Inequities in Indoor Exposure to Wildfire-Related $PM_{2.5}$ Across the Contiguous United States

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Abstract

Exposure to wildfire smoke has been recognized as a major public health concern, but existing studies have focused on outdoor air, despite the fact that most people spend the majority of their time indoors, especially during wildfires. Here, we estimated indoor wildfire-related fine particulate matter ($PM_{2.5}$) concentrations across 72,537 census tracts in the contiguous United States for the year 2020, examining inequalities among various demographic groups regarding race–ethnicity, socioeconomic status, and other factors. Our results indicate that, in contrast to outdoor air, there are significant inequalities in indoor exposure. Once wildfire-related $PM_{2.5}$ infiltrates indoor environments, the population-weighted average exposure in disadvantaged communities (DACs) is significantly greater than that in non-DACs. Furthermore, our findings suggest that patterns of inequality at the national level differ from those at the state level. The racial–ethnic groups most affected vary by state, highlighting the need for localized interventions to address wildfire-related $PM_{2.5}$ exposure.

Introduction

Wildfire-related fine particulate matter (hereafter, wildfire $PM_{2.5}$) has become a critical environmental and public health issue in the United States, particularly due to the intensifying fires in recent years fueled by climate change[1-4]. In the western United States, the contribution of wildfires to daily $PM_{2.5}$ concentrations has increased by up to 5 μg/m^3 over the last decade, reversing decades of steady improvements in ambient air quality driven by policy efforts[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], as well as respiratory morbidity, including asthma exacerbation and chronic obstructive pulmonary disease (COPD)[11-15]. Additionally, wildfire $PM_{2.5}$ adversely affects mental health[16-19], has negative impacts on birth outcomes, including preterm birth and low birth weight[20-24], and can worsen respiratory infections such as influenza and COVID-19[25, 26].

Many previous studies have investigated the exposure and health impacts associated with outdoor wildfire $PM_{2.5}$ while overlooking indoor exposure. However, since people spend most of their time indoors[27] and tend to shelter indoors during wildfire events[28, 29], indoor environments are critical for wildfire $PM_{2.5}$ exposure. Research has shown that in the San Francisco Bay Area, the infiltration factor of $PM_{2.5}$ decreases from 0.4 on non-wildfire days to 0.2 on wildfire days, primarily due to behavioral changes such as closing windows. Despite this reduction, the mean concentration of indoor $PM_{2.5}$ can nearly triple on fire days[28, 30]. Understanding outdoor wildfire $PM_{2.5}$ infiltration and investigating indoor wildfire $PM_{2.5}$ exposure is important for informing the public about effective ways to reduce exposure.

Additionally, while numerous studies have documented that ambient $PM_{2.5}$ disproportionately affects people of color and socioeconomically disadvantaged populations in the United States[31-38], there is a limited understanding of inequalities in wildfire $PM_{2.5}$ exposure[5, 39, 40], particularly regarding indoor environments. There is a knowledge gap regarding the extent to which outdoor wildfire $PM_{2.5}$ infiltrates indoors across the contiguous United States (CONUS) at finer resolutions, such as census tracts. This information is critical for understanding the inequality patterns related to wildfire $PM_{2.5}$ exposure.

To address these knowledge gaps, we seek to answer two research questions: (1) What is the indoor exposure to wildfire $PM_{2.5}$ in the CONUS? (2) Are there any inequalities among different populations? To estimate indoor wildfire $PM_{2.5}$ exposure, we conducted a census tract-level data analysis across the 72,537 census tracts in the CONUS for the year 2020, which was marked by severe wildfires in the United States.[26, 41] To investigate inequalities, we compared different groups using two measures: (1) population-weighted average (PWA) indoor wildfire $PM_{2.5}$ exposure and (2) concentration curves (CCs) and concentration indices (CIs). We calculated the PWA indoor wildfire $PM_{2.5}$ exposure for six racial–ethnic groups at both the CONUS level and the state level, as well as for disadvantaged communities (DACs) and non-DACs within each state. We applied CCs and CIs to characterize inequalities in indoor wildfire $PM_{2.5}$ exposure across populations with varying vulnerabilities related to social factors such as income, age, minority status, and vehicle access that may affect a community' ability to prepare for and respond to hazardous events.

Results

Indoor wildfire $PM_{2.5}$ exposure across the contiguous United States (CONUS)

The outdoor wildfire $PM_{2.5}$ concentrations were obtained from Childs et al.[5] For the year 2020, the estimated annual average outdoor wildfire $PM_{2.5}$ concentrations across each census tract in the CONUS ranged from 0.10 to 25 μg/m^3 (**Fig. 1A**). Using this dataset, along with infiltration factors calculated based on climate zones, seasons, and building ages in each census tract (see **Methods**), we estimated annual average indoor wildfire $PM_{2.5}$ concentrations, which ranged from 0.01 to 6.3 μg/m^3 (**Fig. 1B**). It is important to note that the World Health Organization (WHO) updated the annual exposure limit for $PM_{2.5}$ concentrations to 5 μg/m^3 in 2021[42]. This limit applies to all sources of indoor $PM_{2.5}$, whereas our analysis specifically focuses on wildfire smoke. Despite this specific focus, two census tracts had annual averages of indoor wildfire $PM_{2.5}$ concentrations that surpassed this recommended threshold. One tract in Mono County, located in the east-central region of California, had a population of 8,169 and reported an indoor wildfire $PM_{2.5}$ concentration of 6.3 ± 5.3 μg/m^3. The other tract, which is situated in Mendocino County in the North Coast region of California, had a population of 2,674 and recorded an indoor wildfire $PM_{2.5}$ concentration of 5.4 ± 2.5 μg/m^3. Additionally, of the total 72,537 census tracts, 3,536 (5%) had more than 1 μg/m^3 increase in annual average indoor $PM_{2.5}$ levels attributed to wildfire emissions. **Fig. 1C** shows the PWA indoor wildfire $PM_{2.5}$ exposure for each state. The highest state-level was observed in Oregon at 1.75 ± 0.86 μg/m³, followed by Washington (0.89 ± 0.41 μg/m³) and California (0.76 ± 0.27 μg/m³). The state-level PWA exposure gradually decreased moving eastward, with the lowest concentration recorded in Rhode Island (0.04 ± 0.03 μg/m³).

