median and associated variability. Outdoor wildfire $\text{PM}_{2.5}$ and infiltration factors were modeled as log-normal distributions,⁵⁰ while population data followed a normal distribution.⁵¹ The outdoor wildfire $\text{PM}_{2.5}$ data set⁵ does not provide uncertainty estimates. Therefore, we assigned a CV of 20%, based on the reported performance of a hybrid machine learning model used to estimate $\text{PM}_{2.5}$ concentrations in prior work, which indicates a relative root-mean-square error of $\leq 17.5\%$.⁵⁰ A slightly higher value was adopted to provide a conservative estimate of uncertainty, and this 20% was applied in the Monte Carlo simulations. For infiltration factors, distributions were constructed using median values and along with the 25th (first quartile) and 75th (third quartile) percentiles from Lunderberg et al. (2023).³³ Population uncertainty was represented using averages and margins of error from the ACS.⁴⁴ Results are reported as mean $\pm$ standard deviation (SD) for concentrations and exposures and as medians with 95% confidence intervals for CIs. All simulation outputs are provided in the Data availability section.

2.7. Sensitivity Analysis

We conducted sensitivity analyses to evaluate how assumptions about infiltration factors influence our results by varying both their magnitude and distribution across census tracts. To test magnitude sensitivity, infiltration factor values were uniformly increased and decreased by 20%, reflecting plausible deviations beyond Monte Carlo

uncertainty. To test distributional sensitivity, the width of the infiltration factor distribution was altered by $\pm 20\%$ while keeping the mean constant. For each scenario, indoor wildfire $\text{PM}_{2.5}$ concentrations and corresponding confidence intervals were recalculated, from which exposure levels and associated CIs were derived. Statistical comparisons between DACs and non-DACs, as well as among racial–ethnic groups, were repeated. Results indicated that the direction and significance of exposure levels and disparities remained unchanged, suggesting that observed differences are primarily driven by systematic variations in infiltration factors across sociodemographic groups rather than their absolute magnitude or distributional assumptions. All recalculated data are available in the Data availability section.

2.8. Comparison of Estimated Infiltration Factors with Previous Studies

To assess the consistency of our infiltration factor estimates with prior studies, we compiled them with values reported in prior U.S. studies using PurpleAir network data (Table S1). For each study, we calculated summary statistics of our estimated infiltration factors across census tracts within the same geographic regions ($F_{\text{inf est}}$) and compared them to the reported values ($F_{\text{inf exp}}$). The absolute percentage differences between our estimates and the reported values ranged from 3.7% to 39.1%. Across the reported infiltration factors ($F_{\text{inf exp}}$) in prior studies listed in Table S1, differences between studies (calculated relative to the larger value) reached up to 40% (e.g., 0.45 vs 0.27). Overall, the level of agreement between our estimates and prior studies indicates that our estimates fall within the range of previously reported values and capture the realistic variability in infiltration factors.

3. RESULTS

3.1. Wildfire $\text{PM}_{2.5}$ Concentrations across the CONUS

In this study, the term “concentration” refers to wildfire $\text{PM}_{2.5}$ mass concentration in a geographic area without accounting for population, while “exposure” denotes the population-weighted average (PWA) concentrations. In 2020, estimated annual-average indoor wildfire $\text{PM}_{2.5}$ concentrations across 72,537 census tracts ranged from 0.02 to 6.2 $\mu\text{g}/\text{m}^3$. Detailed results are provided in Text S1, with Figure S1 showing estimated outdoor and indoor concentrations at the census tract level, as well as state-level exposures across the CONUS.

These tract-level estimates form the foundation for our subsequent analysis of inequities.

3.2. Exposure Disparities between DACs and Non-DACs

Based on CEJST, 26,278 of 72,537 (36%) census tracts in CONUS are classified as DACs, with the remainder as non-DACs (Figure S2). At the national scale, outdoor wildfire $\text{PM}_{2.5}$ exposure was $0.925 \pm 0.001 \mu\text{g}/\text{m}^3$ for the DAC population and $0.875 \pm 0.001 \mu\text{g}/\text{m}^3$ for the non-DAC population. Corresponding indoor exposures were 0.263 ± 0.070 and $0.230 \pm 0.061 \mu\text{g}/\text{m}^3$, respectively.

At the state level, DAC populations experienced higher outdoor exposure than non-DAC populations in 30 states, with the largest relative difference observed in Texas (20%, Table S2). After accounting for infiltration, indoor exposure disparities were amplified: DAC indoor exposure exceeded non-DAC exposure in 47 states, with Texas again showing the largest relative difference but increased to 40%. Figure 2 shows these outdoor and indoor exposure disparities between DAC and non-DAC populations across states. A Wilcoxon signed-rank paired test found no significant difference in outdoor exposure between DAC and non-DAC populations ($p = 0.059$). In contrast, DACs experienced significantly higher indoor exposure than non-DACs ($p < 0.001$). This disparity is further illustrated by the paired lines in Figure 2, where most outdoor lines remain flat but indoor lines more frequently slope upward, visually emphasizing the elevated exposure burden faced by DACs in indoor environments.

To investigate potential structural drivers of the amplified indoor exposure disparities, we compared the building construction years and estimated infiltration factors between DACs and non-DACs within each climate zone (Table 1). Across all climate zones, buildings in DACs are consistently older and have significantly higher infiltration factor estimates (two-tailed t -test, $p < 0.001$).

Table 1. Summary Statistics of Building Construction Year and Estimated Infiltration Factors in Census Tracts Classified as Disadvantaged Communities (DACs) and Non-DACs by Climate Zone

climate zone	summary statistics	construction year		infiltration factor (F_{inf})	
		DACs	Non-DACs	DACs	Non-DACs
cold	25th percentile	1939	1957	0.27	0.23
	Median	1952	1971	0.28	0.27
	75th percentile	1968	1981	0.28	0.28
hot-dry	25th percentile	1963	1978	0.23	0.18
	median	1975	1993	0.30	0.23
	75th percentile	1986	2002	0.30	0.25
marine	25th percentile	1964	1969	0.30	0.27
	median	1973	1979	0.35	0.30
	75th percentile	1982	1990	0.35	0.35
others	25th percentile	1957	1965	0.29	0.27
	median	1972	1980	0.30	0.29
	75th percentile	1982	1992	0.34	0.34

