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LETTER

Cooking emissions are a major source of racial-ethnic air pollution exposure disparities in the United States

Provat K Saha[1,2,5], **Albert A Presto**[1,2], **Steve Hankey**[3], **Julian D Marshall**[4] and **Allen L Robinson**[1,2,6,*]

[1] Center for Atmospheric Particle Studies, Carnegie Mellon University, Pittsburgh, PA 15213, United States of America
[2] Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, United States of America
[3] School of Public and International Affairs, Virginia Tech, Blacksburg, VA 24061, United States of America
[4] Department of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195, United States of America
[5] Department of Civil Engineering, Bangladesh University of Engineering and Technology, Dhaka 1000, Bangladesh
[6] Current Address: Department of Atmospheric Science, Colorado State University, Fort Collins, CO 80523, United States of America.
[*] Author to whom any correspondence should be addressed.

E-mail: allen.robinson@colostate.edu

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Abstract

Racial-ethnic minority populations in the US are disproportionately exposed to airborne fine particulate matter ($PM_{2.5}$), but few national studies have focused individually on the sources that contribute to these disparities. We address this gap by conducting a comprehensive analysis of $PM_{2.5}$ exposure disparities by race-ethnicity in the US, focusing on three source-categories: mobile-sources, cooking, and all other sources combined. Our approach is based on high-resolution, national land-use regression estimates of source-resolved $PM_{2.5}$ components, derived from high-resolution aerosol mass spectrometer measurements. We find that each of these sources contributes approximately one-third of the overall $PM_{2.5}$ exposure disparities by race-ethnicity. While the importance of mobile-source tailpipe emissions is well recognized, our study underscores the significance of cooking emissions in creating $PM_{2.5}$ exposure disparities. This finding represents a potentially significant opportunity to reduce these disparities, as cooking emissions are currently largely unregulated. It has important implications for policymakers and public health advocates aiming to address the persistent issue of racial-ethnic disparities in air pollution.

1. Introduction

Fine particulate matter ($PM_{2.5}$) is a major air pollutant that has been shown to have significant health effects [1, 2]. $PM_{2.5}$ consists of particles with an aerodynamic size less than 2.5 μm. They are emitted by various sources; comprised of a complex mix of chemical components; and undergo substantial atmospheric processing [3–5]. Many studies have shown that $PM_{2.5}$ exposure in the United States is higher for racial-ethnic minority populations (people of color : POC; all people except non-Hispanic Whites) than for the White population [6–11]. Despite large decreases in overall $PM_{2.5}$ concentrations in the last two decades, the relative difference among racial-ethnic groups remains persistent [6].

There is growing national interest among US policymakers in reducing racial-ethnic disparities in air pollution; one example is the Biden administration's Justice40 initiative [12]. A cornerstone of US air pollution regulation is the National Ambient Air Quality Standards (NAAQS); however, recent studies suggest that NAAQS-like regulations (emission controls implemented to meet a concentration standard) may not be effective in eliminating $PM_{2.5}$ exposure disparities [13, 14]. For example, cities can comply with NAAQS but still have substantially higher exposure levels for minority communities. To develop more effective policies, it is essential to identify the underlying factors that drive exposure disparities.

In general, prior research on national disparities in air pollution exposure has either (1) considered sources and concentrations, using a reduced-complexity model [13, 15], or (2) considered concentrations only, not sources, using empirical models [6]. A national-scale analysis of reduced complexity air quality model predictions by Tessum *et al* [15] found that many sources contribute to racial-ethnic exposure disparities of $PM_{2.5}$, with mobile source emissions being an important contributor. Shah *et al* [16] used high spatial resolution measurements to demonstrate that urban restaurant emissions create significant $PM_{2.5}$ racial-ethnic exposure disparities in Oakland, CA and Pittsburgh, PA; these measurement-derived disparities are larger than those predicted by Tessum *et al* [15]. The modeling results of Tessum *et al* [15] predicted that cooking is a modest contributor to disparities at the national scale. While the impact of traffic emissions on racial-ethnic exposure disparities is well-established [6, 10, 11, 15, 17], the national-scale importance of cooking emissions remains under-explored. Our research advances the literature and combines strengths across those two prior methods, by using a source-specific empirical model. We capture the measurement-based reliability and the spatial resolution of an empirical model with the utility of source-specific prediction.