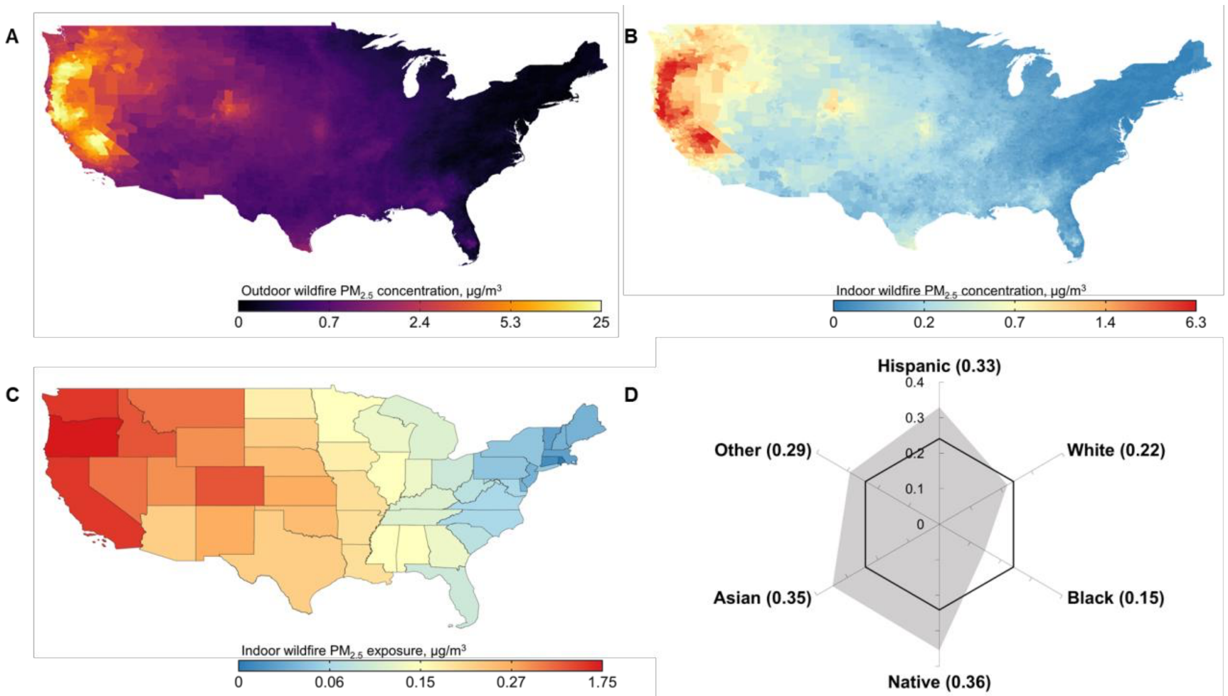

Fig. 1 Estimates of outdoor and indoor wildfire $PM_{2.5}$ concentrations and population-weighted average (PWA) exposure across the contiguous United States (CONUS). (**A**) Annual average outdoor wildfire $PM_{2.5}$ concentrations by census tract for 2020; data sourced from Childs et al. (2022)[5]. (**B**) Estimates of annual average indoor wildfire $PM_{2.5}$ concentrations for the same year and geographic area. (**C**) PWA indoor wildfire $PM_{2.5}$ exposure by state in the CONUS; note that the legend scale differs from that in (**B**). (**D**) Radar chart depicting PWA indoor wildfire $PM_{2.5}$ exposure in μg/m³ for different racial–ethnic groups in the CONUS, with the regular hexagon representing the PWA exposure for the overall population.

Racial–ethnic disparities in indoor wildfire $PM_{2.5}$ exposure

The radar chart in **Fig. 1D** compares the PWA indoor wildfire $PM_{2.5}$ exposure for each racial–ethnic group to the overall population average for the CONUS, represented by a regular hexagon with a value of 0.24 ± 0.06 μg/m³. The PWA indoor wildfire $PM_{2.5}$ exposure, ranked from highest to lowest among racial–ethnic groups, was as follows: Native (0.36 ± 0.10 μg/m³), Asian (0.35 ± 0.10 μg/m³), Hispanic (0.33 ± 0.09 μg/m³), Other (0.29 ± 0.08 μg/m³), White (0.22 ± 0.06 μg/m³), and Black (0.15 ± 0.04 μg/m³). At the CONUS level, Native, Asian, and Hispanic populations, along with individuals classified as "Other," experienced above-average PWA indoor wildfire $PM_{2.5}$ exposure, whereas the White and Black populations had below-average exposure.

The heatmap in **Fig. 2A** shows relative disparities in indoor wildfire $PM_{2.5}$ exposure for each racial–ethnic group compared to the state average across CONUS states, revealing that patterns of disparity vary by state. The relative disparity was calculated as the difference between the group's PWA exposure and the state average, divided by the state average, where a positive value indicates higher exposure for the group than the state average, while a negative value indicates lower exposure. Across all CONUS states, the Black and Native populations each experienced the highest PWA exposure in 17 of the 49 states, followed by the Hispanic population, which had the highest exposure in 10 states (**Table S1**). In many states, state-level patterns are distinct from the national trends observed at the CONUS level (**Fig. 1D**). **Figs. 2B-E** highlight four states where the most affected racial–ethnic group experienced more than 20% greater PWA exposure than the state average. For example, in California (**Fig. 2B**), the Native population had the highest PWA indoor wildfire $PM_{2.5}$ exposure, 0.92 ± 0.30 μg/m³, which was 22% above the state average of 0.76 ± 0.27 μg/m³. The White population, which had a PWA exposure of 0.81 ± 0.28 μg/m³, had the second-highest level, contrasting with the overall trend in the CONUS. In Nevada (**Fig. 2C**), the pattern was similar: the Native population (0.54 ± 0.26 μg/m³) experienced 29% greater exposure than the state average of 0.42 ± 0.17 μg/m³, whereas the White population (0.47 ± 0.21 μg/m³) had 13% greater exposure. In Wyoming (**Fig. 2D**), however, the Asian population faced the highest above-average exposure of 0.47 ± 0.29 μg/m³. In Tennessee (**Fig. 2E**), the Black population had the highest above-average exposure at 0.13 ± 0.07 μg/m³.