3.3. Racial–Ethnic Exposure Disparities

To investigate potential racial–ethnic disparities, exposures were calculated for six groups (AIAN/NHPI, Asian, Black, Hispanic, Other, and White) across the CONUS and within each individual state. Complete exposure estimates are available in Tables S3–S4. Figure 3 summarizes these

racial–ethnic disparities using radar charts, showing indoor (Figure 3A) and outdoor (Figure 3B) disparities at the national level, as well as state-level indoor and outdoor patterns (Figure 3C), highlighting both racial–ethnic disparities and indoor–outdoor contrasts. Each axis of the hexagonal radar chart represents one racial–ethnic group, with values normalized from 0 to 1 (least to most exposed). Nationally, the average indoor exposure for the overall population was $0.241 \pm 0.062 \mu\text{g}/\text{m}^3$. Higher exposures were estimated for Asian ($0.348 \pm 0.107 \mu\text{g}/\text{m}^3$), AIAN/NHPI ($0.334 \pm 0.092 \mu\text{g}/\text{m}^3$), Hispanic ($0.330 \pm 0.098 \mu\text{g}/\text{m}^3$), and Other ($0.289 \pm 0.079 \mu\text{g}/\text{m}^3$) populations. In contrast, White ($0.220 \pm 0.059 \mu\text{g}/\text{m}^3$) and Black ($0.220 \pm 0.059 \mu\text{g}/\text{m}^3$) populations experienced lower-than-average exposure (Figure 3A). National outdoor exposure disparities were similar to indoor (Figure 3B), indicating little difference in racial–ethnic disparities between indoor and outdoor environments at the national level. These patterns largely reflect population distribution, with higher-exposed groups concentrated in the western United States and lower-exposed groups, particularly Black populations, in the southeast; detailed discussion is provided in Section 4, Discussion.

At the state level (Figure 3C), however, racial–ethnic disparities differed markedly from the national level, and indoor–outdoor contrasts became clearer. Outdoors, White populations had the highest exposure in six states, while among People of Color (POC), AIAN/NHPI populations led in 15 states, followed by Black (10 states), Hispanic (8 states), Asian (7 states), and Other (3 states). Indoors, White populations dropped to leading in only one state, while Black populations led in 18 states, followed by AIAN/NHPI (16 states), Hispanic (11 states), and Asian (3 states). Several states showed notable indoor–outdoor shifts in the most-exposed group. Compared with outdoors, five states—Arkansas (AR), Illinois (IL), Louisiana (LA), Oklahoma (OK), and Virginia (VA)—shifted from White to POC groups as the most exposed indoors: White to Black in AR, LA, and VA; White to AIAN/NHPI in IL; and White to Hispanic in OK. In 12 other states, the most-exposed group shifted between two different POC groups. For example, in Oregon (OR), AIAN/NHPI populations had the highest outdoor exposure, whereas Black populations had the highest indoor exposure. In the remaining states, the most-exposed racial–ethnic group remained the same for indoor and outdoor, such as AIAN/NHPI populations in California (CA). Notably, no state showed a shift from POC to White.

Figure 4 provides a broader view of relative disparities by comparing each group's exposure with that of the overall population under indoor (brown shading) and outdoor (blue shading) conditions. Because indoor wildfire $\text{PM}_{2.5}$ concentrations are generally lower than outdoor concentrations due to building infiltration processes, Figure 4 focuses on how disparities between each population group and the overall population change when moving from outdoor to indoor environments across states. State-level absolute exposure levels for each group are detailed in Tables S3 and S4, while State-level relative disparity corresponding to Figure 4 is provided in Table S5. For Black populations (Figure 4C), the indoor peak shifts rightward compared to outdoors, with the outdoor peak centered below zero and the indoor peak centered above zero. From outdoor to indoor, the number of states where Black populations experienced above-average exposure increased from 18 to 31. Hispanic populations show a similar trend (Figure 4D), with above-average exposure states increasing