In this study, we used published empirical models [18–20] to quantify the contributions of specific sources of $PM_{2.5}$ to racial-ethnic exposure disparities at the census block group level for the contiguous United States [21]. We classified total $PM_{2.5}$ mass into three source categories: primary $PM_{2.5}$ from restaurants and household cooking ('cooking $PM_{2.5}$'), primary $PM_{2.5}$ from mobile source tailpipe emissions ('mobile source $PM_{2.5}$'), and 'other $PM_{2.5}$' (including primary $PM_{2.5}$ from all other sources, plus all secondary $PM_{2.5}$). Primary $PM_{2.5}$ is directly emitted from sources; secondary $PM_{2.5}$ is formed in the atmosphere from gas-phase precursors. In this paper, we use the term 'exposure' to refer to outdoor concentrations.

Our analysis revealed that while primary $PM_{2.5}$ from cooking and mobile source tailpipe emissions only contribute approximately 12% of national population-weighted average exposure to total $PM_{2.5}$ mass, they disproportionately impact exposure disparities among racial ethnic communities. Specifically, primary cooking and mobile-source tailpipe emissions each contribute to approximately one-third of overall $PM_{2.5}$ exposure disparities by race-ethnicity. Urban-rural and intra-urban distribution of these sources and racial-ethnic demographic distribution play a significant role in understanding disparities.

2. Materials and methods

2.1. National estimates of source-resolved $PM_{2.5}$

The analysis is based on land-use regression model predicted annual-average outdoor concentrations of source-specific $PM_{2.5}$ components at the centroid of approximately 6 million census blocks [18, 19]. The models were derived from a national dataset of high-resolution aerosol mass spectrometer (HR-AMS) measurements, encompassing a wide range of relevant source-activity-relevant land-use scenarios. The HR-AMS dataset consists of (1) fixed monitoring data from urban and rural background locations across the US and (2) highly spatially resolved mobile measurements conducted in three US cities (Pittsburgh, PA; Oakland, CA; Baltimore, MD). Positive matrix factorization of HR-AMS measured organic mass spectra was employed to estimate source contributions, including cooking organic aerosol (COA) and hydrocarbon-like organic aerosol (HOA).

We provided a comprehensive description of the underlying dataset, model-building process, and validations in our previous publications. In this paper, we apply our previously-validated modeling estimates to investigate exposure disparities for source-specific $PM_{2.5}$ components. Further details about the exposure estimates are available elsewhere [18, 19].

Briefly, we applied a land-use regression (LUR) modeling framework [18, 22] to develop models using measured concentrations and predictor land-use covariates. Subsequently, we applied the cross-validated models to predict concentrations at unmeasured locations, specifically at the centroids of census blocks across the continental US. Our COA and HOA LUR models explain more than 60% of the spatial variability of the measured data (R^2 of 0.63 for the COA model and 0.62 for the HOA model). The main predictor variables for the COA model include restaurant density, urbanicity as measured by the percentage of impervious surface, and commercial land use. The main predictor variables for the HOA model are road density, transportation land use, and urbanicity. The robustness and transferability of the models were evaluated using multiple methods, such as random 10-fold cross-validation, systematic spatial holdout, and comparison with simulations from a chemical transport model [18].

In our analysis, we used the sum of HOA and mobile-source black carbon (BC_{mobile}) as primary $PM_{2.5}$ from mobile source tailpipe emissions. The black carbon (BC) LUR model is described in Saha *et al* [19]. The BC model is derived using high-spatial resolution mobile sampling and fixed site data from the US EPA $PM_{2.5}$ speciation monitoring network (CSN and IMPROVE). The BC model explains about 70% of the spatial variability of measured data (10-fold CV R^2: 0.71), with urbanicity, road density, transportation, and residential land use as important predictor variables.

To apportion the predicted BC concentration into mobile (BC_{mobile}) and other (BC_{other}) sources, we utilized elemental carbon (EC) emission data from mobile and non-traffic sources, obtained from the National Emission Inventory (NEI, 2017) [23]. The detailed estimation method is described in Saha *et al* [19]. In brief, we calculated BC_{other} as the model predicted county average BC multiplied by the fraction of county-average EC emissions from non-traffic sources. NEI emission data are aggregated at the county level. This calculation was done for each US county. We then assigned the same value to all census blocks within each county boundary. This approach is reasonable because BC_{other} is primarily influenced by biomass burning, such as wildfires, which tends to show modest spatial variation within a county. We estimated census block-level BC from mobile sources as $BC_{mobile} = (BC—BC_{other})$.