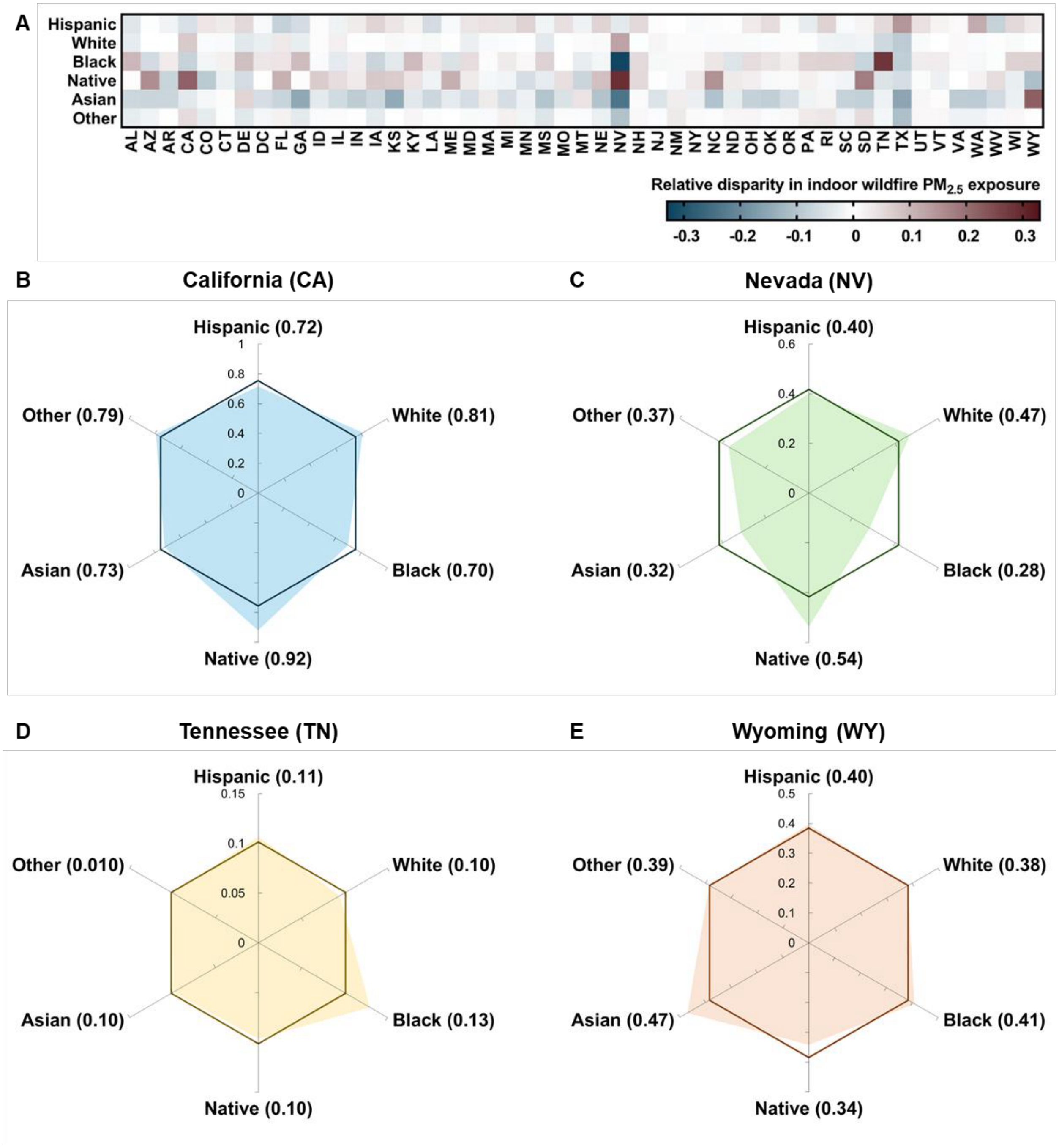

Fig. 2 Racial–ethnic disparities in indoor wildfire $PM_{2.5}$ exposure across CONUS states and selected states. (A) Heatmap depicting relative disparity of PWA indoor wildfire $PM_{2.5}$ exposure for each racial–ethnic group compared with the state average exposure across CONUS states. A positive value indicates higher exposure for the racial–ethnic group than the state average, whereas a negative value indicates lower exposure. Radar chart depicting PWA indoor wildfire $PM_{2.5}$ exposure in μg/m³ for different racial–ethnic groups in (**B**) California, (**C**) Nevada, (**D**)

Wyoming, and (**E**) Tennessee. Each hexagon represents the PWA exposure for the overall population in each state. Note that the scales of the radar axes differ across the four charts.

Disparities in indoor wildfire $PM_{2.5}$ exposure between DACs and non-DACs

DACs, which have been marginalized by society, overburdened by pollution, and underserved by infrastructure and other basic services, are identified using the Climate and Economic Justice Screening Tool (CEJST)[43], a geospatial mapping tool developed by the White House Council on Environmental Quality (CEQ). According to CEJST, 26,278 out of 72,537 (36%) CONUS census tracts are identified as DACs, whereas the rest are identified as non-DACs (**Fig. 3A**). The PWA indoor wildfire $PM_{2.5}$ exposure of DACs in the CONUS was 0.26 ± 0.07 µg/m³, whereas that of non-DACs was 0.23 ± 0.06 µg/m³. As shown in **Fig. 3B**, the PWA indoor wildfire $PM_{2.5}$ exposure in DACs of individual states ranged from 0.04 to 1.78 µg/m³, whereas those of non-DACs ranged from 0.04 to 1.74 µg/m³. The PWA outdoor wildfire $PM_{2.5}$ exposure across individual states ranged from 0.13 to 5.99 µg/m³ for DACs and from 0.12 to 6.24 µg/m³ for non-DACs. A Wilcoxon signed-rank paired test was conducted to compare PWA wildfire $PM_{2.5}$ exposure between DACs and non-DACs in each state for both indoor and outdoor wildfire $PM_{2.5}$. There was no significant difference between DACs and non-DACs in outdoor wildfire $PM_{2.5}$ exposure (P = 0.059). However, the indoor wildfire $PM_{2.5}$ exposure in DACs was significantly greater than that in non-DACs (P < 0.001).

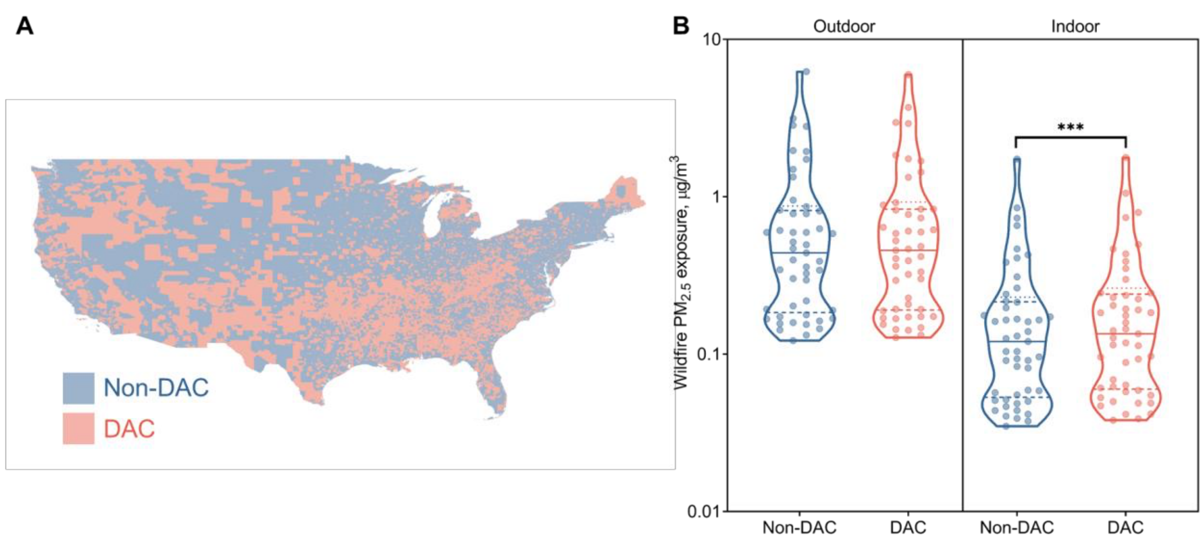

Fig. 3 Disparities in indoor and outdoor wildfire $PM_{2.5}$ exposure between DAC and Non-DAC populations across CONUS states. (**A**) DAC and non-DAC census tracts identified by the

CEJST across the CONUS. (**B**) Indoor and outdoor PWA wildfire $PM_{2.5}$ exposure of DAC and non-DAC populations in each state. Each dot in the violin plot represents a state within the CONUS. The significance of differences between the DAC and non-DAC populations was assessed using the Wilcoxon signed-rank paired test, as the datasets were not normally distributed. Asterisks (***) indicate significance at $P < 0.001$.

Inequality in indoor wildfire $PM_{2.5}$ exposure in relation to social vulnerability

Fig. 4 summarizes the inequalities in indoor wildfire $PM_{2.5}$ exposure in relation to vulnerabilities characterized using concentration curves (CCs) and concentration indices (CIs). These measures, adapted from the Lorenz curve and Gini coefficient, quantify inequalities in environmental exposure by relating the exposure distribution to a social variable, such as minority status[44-46]. To capture local vulnerability, we utilized the Social Vulnerability Index (SVI) at the census tract level[47] (see **Methods**). **Fig. 4A** shows the CC for indoor wildfire $PM_{2.5}$ exposure in relation to the overall SVI. The X-axis represents the cumulative population ranked by the overall SVI, from less vulnerable to more vulnerable, whereas the Y-axis displays the cumulative share of exposure, from low to high. The CI value for indoor wildfire $PM_{2.5}$ exposure in CONUS is 0.094 (95% confidence interval (CI95): 0.046 to 0.146), indicating that more vulnerable communities in CONUS had a disproportionately higher indoor wildfire $PM_{2.5}$ exposure.

This pattern is consistent across the other four SVI themes in the CONUS (**Fig. S1**): socioeconomic status (0.065, CI95: 0.007 to 0.116), household composition & disability (0.025, CI95: -0.022 to 0.066), minority status & language (0.103, CI95: 0.009 to 0.213), and housing type & transportation (0.093, CI95: 0.065 to 0.121). Higher CI values indicate greater inequalities. Among the four SVI themes, the greatest inequality in indoor wildfire $PM_{2.5}$ exposure is observed in the minority status & language theme, suggesting that communities with greater vulnerability due to minority status and English proficiency faced disproportionately higher levels of indoor wildfire $PM_{2.5}$ exposure. Additionally, as shown in **Fig. 4A** and **Fig. S1**, the CI values for outdoor wildfire $PM_{2.5}$ exposure are smaller than those for indoor exposure to varying degrees, indicating that, compared with outdoor wildfire $PM_{2.5}$, the inequality generally increased after the wildfire $PM_{2.5}$ infiltrates indoors.