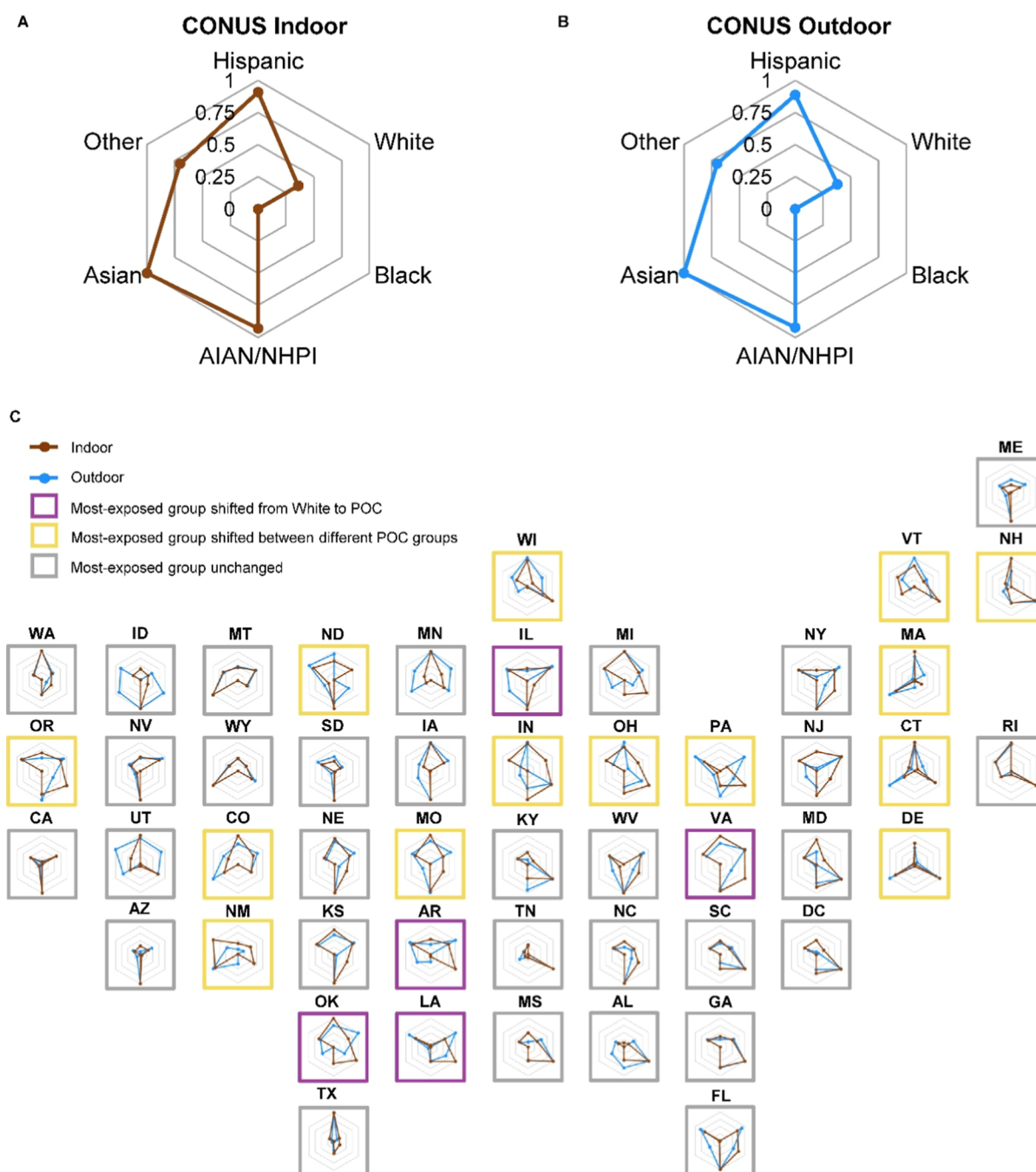


Figure 3. Normalized radar charts depicting racial-ethnic disparities in wildfire $\text{PM}_{2.5}$ exposure, comparing outdoor and indoor environments. Panels show (A) national (CONUS) radar chart indoors, (B) national (CONUS) radar chart outdoors, and (C) individual states both indoors and outdoors. To make indoor and outdoor disparities comparable, values are normalized on a 0 to 1 scale using $(x - \min(x)) / (\max(x) - \min(x))$, where x represents the exposure for a given racial-ethnic group nationally or within a state. Only the national radar charts (A,B) show axis labels and racial-ethnic group names, which are consistent across all state-level charts. Blue hexagons represent outdoor exposure, while brown hexagons represent indoor exposure. Purple outlines highlight states where the most-exposed group shifts from White to a People of Color (POC) group between outdoor and indoor settings; yellow outlines indicate a shift between two POC groups; and gray outlines indicate no change in the most-exposed group.

from 23 outdoors to 30 indoors. This pattern was not consistent across groups. For Asian populations (Figure 4B), the indoor peak shifts leftward, indicating generally lower indoor exposure than the overall population across states. White populations (Figure 4F) show a similar but more modest leftward shift. Compared with other groups, their exposure is more equal to the overall population. For the AIAN/NHPI (Figure 4A) and Other populations (Figure 4E),

shifts between indoor and outdoor relative disparities were minimal, suggesting comparable exposure disparities in both indoor and outdoor environments.

To explore potential structural drivers of these disparities, we examined associations between racial-ethnic population shares and building construction year using Pearson correlation analyses across census tracts in CONUS and within individual states (Table S6). For Black and Hispanic

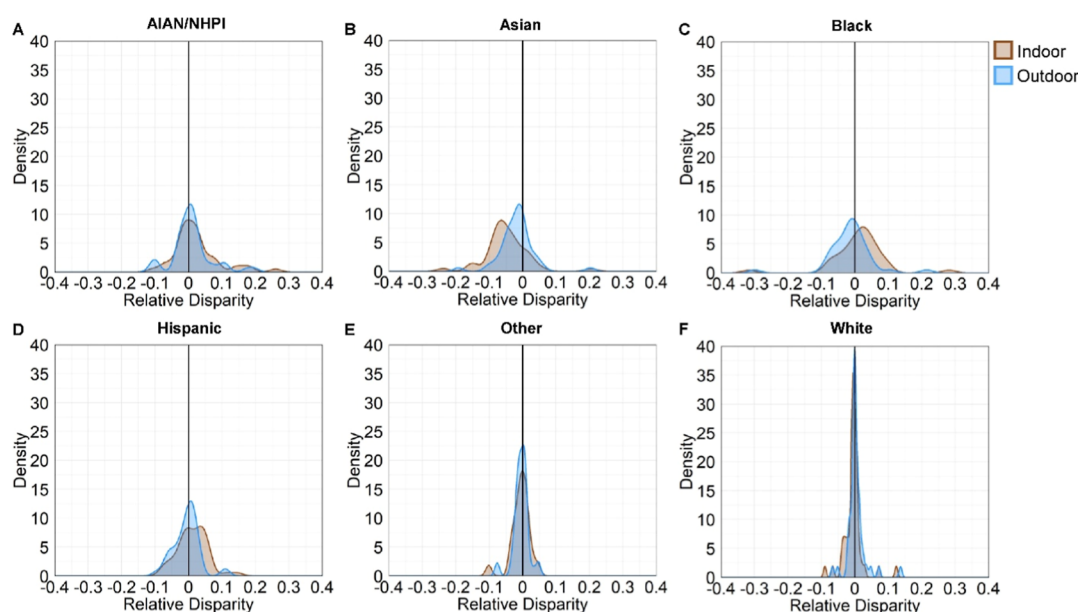


Figure 4. Distribution of relative disparities in indoor and outdoor wildfire $\text{PM}_{2.5}$ exposure across 49 contiguous United States (CONUS) states by the racial–ethnic group. Each panel presents kernel density estimate (KDE) distributions of relative disparities for (A) AIAN/NHPI, (B) Asian, (C) Black, (D) Hispanic, (E) Other, and (F) White populations. Groups are ordered alphabetically by initial. Each KDE is based on 49 data points, one per CONUS state. Blue shadings and lines represent outdoor wildfire $\text{PM}_{2.5}$ exposure, while brown shadings and lines represent indoor exposure. A relative disparity of zero indicates exposure equity, meaning a group’s exposure equals that of the overall population within a given state.

populations, population share was significantly negatively correlated with construction year across CONUS and in 39 of 49 states, indicating that higher proportions of these populations were associated with older housing stock. In contrast, population shares of Asian, White, AIAN/NHPI, and Other groups were significantly positively correlated with construction year in most states, suggesting that these populations tend to reside in census tracts with relatively newer buildings.

3.4. Inequality in Relation to Social Vulnerability

We quantified inequalities using concentration curves (CCs) and concentration indices (CIs), linking wildfire $\text{PM}_{2.5}$ concentrations to SVI. Figure 5A,C presents indoor and outdoor CI values across the CONUS and individual states. The CI is derived from the area between the CC and the line of equality ($y = x$) and quantifies the direction and magnitude of inequality. Positive CI values (purple) indicate that wildfire $\text{PM}_{2.5}$ concentrations are disproportionately higher among more socially vulnerable communities relative to an equal distribution across the population, while negative values (green) indicate higher concentrations among less vulnerable populations. Across the CONUS and most states, wildfire $\text{PM}_{2.5}$, both indoors and outdoors, was generally higher among communities with greater social vulnerability, particularly for Theme 1 (Socioeconomic Status) and its individual factors. Patterns for other themes varied by factor and state. For Theme 2 (Household Composition and Disability), people aged 65 or older and those with disabilities consistently experienced more, while children (aged 17 or younger) generally experienced less. Single-parent households showed mixed patterns across states. For Theme 3 (Minority Status and Language), racial and ethnic minorities and those who speak English “less than well” generally experienced higher concentrations nationally, although this pattern was reversed in some states. In California, for example, White and English-

proficient populations experienced higher concentrations, likely because these populations reside in wealthier communities located closer to wildland areas. For Theme 4 (Housing Type and Transportation), individuals without access to a vehicle consistently experienced higher concentrations across most states, while other housing-related factors showed state-specific effects.