We assumed that all cooking-related primary $PM_{2.5}$ is organic aerosols (COA), which is supported by both source measurements [24] and emission inventory data for cooking-related primary $PM_{2.5}$. For instance, the 2017 NEI [23] reports that approximately 95% of primary $PM_{2.5}$ emissions from commercial cooking consist of organic carbon, with the contribution of EC being only 5%.

Other $PM_{2.5}$ is the difference between total $PM_{2.5}$ and primary $PM_{2.5}$ from cooking (COA) and mobile sources (HOA + BC_{mobile}). The total $PM_{2.5}$ estimates are from Kim *et al* [20]. Other $PM_{2.5}$ is mostly composed of secondary inorganic and organic species [19]. It also includes primary $PM_{2.5}$ from various other sources such as industrial emissions, biomass burning, non-tailpipe primary $PM_{2.5}$ emissions from mobile sources, such as brake and tire wear, and resuspended road dust. Since the 'other' category was derived via mass balance with total $PM_{2.5}$, 'other' is comprehensive—it includes $PM_{2.5}$ contributions from all sources, other than the two we specifically studied (i.e. cooking; tailpipe mobile). In our analysis, non-tailpipe primary $PM_{2.5}$ (e.g. brake and tire wear) were included in the 'other' category.

2.2. National demographic data

We used publicly available race, ethnicity, and household income data from National Historical Geographic Information System (NHGIS) [25]. NHGIS provides information on the number of households in each census block group by eight racial and two ethnic categories (16 total categories). For our analysis, we grouped these sixteen racial-ethnic groups into five categories: (i) not Hispanic or Latino White (65.4% of the total population), (ii) not Hispanic or Latino Black (12.1% of total population), (iii) not Hispanic or Latino Asian (4.3% of total population), (iv) Hispanic or Latino from any race: Hispanic; 15.5% of total population, and (v) not Hispanic or Latino other racial minority including American Indian, Alaska Native, Native Hawaiian, Other Pacific Islander, Two or more races: Other POC; 2.7% of total population. In some analyses, we used two racial-ethnic population bins: (i) not Hispanic or Latino, White alone (65.4% of the total population), and (ii) racial-ethnic minority population (POC; 34.6% of the total population).

NHGIS provides household income data at the block-group level. We used this block group level data for separate assessment of exposure disparity by race-ethnicity or income.

The NHGIS does not report household income data disaggregated by race ethnicity at the block group level. It does provide it at the census tract level. Therefore, for our analysis of race-ethnicity and income, we used household income data at the census tract level. For this combined analysis, we used a total of twenty combined racial-ethnic-income groups: four income groups ('<\$15 000': extremely low-income, '\$15 000–\$50 000': low-income, '\$50 000–\$100 000': medium-income, and '>\$100 000': high-income) and five race-ethnicity groups (as described above).

We used 2010 census demographic data as our air pollution concentration estimates [18] were based on predictor variables computed at the centroids of 2010 census blocks. Our analysis included 210 000 census block groups, with an average population of 1400, and 70 000 census tracts, with an average population of 4200, across the continental US.

2.3. Exposure disparities analyses

We calculated exposure disparities in $PM_{2.5}$ and its components, specifically cooking emitted primary $PM_{2.5}$, mobile source tailpipe primary $PM_{2.5}$, and other $PM_{2.5}$, by race-ethnicity and income by combining air pollution and demographic data. Previously we have applied a similar approach for investigating national-scale exposure disparities for ultrafine particles [17]. We matched air pollution concentration data at the block-level with demographic data at the block-group or tract level. To do so, we computed population-weighted means of census block level concentration within each block-group or tract spatial boundaries. Our analysis included comparisons of concentrations in all census block groups nationwide, binned into deciles by the proportion of POC in each block group, as well as comparisons of urban and rural census block groups as defined in census. We also computed population-weighted mean concentrations for various race-ethnicity and income groups to compare state, county, and national average exposure disparities. Finally, we performed a similar analysis using directly measured air pollution concentration data from 100 to 350 locations across the US, which were used to develop the empirical models [18, 19].