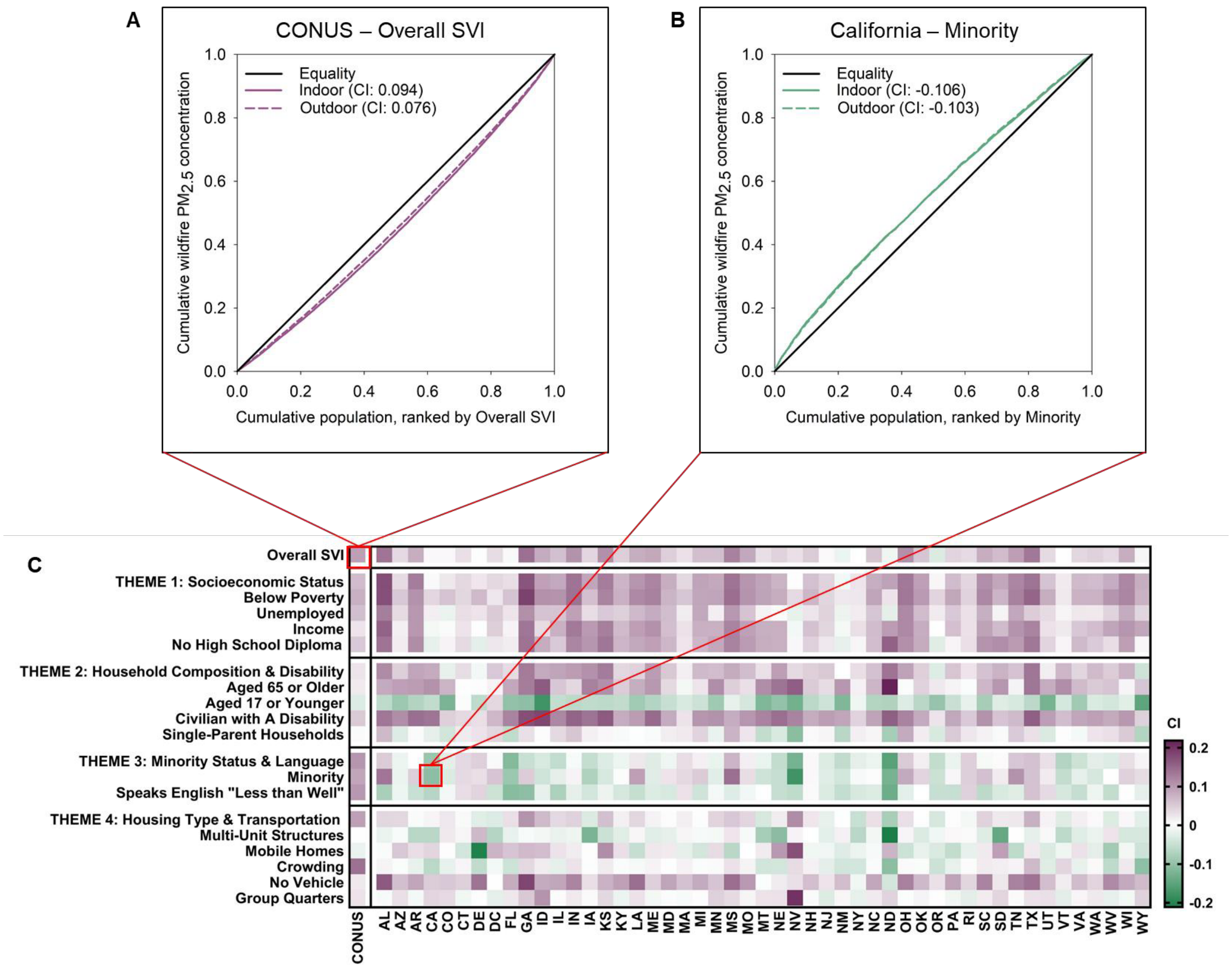

Fig. 4 Inequality in indoor wildfire $PM_{2.5}$ exposure regarding various vulnerability metrics. (**A**) Concentration curves (CCs) and concentration indices (CIs) for indoor and outdoor wildfire $PM_{2.5}$ exposure in relation to overall SVI in the CONUS. (**B**) CCs and CIs for wildfire PM2.5 exposure by minority status in California (CA). The black solid 1:1 line indicates equal wildfire $PM_{2.5}$ exposure across different vulnerability levels, corresponding to a CI of zero. CCs below the equality line indicates that disproportionately higher exposure for more vulnerable communities, resulting in positive CI values. (**C**) Heat map showing CIs for indoor wildfire $PM_{2.5}$ exposure with respect to the overall SVI and four themes including 15 individual factors, for the CONUS and each individual state. CIs range from -0.211 to 0.218; positive values (purple) indicate that more vulnerable communities experience a disproportionately higher share of indoor wildfire $PM_{2.5}$ exposure, whereas negative values (green) indicate that less vulnerable communities are disproportionately affected.

Unlike the Lorenz curve, which always remains below the equality line and has a Gini coefficient that is always positive, the CC can lie above the equality line, resulting in a negative CI if exposure is disproportionately concentrated among less vulnerable communities. For example, **Fig. 4B** shows the CCs and CIs for both indoor and outdoor wildfire $PM_{2.5}$ exposure in relation to minority status in California. The CI for indoor wildfire $PM_{2.5}$ exposure is -0.105 (CI95: -0.164 to -0.063), indicating that minority populations in California bear a smaller share of indoor wildfire $PM_{2.5}$ exposure, whereas the White population experience a disproportionate burden, likely because the majority of those living in areas with greater wildfire potential are White[48, 49]. The CI for outdoor wildfire $PM_{2.5}$ exposure is similar at -0.103 (CI95: -0.104 to -0.102), suggesting that the infiltration of wildfire $PM_{2.5}$ indoors has little impact on inequality in relation to minority status in California.

Fig. 4C presents CIs categorized by 15 individual factors, their four SVI themes, and the overall SVI, analyzed for both the CONUS and individual states. Positive CI values (shown in purple) indicate more exposure for more vulnerable communities relative to their corresponding vulnerability metrics, whereas negative values (shown in green) indicate less exposure for these groups. This breakdown offers a comprehensive view and local insights into the inequality in indoor wildfire $PM_{2.5}$ exposure. At the CONUS level, more vulnerable communities, as indicated by the overall SVI, experienced a disproportionate burden of indoor wildfire $PM_{2.5}$ exposure, which is also illustrated in **Fig. 4A**. Indoor wildfire $PM_{2.5}$ exposure was disproportionately concentrated among more vulnerable communities across all SVI themes and nearly all individual factors.

The inequality patterns for Theme 1—socioeconomic status and its individual factors (below poverty, unemployed, income, and no high school diploma)—was consistent for both the CONUS and most individual states, with positive CIs indicating that socially and economically vulnerable communities disproportionately experienced higher levels of indoor wildfire $PM_{2.5}$. In contrast, the inequality patterns for the other three themes varied by individual factor or state. In Theme 2—household composition & disability—the population aged 65 years or older and those with a disability disproportionately bore the burden of indoor wildfire $PM_{2.5}$ at both the CONUS and state levels, whereas the population aged 17 years or younger experienced a lesser share. The impact from single-parent households varied among states. For Theme 3—minority status & language—more vulnerable groups, including racial–ethnic minorities and those who speak English "less than well", disproportionately faced increased indoor wildfire $PM_{2.5}$ exposure within the CONUS. However, at the state level, the inequality patterns differ by state. In some states, such as California (see **Fig. 4B**), the White population and those who speak English "well" shared a larger portion of the burden, whereas in Texas, the minority population and those who speak English "less than well" experienced a greater burden. In theme 4—housing type & transportation—most states and the CONUS revealed that individuals without access to a vehicle faced a greater burden of indoor wildfire $PM_{2.5}$ exposure, although the inequality patterns for other factors varied by state.