Figure 5B,D further illustrates the interpretation of positive and negative CI values through two examples. Figure 5B shows CCs for indoor and outdoor wildfire $\text{PM}_{2.5}$ relative to the overall SVI across the CONUS. The x -axis represents the cumulative population ranked from least to most vulnerable and the y -axis shows the cumulative share of wildfire $\text{PM}_{2.5}$. Both indoor and outdoor CCs lie below the equality line, indicating that wildfire $\text{PM}_{2.5}$ is concentrated among more vulnerable communities. The indoor CI value was 0.094 (95% CI: 0.045 to 0.150) and the outdoor CI value was 0.075 (95% CI: 0.075 to 0.076), suggesting that inequality is amplified when wildfire $\text{PM}_{2.5}$ infiltrates indoors. In contrast, Figure 5D presents CCs for indoor and outdoor wildfire $\text{PM}_{2.5}$ relative to the proportion of the population aged 17 years or younger. Here, curves lie above the equality line with indoor and outdoor CI values below zero. These negative values indicate that children experienced a smaller share of wildfire $\text{PM}_{2.5}$ relative to the overall population, with concentrations disproportionately lower in census tracts with a higher proportion of the population aged 17 or younger.

Higher CI values indicate greater inequalities. To assess how indoor infiltration alters inequality, Figure 5E shows the difference between indoor and outdoor CI values (i.e., Indoor CI minus Outdoor CI) for each vulnerability factor across the CONUS and individual states. In most cases, indoor infiltration amplified inequalities, particularly for Theme 1 and its components, Theme 3 and its components (minority and speaks English “less than well”), and many factors in

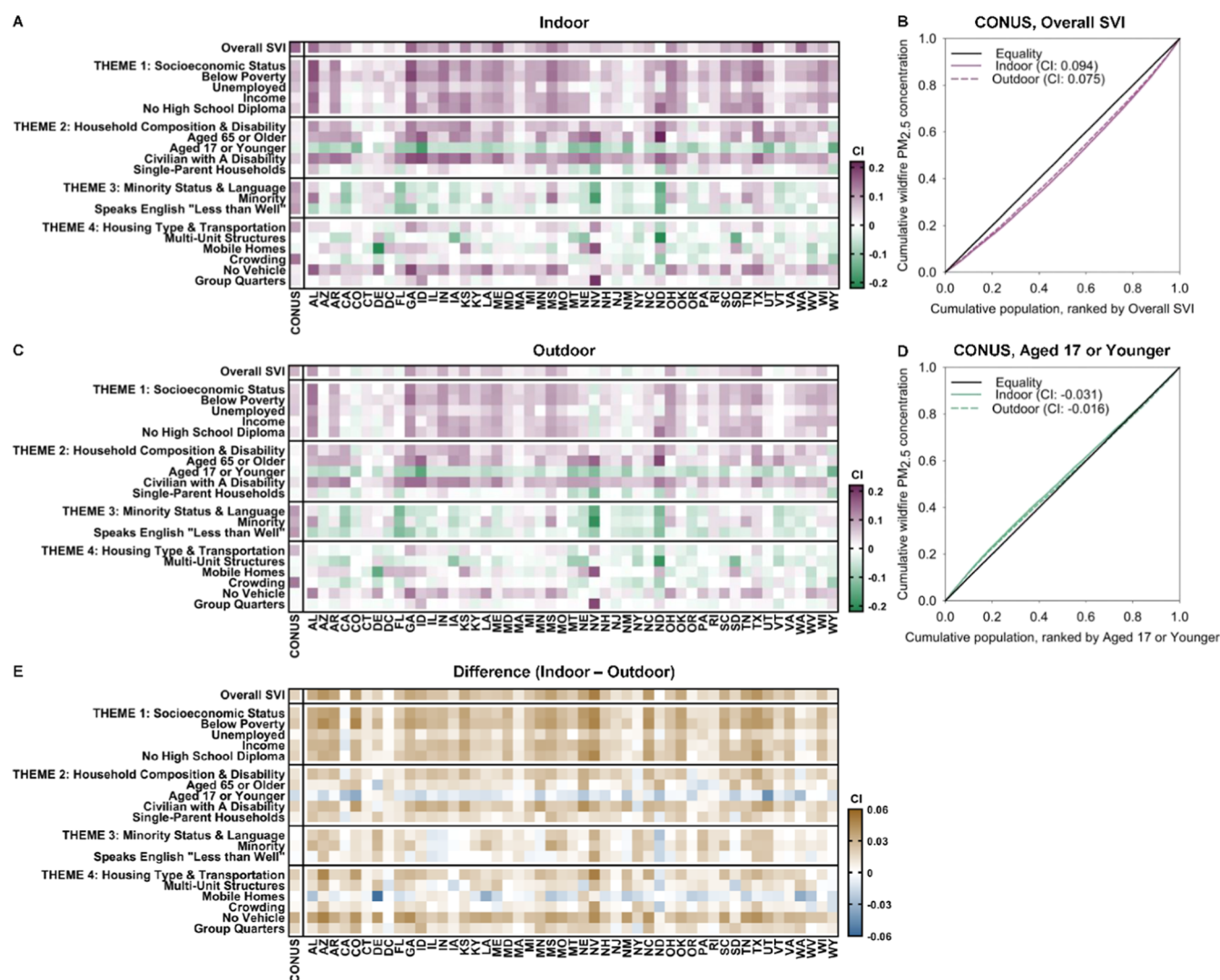


Figure 5. Inequality in wildfire PM_{2.5} concentrations across social vulnerability dimensions at national and state levels. (A,C) Concentration indices (CIs) for indoor (A) and outdoor (C) wildfire PM_{2.5} concentrations across the contiguous United States (CONUS) and individual states, ranked by the overall social vulnerability index (SVI), its four themes, and 15 individual vulnerability factors. Positive values (purple tones) indicate disproportionately higher concentrations among more vulnerable communities, while negative values (green tones) indicate higher concentrations among less vulnerable populations. (B,D) Concentration curve (CC) and CI examples of positive and negative inequality. (B) Indoor and outdoor concentrations in relation to overall SVI in CONUS. (D) Indoor and outdoor concentrations by the proportion of population aged 17 or younger in CONUS. The black solid 1:1 line indicates equal wildfire PM_{2.5} concentrations across different vulnerability levels, corresponding to a CI of zero. CCs below the equality line indicate that there are disproportionately higher concentrations for more vulnerable communities, resulting in positive CI values. (E) Difference in CI values between indoors and outdoors (Indoor CI–Outdoor CI) to visualize how inequality changes with indoor infiltration. Brown tones indicate amplified inequality indoors, while blue tones represent reduced inequality.

Themes 2 and 4. However, this amplification was not uniform across all vulnerability factors. For two specific factors—aged 17 or younger (Theme 2) and mobile homes (Theme 4)—inequality decreased in many states after outdoor wildfire PM_{2.5} infiltrated indoors.