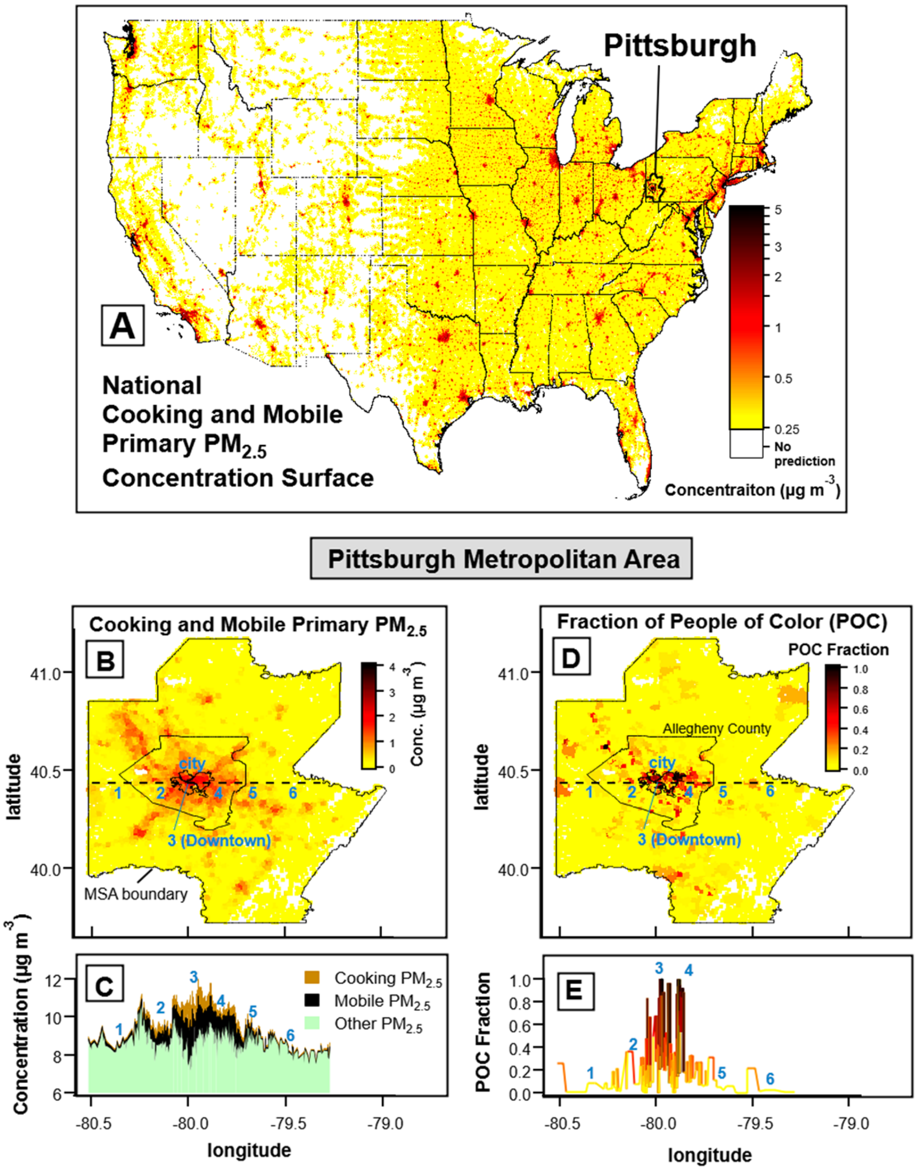

Figure 1. Spatial distribution of cooking and mobile source primary $PM_{2.5}$ and racial-ethnic demographic data. (A) National data across the contiguous US and (B) Pittsburgh Metropolitan Statistical Area (MSA), a representative urban area. (C) Concentration profile of cooking, mobile source primary $PM_{2.5}$ and other $PM_{2.5}$ along transect line 1–6, as marked on panel B. (D) Distribution of racial-ethnic minority population (people of color; POC) across the Pittsburgh MSA. (E) Profile of racial-ethnic minority population along transect line 1–6, as marked on panel D. Transect lines pass through the city center (downtown Pittsburgh). The color scale in panel A is a log scale, while in other panels, the color scale is linear. The spatial resolution of $PM_{2.5}$ concentrations (panels (A)–(C)) is at the census block. The spatial resolution of the demographic data (panels (D), (E)) is at the census block-group. In panel A, 'no prediction' locations refer to the census blocks where our model was not used to predict concentrations. We made predictions only for census blocks with a non-zero population and for those with predictor variable values falling within the 1st and 99th percentile range of the measurement dataset used for model development. This approach resulted in the exclusion of approximately 3% of census blocks nationwide, primarily those in extremely urban or rural areas where the predictor land-use features were outside our model's training dataset.