Discussion

Our results address the knowledge gap regarding indoor exposure to wildfire $PM_{2.5}$ and its associated inequalities across the CONUS. We used data for the entire year of 2020 to examine indoor exposure to wildfire $PM_{2.5}$, with a particular focus on inequality. The results highlight the importance of the indoor environment as a key exposure setting for wildfire $PM_{2.5}$. For example, 3,536 census tracts exhibited an increase of more than 1 μg/m³ in annual average indoor $PM_{2.5}$ levels due to wildfire smoke infiltration. Notably, two census tracts even had annual average indoor wildfire $PM_{2.5}$ levels exceeding the WHO's guideline limit of 5 μg/m³ [42]. Given that there were already existing indoor $PM_{2.5}$ sources, this increase warrants attention, highlighting the cumulative impact of wildfire $PM_{2.5}$ exposure over the course of the year. At the state level, Oregon, California, and Washington exhibited the highest exposure to indoor wildfire $PM_{2.5}$, collectively accounting for 90% of the population exposed to wildfires in the western United States[50]. Although the exposure and health impacts of wildfire $PM_{2.5}$ have been studied in these three states[7, 8, 19, 20, 22, 40], few studies have focused specifically on indoor exposure [28, 30]. Public health advisories often recommend that people stay indoors during wildfire events[51]; however, our results show this may not be sufficient to protect health, as people can still be exposed to high levels of wildfire $PM_{2.5}$ indoors.

Disparities in air pollution exposure are rooted in historical race-based planning[52]. This is also reflected in our results showing that indoor wildfire $PM_{2.5}$ concentrations are higher among people of color across the CONUS and in most states, with the exception of New Jersey and Virginia. A previous study has found racial–ethnic disparities in outdoor wildfire $PM_{2.5}$ exposure in the United States, noting that Hispanic individuals experienced above-average levels, whereas White and Black individuals had below-average levels of exposure[5]. However, our study found that the patterns of racial–ethnic disparity at the state level differ from those observed at the CONUS level. In California, for example, the Native population faced the highest exposure, while the White population and those classified as "Other" (see **Methods**) had above-average exposure, and the Hispanic population had below-average exposure. These findings are corroborated by previous research indicating that Native American and Alaska Native, multiracial, and non-Hispanic white populations consistently faced disproportionately higher outdoor wildfire $PM_{2.5}$ exposure[40]. The CONUS-level results are likely due to the population distribution (**Fig. S2**), with Hispanic, Native, and Asian populations being more concentrated in the western United States, where wildfires tend to be more severe. In contrast, White populations are more evenly distributed across the country, while Black populations are located primarily in the southeastern United States, where wildfire severity and exposure levels are generally lower. Consequently, the disparity patterns observed at the CONUS level largely reflect these national geographic trends and may not capture variations in disparity patterns across individual states. To effectively address the inequalities in wildfire $PM_{2.5}$ exposure related to race and ethnicity, location-specific exposure-reduction strategies are essential. This is also supported by studies on emission-reduction strategies for ambient $PM_{2.5}$, which indicate that location-specific approaches outperform current regulatory methods (i.e., sector-specific regulations and concentration standards) in reducing pollution burdens and eliminating national inequalities[53].

Our results call for more attention to indoor $PM_{2.5}$ exposure during wildfires. Notably, the differences in indoor wildfire $PM_{2.5}$ exposure between DACs and non-DACs were significant, unlike those in outdoor wildfire $PM_{2.5}$, where no such differences were observed. This finding suggests that the estimated infiltration factors (considering climate zones, seasons, and building ages in each census tract) exacerbate the disparity between DACs and non-DACs. This is likely because DACs tend to have a higher proportion of older buildings compared to non-DACs (see **Methods**), and the leakiness of a building's envelope is associated with its age[54]. Compared with census tracts with a median construction year of 2010, those with a median construction year of

1970 had 37% greater infiltration factors[55]. Our findings could also potentially contribute to advancing the goals of the Biden-Harris Administration's Justice40 Initiative by highlighting the importance of addressing indoor wildfire $PM_{2.5}$ exposure in DACs. The Justice40 Initiative, which employs the CEJST to identify DACs, prioritize these communities for government programs and funding based on climate and environmental burdens as well as socioeconomic indicators[43, 56]. DACs identified by CEJST constitute approximately 34% of the United States population, and Justice40 aims to deliver 40% of benefits to DACs that are marginalized, underserved, and overburdened by pollution[56]. Given that $PM_{2.5}$ is an important air pollutant, our findings suggest that targeted efforts to reduce indoor wildfire $PM_{2.5}$ exposure in DACs could help mitigate health disparities and promote environmental equity in line with Justice40's objectives.

The inequality analysis using CCs and CIs provided insights for informing local wildfire preparedness plans by identifying the populations most affected by wildfire $PM_{2.5}$. Across most CONUS states, indoor wildfire $PM_{2.5}$ exposure was, as expected, disproportionately concentrated in socioeconomically vulnerable communities. Socioeconomic status has consistently been identified as the most significant driver of vulnerability to natural hazards in the United States[57]. These communities require greater attention and targeted interventions.

In addition, previous research on wildfire hazards in the West Coast states highlighted the need for special attention to elderly individuals, people with disabilities, and those with limited English-speaking skills when developing policies and responses to wildfires[48]. In our study, we found that English proficiency had varying effects on the distribution of indoor wildfire $PM_{2.5}$ across different states. For example, in California, individuals who speak English "less than well" experienced a lower burden of indoor wildfire $PM_{2.5}$ exposure. This can be attributed to the fact that the proportion of the wildfire-exposed population who spoke English less proficiently was generally lower than that of the overall state population[48]. Despite this, it was reported that in the case of the Thomas Fire in California's Ventura and Santa Barbara counties (December 4, 2017, to January 20, 2018), most of the emergency information, including mitigation and evacuation resources, was provided primarily in English. This limited accessibility for non-English speakers, such as Spanish-speaking and Indigenous populations[58]. To address such disparities, equitable language access to preparedness resources and emergency information must be improved, particularly in demographically diverse areas. Moreover, we found that the White population in California faced a disproportionately greater burden of indoor wildfire $PM_{2.5}$ exposure, likely because a majority of residents in areas with higher wildfire risk are White[48, 49]. Previous research also corroborated that from 2011 to 2018, the wildfire hazard and associated impacts were disproportionately borne by the White population living in the western United States[59]. However, our findings do not imply that minority populations should be overlooked with respect to indoor wildfire $PM_{2.5}$ exposure. They often live in communities that are more vulnerable and less equipped to respond to and adapt to wildfires, even if their areas of residence may experience fewer wildfires than the areas of residence of White populations[49].

Overall, our work contributes to the ongoing conversation about addressing wildfire $PM_{2.5}$ exposure and its associated inequalities, with a particular focus on the often-overlooked issue of indoor infiltration of wildfire smoke. Our findings reveal that indoor wildfire $PM_{2.5}$ exposure in DACs was significantly greater than in non-DACs, while outdoor exposure levels showed no such disparity, reinforcing the need for targeted policies addressing indoor air quality. Additionally, our results highlight the importance of prioritizing vulnerable populations, including socioeconomically disadvantaged groups, individuals aged 65 and older, and those with disabilities. Moreover, our study suggests that national racial–ethnic disparity patterns may not fully capture local disparities, emphasizing the need to consider local contexts when addressing these inequalities. Policy development should be tailored to specific communities, such as improving access to emergency information in multiple languages, to effectively support disadvantaged groups and reduce exposure disparities.