4. DISCUSSION

Our results highlight the critical role of the indoor environment as a key setting for wildfire PM_{2.5} exposure. Given that other indoor sources of PM_{2.5} are also present, the increases of wildfire PM_{2.5} warrant attention, highlighting the cumulative impact of wildfire smoke. Especially Oregon, California, and Washington exhibited the highest indoor exposure to wildfire PM_{2.5}, collectively accounting for 90% of the population exposed to wildfires in the western United States.⁵² More

importantly, our findings reveal that indoor infiltration substantially amplifies disparities among communities. While outdoor disparities between DACs and non-DACs were modest, these differences became statistically significant indoors across the states. This amplification is driven by variations in estimated infiltration factors, which were significantly higher in DACs than in non-DACs (Table 1), indicating that buildings in DACs tend to be leakier and more susceptible to wildfire smoke intrusion. This infiltration pattern is driven by differences in median building construction years, which were significantly older in DACs than those in non-DACs (Table 1). Building leakiness is closely associated with building age.⁵³ Previous research reported that compared with census tracts with a median construction year of 2010, those with a median construction year of 1970 had 37% greater

infiltration factors.³³ These results suggest that disparities that seem negligible when examining outdoor air alone could be magnified indoors, highlighting the critical role of the built environment and infiltration factors in shaping the environmental inequality.

National racial–ethnic exposure disparities largely reflect population distribution (Figure S3): AIAN/NHPI, Asian, and Hispanic populations are more concentrated in the western United States, where wildfire activity tends to be more severe, whereas Black populations are primarily located in the southeastern United States, where wildfire exposure is generally lower. White populations are more evenly distributed across the country. However, state-level patterns reveal disparities that national averages do not capture. For example, in California, AIAN/NHPI populations faced the highest exposure, while White and Other populations had above-average exposure, and the Hispanic population had below-average exposure. These findings align with prior research indicating that American Indian and Alaska Native, multiracial, and non-Hispanic white populations consistently experienced disproportionately higher outdoor wildfire PM_{2.5} exposure in California.³²

Additionally, although indoor–outdoor differences in racial–ethnic disparity patterns were not apparent nationally, clear differences emerged at the state level, particularly for Black and Hispanic populations in many states. Prior research has shown that, in the United States, homes in African-American neighborhoods are on average a decade older than those in other communities, and the average building age increases with higher proportions of African-American residents in a ZIP code.⁵⁴ Consistent with this literature, our analysis found that higher proportions of Black and Hispanic populations were significantly associated with older housing stock across census tracts in CONUS and within most states (Table S6). Older buildings are generally leakier,^{33,53} which may help explain the amplified indoor exposure observed for Black and Hispanic populations.

Our work highlights that the national-level inequities primarily reflect broad population distribution trends and may not capture variations at the state level. To effectively address racial and ethnic disparities in wildfire PM_{2.5} exposure, location-specific strategies are needed. This is also reflected in prior research on ambient PM_{2.5} emission-reduction strategies, which shows that location-specific approaches are more effective than conventional sector-specific regulations or concentration standards in reducing pollution burdens and eliminating inequalities.⁵⁵

Our inequality analysis using CCs and CIs provides insights for informing local wildfire preparedness by identifying which components of social vulnerability contribute most to disparities in wildfire PM_{2.5} concentrations. Across most states, wildfire PM_{2.5} concentrations were disproportionately higher in socioeconomically vulnerable communities, consistent with prior evidence that socioeconomic status is the strongest driver of natural hazard vulnerability in the United States.⁵⁶ Previous research on wildfire hazards in West Coast states also emphasized the importance of considering elderly individuals, people with disabilities, and those with limited English proficiency when developing policies and responses to wildfires.³⁸ In our study, the effects of English proficiency on wildfire PM_{2.5} varied by state. In California, for example, those speaking English “less than well” experienced lower concentrations. This trend likely reflects residential location,

specifically a smaller representation of wildfire-exposed populations,³⁸ rather than reduced vulnerability or need for protection. Indeed, it was reported that emergency information during previous fire events was primarily provided in English, limiting access for Spanish-speaking and Indigenous groups.⁵⁷ Together, these findings underscore the need for equitable language access in preparedness and response resources.

Additionally, we found that indoor infiltration generally amplifies inequalities across most social vulnerability factors, underscoring the critical role of social vulnerabilities in shaping disparities in indoor wildfire PM_{2.5}. Previous research in British Columbia, Canada, provided supporting evidence, where the Canadian Index of Multiple Deprivation (CIMD), closely aligned with the SVI, was incorporated into a machine learning model predicting indoor wildfire PM_{2.5}. In that study, four CIMD dimensions (economic dependency, situational vulnerability, ethno-cultural composition, and residential instability) ranked among the third to seventh most important predictors, contributing to highly accurate predictions with most estimates within $\pm 5\%$ of observed values.⁵⁸ These findings reinforce our conclusion that social vulnerabilities are key determinants of disparities in indoor wildfire PM_{2.5}.

Notably, this amplification was not uniform across all vulnerability factors. One exception was the factor aged 17 or younger (Theme 2), for which inequality decreased in many states after outdoor wildfire PM_{2.5} infiltrated indoors. This may reflect housing patterns, as households with children are more likely to occupy newer constructions.^{59,60} We also observed that compared with outdoors, census tracts with more mobile homes experience relatively lower indoor wildfire PM_{2.5}. One possible reason is that the “mobile homes” category likely captures not only pre-1976 mobile homes but also newer manufactured homes,⁶¹ resulting in lower infiltration factors in our study. However, because the underlying database does not distinguish between older pre-1976 mobile homes and newer units, interpretations should be made with caution.

Several limitations of our study should be acknowledged. First, the estimation of the infiltration factor relied on published distributions by climate zone, season, and construction year, which captured broad spatial heterogeneity but did not reflect household behaviors such as window opening or HVAC operation. However, this limitation does not invalidate our disparity assessment; instead, it likely renders our estimates conservative. Prior research indicates that protective behaviors and air filtration adoption are more common in wealthier communities,²⁹ suggesting that accounting for behavioral differences would likely widen, rather than reduce, estimated indoor exposure inequalities. Second, our infiltration estimates do not fully capture building characteristics beyond construction year. Factors such as renovations or retrofits that alter building airtightness, as well as housing types (e.g., single-family homes, multifamily buildings, and mobile homes), can also affect infiltration factors. All of these will introduce additional building-level variability in real-world infiltration that is not fully captured in our estimates. Third, the published infiltration factor distributions were derived from the PurpleAir monitoring network, which tends to overrepresent higher-income households,²⁹ potentially underestimating exposure and inequities in environmental justice communities. Fourth, we investigated annual-average wildfire PM_{2.5} exposure, which may obscure short-term, high-concentration smoke episodes. Because exposure during active wildfire events is influenced by both behavioral responses (e.g., ventilation practices and air

filtration use) and geographic proximity to wildfire sources, additional studies are needed to evaluate how these factors affect exposure disparities during episodic smoke events. Finally, our analysis reflects inequities in residential indoor wildfire PM_{2.5} exposure rather than full time-weighted personal exposure across multiple microenvironments such as workplaces, schools, or commuting settings. Future work should consider incorporating higher temporal resolution (e.g., daily or episodic data) and occupant behaviors, and time–activity patterns across multiple indoor microenvironments to refine infiltration estimates and provide a more comprehensive assessment of wildfire smoke exposure inequities.⁶²

Despite these limitations, our work advances the ongoing conversation on wildfire PM_{2.5} exposure and inequities by highlighting the often overlooked role of indoor environments. We show that disparities that appear modest outdoors can become substantially amplified indoors. For example, DAC populations experienced higher exposure in 30 of 49 states outdoors, which increased to 47 states indoors. Similarly, Black populations experienced below-average exposure in 18 states outdoors and increased to 31 indoors. Indoor infiltration magnifies inequalities across many dimensions of social vulnerability. Importantly, national-level patterns may mask local disparities, underscoring the need for context-specific assessments and interventions. Locally tailored policies, such as improving building airtightness and filtration in vulnerable communities, expanding equitable access to clean air technologies, and ensuring culturally and linguistically appropriate messaging, will be critical for reducing the disproportionate health burden of wildfire smoke.

■ ASSOCIATED CONTENT

Data Availability Statement

All input data sets used in this study are publicly available. Outdoor wildfire PM_{2.5} concentration data: https://www.stanfordecholab.com/wildfire_smoke. Demographic data: <https://data.census.gov/table/ACSDP5Y2019.DP05>. CDC SVI data: <https://www.atsdr.cdc.gov/place-health/php/svi/svi-data-documentation-download.html>. CEJST for DACs identification: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/B6ULET>. Building construction year data: <https://www.hec.usace.army.mil/confluence/hsi>. Climate zone data: <https://www.energy.gov/eere/buildings/climate-zones>. All input data sets and output data sets generated in this study are available on Zenodo at [10.5281/zenodo.1606399](https://zenodo.org/record/1606399). The code to reproduce the analysis is available on Zenodo at [10.5281/zenodo.1606399](https://zenodo.org/record/1606399)

SI Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.5c18065>.

Estimates of outdoor and indoor wildfire PM_{2.5} concentrations; estimated outdoor and indoor wildfire PM_{2.5} concentrations at the census tract level and population-weighted state-level exposures across the contiguous United States; identification of disadvantaged and nondisadvantaged communities using the Climate and Economic Justice Screening Tool; census tract–level population distributions of racial–ethnic groups; comparison of infiltration factor estimates between this study and prior studies; state-level indoor and outdoor exposure metrics for disadvantaged and nondisadvantaged communities; racial–ethnic dispar-

ities in indoor and outdoor wildfire PM_{2.5} exposure, including mean, variability, and relative differences; and associations between demographic composition and building characteristics based on correlation analyses (PDF)

■ AUTHOR INFORMATION

Corresponding Author

Yifang Zhu – Department of Environmental Health Sciences, Fielding School of Public Health, University of California, Los Angeles, Los Angeles, California 90095, United States; orcid.org/0000-0002-0591-3322; Email: yifang@ucla.edu

Authors

Jing Li – Department of Environmental Health Sciences, Fielding School of Public Health, University of California, Los Angeles, Los Angeles, California 90095, United States; orcid.org/0000-0003-0639-9422

Xinlei Liu – Department of Environmental Studies, New York University, New York, New York 10003, United States

Qiao Yu – Department of Environmental Health Sciences, Fielding School of Public Health, University of California, Los Angeles, Los Angeles, California 90095, United States

Complete contact information is available at:

<https://pubs.acs.org/doi/10.1021/acs.est.5c18065>

Author Contributions

Conceptualization: J.L., X.L., and Y.Z. Methodology: J.L., X.L., and Y.Z. Investigation: J.L., X.L., and Q.Y. Visualization: J.L. Supervision: Y.Z. Writing—original draft: J.L. and X.L. Writing—review and editing: J.L. and Y.Z.

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This work was partially funded by the University of California Office of the President (UCOP) Laboratory Fees program under award LFR-20-651032. We thank Dr. David M. Lunderberg for sharing the summary statistics of infiltration factors based on the construction year.

■ REFERENCES

- (1) Abatzoglou, J. T.; Williams, A. P. Impact of anthropogenic climate change on wildfire across western U.S. forests. *Proc. Natl. Acad. Sci. U.S.A.* **2016**, *113*, 11770–11775.
- (2) Zhuang, Y.; Fu, R.; Santer, B. D.; Dickinson, R. E.; Hall, A. Quantifying contributions of natural variability and anthropogenic forcings on increased fire weather risk over the western United States. *Proc. Natl. Acad. Sci. U.S.A.* **2021**, *118*, No. e2111875118.
- (3) Diffenbaugh, N. S.; Konings, A. G.; Field, C. B. Atmospheric variability contributes to increasing wildfire weather but not as much as global warming. *Proc. Natl. Acad. Sci. U.S.A.* **2021**, *118*, No. e2117876118.
- (4) Iglesias, V.; Balch, J. K.; Travis, W. R. U.S. fires became larger, more frequent, and more widespread in the 2000s. *Sci. Adv.* **2022**, *8*, No. eabc0020.
- (5) Childs, M. L.; Li, J.; Wen, J.; Heft-Neal, S.; Driscoll, A.; Wang, S.; Gould, C. F.; Qiu, M.; Burney, J.; Burke, M. Daily local-level estimates of ambient wildfire smoke PM_{2.5} for the contiguous U.S. *Environ. Sci. Technol.* **2022**, *56*, 13607–13621.