Methods

Outdoor wildfire $PM_{2.5}$ concentration data. We aimed to estimate indoor exposure to wildfire $PM_{2.5}$ at the census tract level in the CONUS for 2020. The outdoor wildfire $PM_{2.5}$ concentrations were sourced from Childs et al.[5], who provided daily estimates of wildfire $PM_{2.5}$ across 72,537 census tracts in CONUS using machine learning models. This dataset has been widely used in research on inequalities and health impacts related to outdoor wildfire $PM_{2.5}$[35, 39, 60, 61]. A limitation of this dataset is the lack of uncertainty estimates, which we addressed by assuming a 20% coefficient of variation (CV)[62] (see **Uncertainty analysis**). For each census tract, we calculated the seasonal averages of outdoor $PM_{2.5}$ concentrations for spring (March-May), summer (June-August), fall (September-November), and winter (December-February) to align with the seasonal data used to calculate infiltration factors (see **Indoor wildfire $PM_{2.5}$ concentrations**).

Indoor wildfire $PM_{2.5}$ concentrations. Indoor wildfire $PM_{2.5}$ concentrations at the census tract level were calculated by multiplying outdoor wildfire $PM_{2.5}$ concentrations by infiltration factors (F_{inf}), which quantify the proportion of outdoor $PM_{2.5}$ that infiltrates indoor environments. Data for calculating F_{inf} estimates for each census tract were obtained from Lunderberg et al. (2023), who assessed F_{inf} using data from crowdsourced sensors and a random component superposition method. This dataset includes (1) F_{inf} values for four climate zones (Marine, Hot–Dry, Cold, and "Other," which includes Mixed–Humid, Mixed–Dry, Hot–Humid, and Very Cold) across four seasons, and (2) F_{inf} values for eight construction year subgroups (1935-1945, 1945-1955, 1955-1965, 1965-1975, 1975-1985, 1985-1995, 1995-2005, and 2005-2015). In this study, each census tract was initially assigned a base F_{inf} value corresponding to its climate zone for each season, as identified using data from the U.S. Department of Energy's (DOE) Building America Program (U.S. DOE, https://www.energy.gov/eere/buildings/climate-zones). The base F_{inf} was then adjusted based on the relationship between F_{inf} values for different construction year subgroups identified by Lunderberg et al. (2023)[55]. Specifically, the percentage increase or decrease in F_{inf} values was applied by comparing the median construction year of all structures within the tract to the median construction year within the climate zone using the following equations:

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

$$P_{yy}=(F_{inf,yy}-F_{inf,m})/F_{inf,m} \qquad \text{(Equation 2)}$$

where $F_{inf,c}$ denotes the final F_{inf} used for census tract c, $F_{inf,c,s}$ indicates F_{inf} for census tract c and season s without considering the impact of construction year, $F_{inf,yy}$ represents F_{inf} for construction year subgroups yy, $F_{inf,m}$ is the median value of F_{inf} for all construction year subgroups, P_{yy} represents the percentage increase or decrease in F_{inf} for construction year subgroups yy compared with $F_{inf,m}$, with positive values indicating a percentage increase and negative values indicating a percentage decrease. Data on construction years were obtained from the National Structure Inventory (U.S. Army Corps of Engineers, https://www.hec.usace.army.mil/confluence/nsi), which originally provided median values for each block. We then aggregated these median construction years to derive a single median for each census tract based on the relationships among blocks and census tracts. After calculating indoor concentrations by multiplying outdoor concentrations with F_{inf} for each season in every census tract, the annual average indoor concentration was determined by averaging the seasonal indoor concentrations.

PWA wildfire $PM_{2.5}$ exposure. Disparities in wildfire $PM_{2.5}$ exposure among different racial–ethnic groups, as well as between DACs and non-DACs, were illustrated using a PWA format, which means that the size of each population group was considered in calculations, assigning greater significance to groups with larger populations to more accurately reflect the overall impact or distribution across the total population. The PWA exposure for different groups in the CONUS or in each state was calculated according to Equation 3:

$$E_{\mathrm{PWA,g,s}}=\frac{\sum_{\mathrm{c}}(P_{\mathrm{g,n/s,c}}\times E_{\mathrm{g,n/s,c}})}{\sum_{\mathrm{c}}P_{\mathrm{g,n/s,c}}} \quad \text{(Equation 3)}$$

where *PWA* is the population-weighted average, *E* represents the wildfire $PM_{2.5}$ concentration, *P* denotes the population, *g* represents a racial–ethnic group or DACs or non-DACs, *n* denotes the nation, *s* indicates a specific state, and *c* refers to a particular census tract. The population data by race-ethnicity are from the U.S. Census 2016-2019 ACS estimates at the census tract level (https://data.census.gov/table/ACSDP5Y2019.DP05). We focused on six racial–ethnic groups as determined by self-identification in the Census: 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%), Native (including American Indian, Alaska Native, Native Hawaiian, and Other Pacific Islander, 1%), and Other (including some other race and people identifying with two or more races, 3%). We also calculated the relative disparity for each racial–ethnic group by taking the difference between the group's PWA exposure and the overall population's PWA exposure, then dividing this difference by the overall population's PWA exposure. The population data for census tracts classified as DACs and non-DACs were obtained from CEJST[43].

CCs and CIs. The CI quantifies inequality in wildfire $PM_{2.5}$ exposure, following the method recommended by the World Bank[63]. To construct the index, the population is first rank ordered based on a demographic grouping of interest (e.g., the proportion of racial–ethnic minorities, from lowest to highest) using the SVI. The SVI, developed by the U.S. Centers for Disease Control and Prevention (CDC), measures a community's ability to respond to hazardous events and is traditionally used to help public health officials identify populations in most need of support[47]. The SVI includes variables in a nested hierarchy: the overall SVI, its four dimension or themes (socioeconomic status, household composition and disability, minority status and language, and housing type and transportation), and all 15 subdimensions of individual factors, including unemployment, minority status, disability, etc. Next, the cumulative population is plotted against the cumulative share of wildfire $PM_{2.5}$ exposure estimates to generate the CC. The CI is then calculated using Equation 4:

$$CI = 1 - 2\int_0^1 CC(p)dp \qquad \text{(Equation 4)}$$

where $-1 \leq CI \leq 1$ and CC denotes the concentration curve, which indicates the relationship between the cumulative population and cumulative wildfire $PM_{2.5}$ exposure; the variable p represents the cumulative rank proportion, which usually ranges between [0, 1]. In the current study, we calculate CIs for the overall SVI, its four themes, and all 15 individual factors, against wildfire $PM_{2.5}$ exposure estimates for both the CONUS and each state.

Uncertainty analysis. To address uncertainty in our estimates, we conducted 1,000 Monte Carlo simulations for each calculation. Each dataset was represented by a distribution based on its mean or median values and the associated variation. Specifically, we assume a log-normal distribution[62] for the outdoor wildfire $PM_{2.5}$ and F_{inf} datasets and a normal distribution[64] for the population dataset. For outdoor wildfire $PM_{2.5}$, the source data[5] did not report uncertainty. To address this, we referenced findings from previous research that evaluated a hybrid machine learning model for measuring concentrations of various air pollutants. For $PM_{2.5}$, the relative root mean square error was roughly estimated to be 17.5% or lower[62]. Given the differences in modeling algorithms between the source data[5] and the previous research[62], we adopted a slightly higher CV of 20% to ensure the robustness of our results. This 20% CV was applied to the seasonal averages of outdoor $PM_{2.5}$ concentrations for each census tract to generate the distributions. F_{inf} distributions were generated using the medium value along with the low and high quantiles, whereas the population distribution was based on the average value and its margin of error.

Using simulated distributions for outdoor wildfire $PM_{2.5}$, F_{inf}, and population datasets, we calculated indoor wildfire $PM_{2.5}$ concentrations, wildfire $PM_{2.5}$ exposure, and CIs, along with their mean, median, and associated uncertainties. Indoor wildfire $PM_{2.5}$ concentrations and exposure levels are reported as mean ± standard deviation, while CIs are represented by median values with 95% confidence intervals to reflect uncertainty (detailed data are provided in **Data availability**).

Data availability

The input datasets related to this paper are publicly available. Wildfire $PM_{2.5}$ concentration data can be accessed at https://www.stanfordecholab.com/wildfire_smoke. The demographic data used in this study are available at https://data.census.gov/table/ACSDP5Y2019.DP05. The CDC SVI database can be found at https://www.atsdr.cdc.gov/placeandhealth/svi/index.html. The White House CEQ CEJST to identify DACs can be accessed at https://screeningtool.geoplatform.gov/en/downloads#3/33.47/-97.5. The construction year data can be found at https://www.hec.usace.army.mil/confluence/nsi. The climate zone data are available at https://www.energy.gov/eere/buildings/climate-zones. We compiled the input datasets and primary datasets generated during calculations, which are available at https://doi.org/10.5281/zenodo.13371454.

Code availability

The MATLAB code needed to reproduce all the results in the paper, along with all the data used to generate the figures in both the main text and the Supporting Information, are available at https://github.com/leileiab/fire-justice.git.

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Author contributions

J.L., X.L., and Y.Z. designed the research. J.L., X.L., and Q.Y. collected data and performed the analysis. J.L. visualized the results. Y.Z. supervised the research. J.L. and X.L. wrote the manuscript and all authors edited the manuscript.

Competing interests

The authors declare that they have no competing interests.

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Supplementary Figures

Figure S1

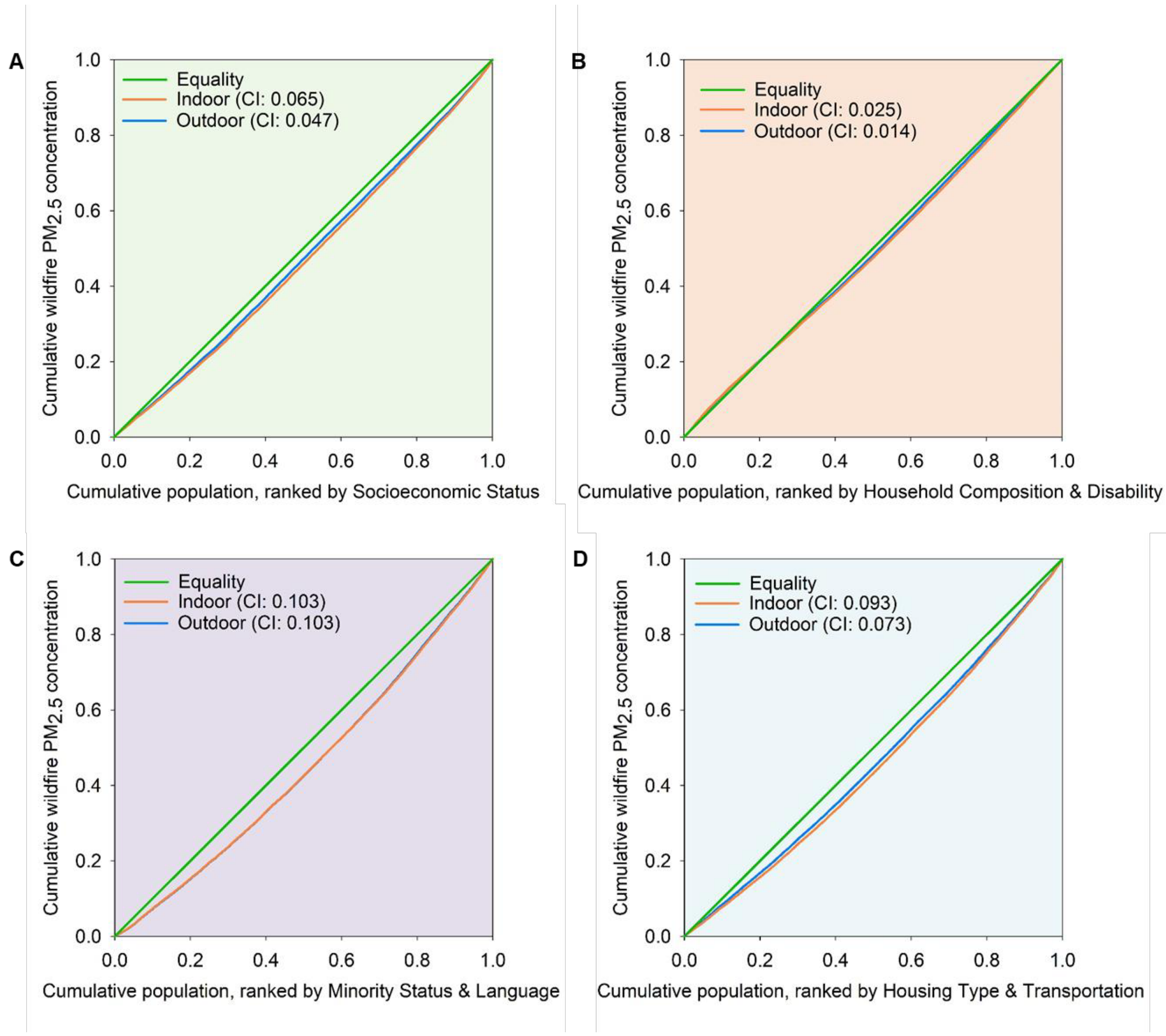
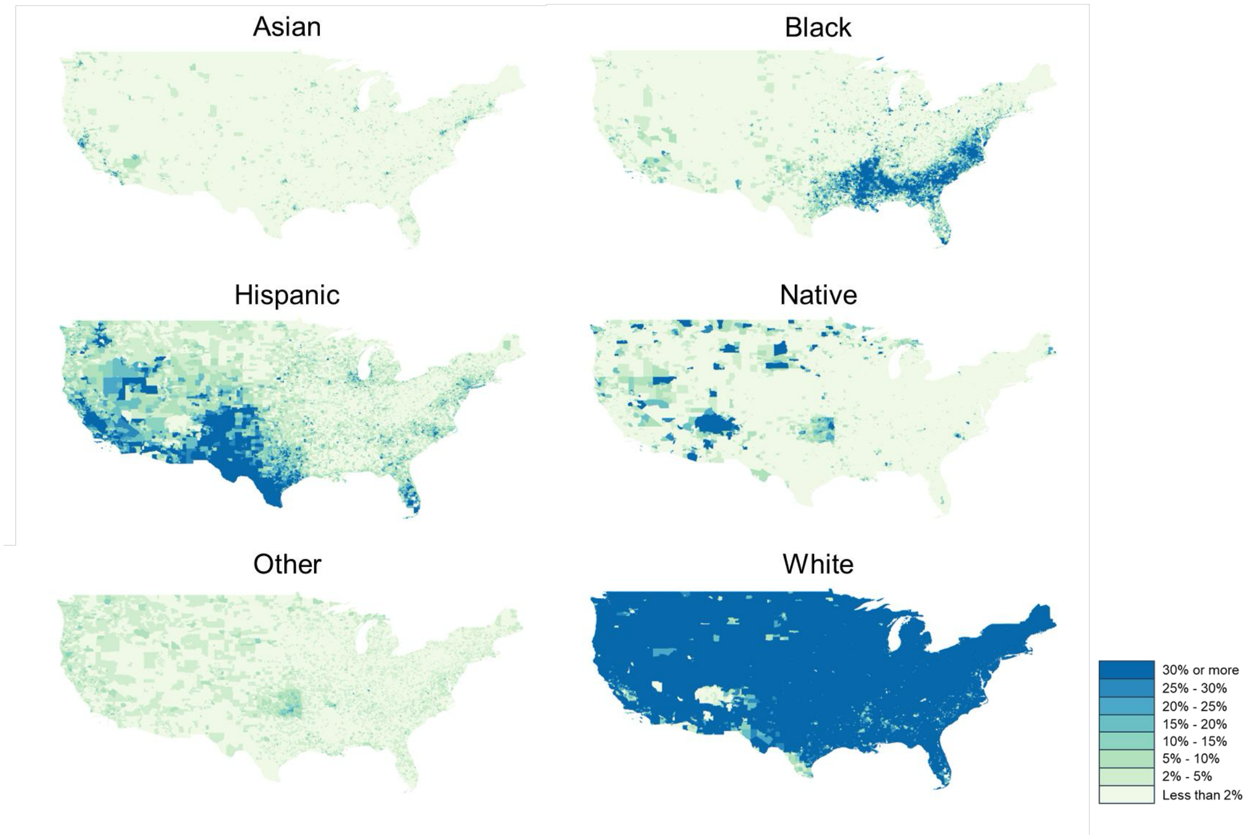