- (6) Burke, M.; Childs, M. L.; de la Cuesta, B.; Qiu, M.; Li, J.; Gould, C. F.; Heft-Neal, S.; Wara, M. The contribution of wildfire to PM_{2.5} trends in the U.S.A. *Nature* **2023**, *622*, 761–766.
- (7) Wegesser, T. C.; Pinkerton, K. E.; Last, J. A. California wildfires of 2008: Coarse and fine particulate matter toxicity. *Environ. Health Perspect.* **2009**, *117*, 893–897.
- (8) Aguilera, R.; Corringham, T.; Gershunov, A.; Benmarhnia, T. Wildfire smoke impacts respiratory health more than fine particles from other sources: Observational evidence from Southern California. *Nat. Commun.* **2021**, *12*, 1493.
- (9) Zu, K.; Tao, G.; Long, C.; Goodman, J.; Valberg, P. Long-range fine particulate matter from the 2002 Quebec forest fires and daily mortality in Greater Boston and New York City. *Air Qual., Atmos. Health* **2016**, *9*, 213–221.
- (10) Park, C. Y.; Takahashi, K.; Fujimori, S.; Jansakoo, T.; Burton, C.; Huang, H.; Kou-Giesbrecht, S.; Reyer, C. P.; Mengel, M.; Burke, E.; Li, F.; et al. Attributing human mortality from fire PM_{2.5} to climate change. *Nat. Clim. Change* **2024**, *14*, 1193–1200.
- (11) Kollanus, V.; Tiittanen, P.; Niemi, J. V.; Lanki, T. Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland. *Environ. Res.* **2016**, *151*, 351–358.
- (12) Alman, B. L.; Pfister, G.; Hao, H.; Stowell, J.; Hu, X.; Liu, Y.; Strickland, M. J. The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: A case crossover study. *Environ. Health* **2016**, *15*, 64.
- (13) Reid, C. E.; Brauer, M.; Johnston, F. H.; Jerrett, M.; Balmes, J. R.; Elliott, C. T. Critical review of health impacts of wildfire smoke exposure. *Environ. Health Perspect.* **2016**, *124*, 1334–1343.
- (14) Vicedo-Cabrera, M.; Esplugues, A.; Iníguez, C.; Estarlich, M.; Ballester, F. Health effects of the 2012 Valencia (Spain) wildfires on children in a cohort study. *Environ. Geochem. Health* **2016**, *38*, 703–712.
- (15) Stowell, J. D.; Geng, G.; Saikawa, E.; Chang, H. H.; Fu, J.; Yang, C. E.; Zhu, Q.; Liu, Y.; Strickland, M. J. Associations of wildfire smoke PM_{2.5} exposure with cardiorespiratory events in Colorado, 2011–2014. *Environ. Int.* **2019**, *133*, 105151.
- (16) To, P.; Ebooreime, E.; Agyapong, V. I. The impact of wildfires on mental health: A scoping review. *Behav. Sci.* **2021**, *11*, 9126.
- (17) Zhang, Y.; Workman, A.; Russell, M. A.; Williamson, M.; Pan, H.; Reifels, L. The long-term impact of bushfires on the mental health of Australians: A systematic review and meta-analysis. *Eur. J. Psychotraumatol.* **2022**, *13*, 2087980.
- (18) Eisenman, D. P.; Galway, L. P. The mental health and well-being effects of wildfire smoke: A scoping review. *BMC Public Health* **2022**, *22*, 2274.
- (19) Wettstein, Z. S.; Vaidyanathan, A. Psychotropic medication prescriptions and large California wildfires. *JAMA Netw. Open* **2024**, *7*, No. e2356466.
- (20) Holstius, D. M.; Reid, C. E.; Jesdale, B. M.; Morello-Frosch, R. Birth weight following pregnancy during the 2003 Southern California wildfires. *Environ. Health Perspect.* **2012**, *120*, 1340–1345.
- (21) Evans, J.; Bansal, A.; Schoenaker, D. A. J. M.; Cherbuin, N.; Peek, M. J.; Davis, D. L. Birth outcomes, health, and health care needs of childbearing women following wildfire disasters: An integrative, state-of-the-science review. *Environ. Health Perspect.* **2022**, *130*, 086001.
- (22) Heft-Neal, S.; Driscoll, A.; Yang, W.; Shaw, G.; Burke, M. Associations between wildfire smoke exposure during pregnancy and risk of preterm birth in California. *Environ. Res.* **2022**, *203*, 111872.
- (23) Requia, W. J.; Amini, H.; Adams, M. D.; Schwartz, J. D. Birth weight following pregnancy wildfire smoke exposure in more than 1.5 million newborns in Brazil: A nationwide case-control study. *Lancet Reg. Health Am.* **2022**, *11*, 100229.
- (24) Ha, S.; Abatzoglou, J. T.; Adebisi, A.; Ghimire, S.; Martinez, V.; Wang, M.; Basu, R. Impacts of heat and wildfire on preterm birth. *Environ. Res.* **2024**, *252*, 119094.
- (25) Landguth, E. L.; Holden, Z. A.; Graham, J.; Stark, B.; Mokhtari, E. B.; Kalczyk, E.; Anderson, S.; Urbanski, S.; Jolly, M.; Semmens, E. O.; Warren, D. A.; et al. The delayed effect of wildfire season particulate matter on subsequent influenza season in a mountain west region of the U.S.A. *Environ. Int.* **2020**, *139*, 105668.
- (26) Zhou, X.; Josey, K.; Kamareddine, L.; Caine, M. C.; Liu, T.; Mickley, L. J.; Cooper, M.; Dominici, F. Excess of COVID-19 cases and deaths due to fine particulate matter exposure during the 2020 wildfires in the United States. *Sci. Adv.* **2021**, *7*, No. eabi8789.
- (27) Klepeis, N. E.; Nelson, W. C.; Ott, W. R.; Robinson, J. P.; Tsang, A. M.; Switzer, P.; Behar, J. V.; Hern, S. C.; Engelmann, W. H. The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *J. Expo. Sci. Environ. Epidemiol.* **2001**, *11*, 231–252.
- (28) Liang, Y.; Sengupta, D.; Campmier, M. J.; Lunderberg, D. M.; Apte, J. S.; Goldstein, A. H. Wildfire smoke impacts on indoor air quality assessed using crowdsourced data in California. *Proc. Natl. Acad. Sci. U.S.A.* **2021**, *118*, No. e2106478118.
- (29) Burke, M.; Heft-Neal, S.; Li, J.; Driscoll, A.; Baylis, P.; Stigler, M.; Weill, J. A.; Burney, J. A.; Wen, J.; Childs, M. L.; Gould, C. F. Exposures and behavioural responses to wildfire smoke. *Nat. Hum. Behav.* **2022**, *6*, 1351–1361.
- (30) Wallace, L. A.; Zhao, T.; Klepeis, N. E. Indoor contribution to PM_{2.5} exposure using all PurpleAir sites in Washington, Oregon, and California. *Indoor Air* **2022**, *32*, No. e13105.
- (31) Han, D.; Guo, Y.; Wang, J.; Zhao, B. Global disparities in indoor wildfire-PM_{2.5} exposure and mitigation costs. *Sci. Adv.* **2025**, *11*, No. eads4360.
- (32) Casey, J. A.; Kioumourtoglou, M. A.; Padula, A.; González, D. J.; Elser, H.; Aguilera, R.; Northrop, A. J.; Tartof, S. Y.; Mayeda, E. R.; Braun, D.; Dominici, F.; et al. Measuring long-term exposure to wildfire PM_{2.5} in California: Time-varying inequities in environmental burden. *Proc. Natl. Acad. Sci. U.S.A.* **2024**, *121*, No. e2306729121.
- (33) Lunderberg, D. M.; Liang, Y.; Singer, B. C.; Apte, J. S.; Nazaroff, W. W.; Goldstein, A. H. Assessing residential PM_{2.5} concentrations and infiltration factors with high spatiotemporal resolution using crowdsourced sensors. *Proc. Natl. Acad. Sci. U.S.A.* **2023**, *120*, No. e2308832120.
- (34) Azimi, P.; Zhao, D.; Stephens, B. Modeling the impact of residential HVAC filtration on indoor particles of outdoor origin (RP-1691). *Sci. Technol. Built Environ.* **2016**, *22*, 431–462.
- (35) U.S. Census Bureau. *Geographic Areas Reference Manual: Chapter 10 Census Tracts and Block Numbering Areas*. U.S. Department of Commerce, Washington, DC (accessed 2026–03–06)
- (36) Burke, M.; Driscoll, A.; Heft-Neal, S.; Xue, J.; Burney, J.; Wara, M. The changing risk and burden of wildfire in the United States. *Proc. Natl. Acad. Sci. U.S.A.* **2021**, *118*, No. e2011048118.
- (37) Heft-Neal, S.; Gould, C. F.; Childs, M. L.; Kiang, M. V.; Nadeau, K. C.; Duggan, M.; Bendavid, E.; Burke, M. Emergency department visits respond nonlinearly to wildfire smoke. *Proc. Natl. Acad. Sci. U.S.A.* **2023**, *120*, No. e2302409120.
- (38) Modaresi Rad, A.; Abatzoglou, J. T.; Fleishman, E.; Mockrin, M. H.; Radeloff, V. C.; Pourmohamad, Y.; Cattau, M.; Johnson, J. M.; Higuera, P.; Nauslar, N. J.; Sadeh, M. Social vulnerability of the people exposed to wildfires in US West Coast states. *Sci. Adv.* **2023**, *9*, No. eadh4615.
- (39) Liu, J.; Marshall, J. D. Spatial decomposition of air pollution concentrations highlights historical causes for current exposure disparities in the United States. *Environ. Sci. Technol. Lett.* **2023**, *10*, 280–286.
- (40) Krebs, B.; Neidell, M. Wildfires exacerbate inequalities in indoor pollution exposure. *Environ. Res. Lett.* **2024**, *19*, 024043.
- (41) U.S. Department of Energy. Climate Zones. <https://www.energy.gov/eere/buildings/climate-zones> (accessed 01 15, 2024).
- (42) U.S. Army Corps of Engineers. National Structure Inventory (NSI). <https://www.hec.usace.army.mil/confluence/hsi> (accessed 06 13, 2024).
- (43) CEQ. Climate and Economic Justice Screening Tool (CEJST). *Harvard Dataverse* **2024**.