Fig. S1 Concentration curves and CIs (indicated in brackets in the legends) for both indoor and outdoor wildfire $PM_{2.5}$ concentrations in relation to (**A**) socioeconomic status, (**B**) household composition & disability, (**C**) minority status & language, and (**D**) housing type & transportation in the CONUS. In each plot, the orange and blue lines represent indoor and outdoor wildfire $PM_{2.5}$ concentrations, respectively. The green 1:1 line indicates equal wildfire $PM_{2.5}$ concentrations across different vulnerability levels, corresponding to a concentration index of zero. When the concentration curve falls below the equality line, it signifies that more vulnerable communities experience a disproportionate share of the wildfire $PM_{2.5}$ burden, and the concentration index is positive

666 **Figure S2**



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668 **Fig. S2** Population distribution of different racial-ethnic groups as a percentage of the total

669 census tract population across the CONUS. Source: U.S. Census 2016-2019 ACS estimates at the

670 census tract level (https://data.census.gov/table/ACSDP5Y2019.DP05).

Table S1 Relative disparity in the percentage of PWA indoor wildfire $PM_{2.5}$ exposure for each racial–ethnic group, compared to the state average exposure across all CONUS states. The racial–ethnic group with the highest exposure is highlighted in red. Mean ± standard deviation values for PWA indoor wildfire $PM_{2.5}$ exposure can be accessed at https://doi.org/10.5281/zenodo.13371454.

	Hispanic	White	Black	Native	Asian	Other
CONUS	0.3646	-0.0828	-0.3855	0.4694	0.4451	0.2097
Alabama	-0.0429	-0.0348	0.0988	0.0018	-0.0693	-0.0317
Arizona	-0.0030	-0.0003	-0.0614	0.1577	-0.0725	-0.0200
Arkansas	-0.0208	-0.0011	0.0272	-0.0744	-0.0724	-0.0022
California	-0.0528	0.0731	-0.0762	0.2194	-0.0390	0.0484
Colorado	0.0350	-0.0081	-0.0172	-0.0923	-0.0142	-0.0336
Connecticut	0.0263	-0.0090	0.0190	-0.0275	0.0031	-0.0048
Delaware	0.0525	-0.0398	0.0879	-0.0607	0.0575	-0.0396
District of Columbia	-0.0121	-0.0292	0.0324	-0.0021	-0.0571	-0.0162
Florida	-0.0790	0.0295	0.0369	0.1081	-0.0747	0.0177
Georgia	-0.0599	-0.0303	0.0930	0.0029	-0.1517	-0.0373
Idaho	0.0028	-0.0053	-0.0072	0.0700	-0.0374	-0.0070
Illinois	-0.0226	0.0197	-0.0355	0.0467	-0.0627	0.0046
Indiana	0.0247	-0.0025	0.0242	0.0287	-0.0882	-0.0018
Iowa	0.0596	0.0013	-0.0725	0.0749	-0.0677	-0.0359
Kansas	0.0337	0.0083	-0.0390	0.0702	-0.1473	-0.0002
Kentucky	0.0161	-0.0080	0.0937	0.0387	-0.0403	0.0138
Louisiana	-0.0603	-0.0104	0.0330	-0.0197	-0.0690	-0.0067
Maine	-0.0111	0.0006	-0.0496	0.1095	-0.0364	-0.0012
Maryland	0.0345	-0.0264	0.0472	0.0259	-0.0592	-0.0082
Massachusetts	0.0393	-0.0088	0.0037	-0.0137	0.0264	-0.0100
Michigan	0.0375	-0.0054	0.0263	-0.0178	-0.0593	0.0191
Minnesota	0.0604	-0.0021	0.0110	-0.0576	-0.0247	-0.0188
Mississippi	-0.0190	-0.0369	0.0617	-0.0339	-0.1030	-0.0439
Missouri	0.0416	-0.0013	-0.0004	0.0432	-0.0498	0.0050
Montana	-0.0215	0.0045	-0.0328	-0.0719	0.0379	-0.0076
Nebraska	0.0597	0.0064	-0.0154	0.0871	-0.1034	-0.0271
Nevada	-0.0370	0.1261	-0.3226	0.2893	-0.2401	-0.1055
New Hampshire	0.0528	-0.0034	0.0508	0.0525	0.0053	0.0101
New Jersey	-0.0040	0.0126	-0.0124	0.0003	-0.0473	-0.0057
New Mexico	-0.0003	0.0052	0.0083	-0.0105	0.0230	0.0279
New York	-0.0091	0.0045	0.0084	0.0319	-0.0267	0.0065
North Carolina	0.0047	-0.0093	0.0324	0.1508	-0.1055	0.0035

North Dakota	0.0025	0.0067	-0.0451	0.0277	-0.0330	0.0124
Ohio	0.0272	-0.0069	0.0470	0.0226	-0.0790	0.0127
Oklahoma	0.0463	-0.0059	0.0353	-0.0112	-0.0842	-0.0076
Oregon	-0.0065	0.0033	0.0221	0.0062	-0.0565	0.0080
Pennsylvania	-0.0317	-0.0051	0.0590	0.0189	-0.0209	0.0280
Rhode Island	0.0615	-0.0201	0.0623	-0.0125	0.0129	0.0329
South Carolina	-0.0095	-0.0216	0.0603	-0.0177	-0.0771	-0.0202
South Dakota	0.0143	-0.0177	-0.0733	0.1796	-0.0828	0.0478
Tennessee	0.0507	-0.0655	0.2798	-0.0479	-0.0233	-0.0153
Texas	0.1451	-0.0881	-0.0845	-0.0579	-0.1559	-0.1098
Utah	0.0406	-0.0084	0.0256	-0.0067	0.0112	0.0106
Vermont	0.0151	-0.0008	0.0253	-0.0255	0.0036	0.0110
Virginia	0.0071	0.0086	0.0079	-0.0006	-0.0884	-0.0224
Washington	0.1142	-0.0080	-0.0125	0.0170	-0.0899	-0.0223
West Virginia	-0.0783	0.0022	-0.0052	0.0470	-0.0631	-0.0124
Wisconsin	0.0525	-0.0083	0.0622	-0.0295	-0.0261	0.0108
Wyoming	0.0306	-0.0033	0.0635	-0.1115	0.2223	0.0021