- (44) U.S. Census Bureau. DP05: ACS Demographic and Housing Estimates. <https://data.census.gov/table/ACSDP5Y2019.DP05> (accessed 08/8, 2024).
- (45) CDC/ATSDR, CDC/ATSDR Social Vulnerability Index 2020 Database US. <https://www.atsdr.cdc.gov/place-health/php/svi/svi-data-documentation-download.html> (accessed 06/17, 2024).
- (46) Su, J. G.; Morello-Frosch, R.; Jesdale, B. M.; Kyle, A. D.; Shamasunder, B.; Jerrett, M. An index for assessing demographic inequalities in cumulative environmental hazards with application to Los Angeles, California. *Environ. Sci. Technol.* **2009**, *43*, 7626–7634.
- (47) Su, J. G.; Jerrett, M.; Morello-Frosch, R.; Jesdale, B. M.; Kyle, A. D. Inequalities in cumulative environmental burdens among three urbanized counties in California. *Environ. Int.* **2012**, *40*, 79–87.
- (48) Luo, Z.; Shen, G.; Men, Y.; Zhang, W.; Meng, W.; Zhu, W.; Meng, J.; Liu, X.; Cheng, Q.; Jiang, K.; Yun, X.; et al. Reduced inequality in ambient and household PM_{2.5} exposure in China. *Environ. Int.* **2022**, *170*, 107599.
- (49) Wagstaff, A.; O'Donnell, O.; Van Doorslaer, E.; Lindelow, M. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*; World Bank Publications, 2007.
- (50) Hu, S.; Liu, P.; Qiao, Y.; Wang, Q.; Zhang, Y.; Yang, Y. PM_{2.5} concentration prediction based on WD-SA-LSTM-BP model: A case study of Nanjing city. *Environ. Sci. Pollut. Res.* **2022**, *29*, 70323–70339.
- (51) Ericksen, E. P.; Kadane, J. B. Estimating the Population in a Census Year 1980 and beyond. *J. Am. Stat. Assoc.* **1985**, *80*, 98–109.
- (52) Modaresi, R.; Abatzoglou, J. T.; Kreidler, J.; Alizadeh, M. R.; AghaKouchak, A.; Hudyma, N.; Nauslar, N. J.; Sadeh, M. Human and infrastructure exposure to large wildfires in the United States. *Nat. Sustain.* **2023**, *6*, 1343–1351.
- (53) Chan, W. R.; Nazaroff, W. W.; Price, P. N.; Sohn, M. D.; Gadgil, A. J. Analyzing a database of residential air leakage in the United States. *Atmos. Environ.* **2005**, *39*, 3445–3455.
- (54) Goldstein, B.; Reames, T. G.; Newell, J. P. Racial inequity in household energy efficiency and carbon emissions in the United States: An emissions paradox. *Energy Res. Soc. Sci.* **2022**, *84*, 102365.
- (55) Wang, Y.; Apte, J. S.; Hill, J. D.; Ivey, C. E.; Patterson, R. F.; Robinson, A. L.; Tessum, C. W.; Marshall, J. D. Location-specific strategies for eliminating US national racial-ethnic PM_{2.5} exposure inequality. *Proc. Natl. Acad. Sci. U.S.A.* **2022**, *119*, No. e2205548119.
- (56) Cutter, S. L.; Finch, C. Temporal and spatial changes in social vulnerability to natural hazards. *Proc. Natl. Acad. Sci. U.S.A.* **2008**, *105*, 2301–2306.
- (57) Méndez, M.; Flores-Haro, G.; Zucker, L. The (in)visible victims of disaster: Understanding the vulnerability of undocumented Latino/a and indigenous immigrants. *Geoforum* **2020**, *116*, 50–62.
- (58) Coker, E. S.; Ho, W.; Paul, N.; Lee, M. J.; Dickson, J. M.; Greif, O.; Nilson, B.; Cleland, S. E.; Henderson, S. B. Enhancing wildfire smoke exposure assessment. In *A Machine Learning Approach to Predict Indoor PM_{2.5} in British Columbia*; ACS ES&T Air: Canada, 2024; Vol. 2, pp 73–89.
- (59) Dietz, R. *Who Lives in New Housing? Eye on Housing*, 2012; <https://eyeonhousing.wordpress.com/2012/04/12/who-lives-in-new-housing/> (accessed 08/30, 2025).
- (60) Herbert, A. *Young Families and the Growing Number of New single-family Rentals*. Joint Center for Housing Studies of Harvard University (2017); <https://www.jchs.harvard.edu/blog/young-families-and-growing-number-new-single-family-rentals> (accessed 08/30, 2025).
- (61) Consumer Financial Protection Bureau, Data Spotlight: Profiles of older adults living in mobile homes. (2022); <https://www.consumerfinance.gov/data-research/research-reports/data-spotlight-profiles-of-older-adults-living-in-mobile-homes/full-report/> (accessed 08/30, 2025).
- (62) Li, J.; Zhu, Y. The cost of clean air: Global disparities in reducing indoor wildfire-related PM_{2.5} exposure. *Sci. Adv.* **2025**, *11*, No. eady0890.