3. Results and discussion

Figure 1(A) shows predicted cooking and mobile-source tailpipe $PM_{2.5}$ concentrations across the continental US with census block resolution. There are hotspots in cities and along interstate highways. Figures 1(B)–(E) shows the spatial patterns within a typical urban area—the Pittsburgh Metropolitan Statistical Area (MSA). The concentrations of cooking and mobile source primary $PM_{2.5}$ are highest in the central business district. The distribution of POC follows a similar pattern. Other MSAs show similar trends (figure S1).

In general, primary $PM_{2.5}$ from cooking and mobile source tailpipe emissions is more pronounced in densely populated MSAs. There is a moderate positive association between primary $PM_{2.5}$ from these sources and MSA population density, as indicated by R^2 values of 0.22 for cooking primary $PM_{2.5}$ and 0.36 for mobile-source tailpipe $PM_{2.5}$ when regressed against log MSA population. This association is likely attributed to the greater prevalence of these sources in

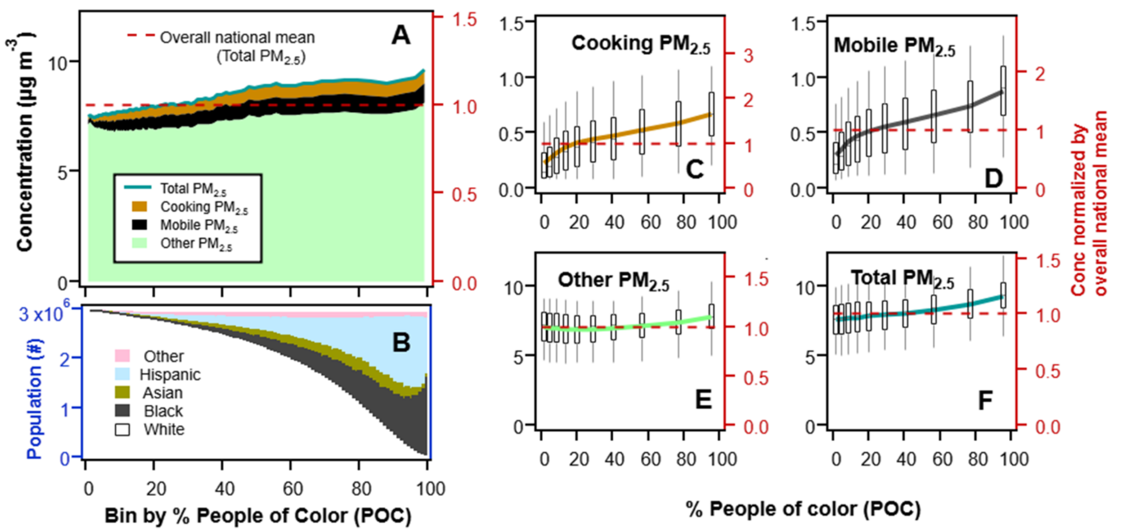

Figure 2. Concentration of total $PM_{2.5}$, cooking primary $PM_{2.5}$, mobile source primary $PM_{2.5}$, and other $PM_{2.5}$ in census block-groups rank-ordered by increasing percentage of people of color (POC). Left: Panels (A) and (B) show data grouped 100 equal population bins. (A) Average concentrations for each bin. The right axis shows the total $PM_{2.5}$ concentration relative to the all population-weighted national mean of $PM_{2.5}$ (red dashed line). (B) Population of White, Black, Asian, Hispanic, and other POC in each bin. Panels (C) through (F) show data grouped into deciles. Right: Box whisker plots of concentrations of (C) cooking, (D) mobile, (E) other $PM_{2.5}$, and (F) total $PM_{2.5}$. Boxes show 25th and 75th percentile, whiskers show 5th and 95th percentile, and the thick colored lines show the mean. The right axis in each panel shows concentrations relative to the all population-weighted mean concentrations. The red dashed line serves as a visual guide, indicating the all population-weighted mean concentrations.

densely populated metro areas with higher restaurant and traffic densities. Furthermore, these sources are disproportionately located near communities with a higher fraction of POC.

To quantify the exposure disparities across the continental US, we rank ordered all census-block groups in continental US by proportion of POC and then divided the data into decile bins. The results from this analysis are shown in figure 2, which demonstrates that census block groups with higher fractions of POC have significantly higher concentrations of cooking and mobile source primary $PM_{2.5}$ compared to the national population-weighted average. For example, the exposure disparity between the highest and lowest decile bins of POC is 1.7 μg m^{-3} for total $PM_{2.5}$ mass (figure 2(F)), with 0.48 μg m^{-3} attributed to cooking primary $PM_{2.5}$ (figure 2(C)) and 0.57 μg m^{-3} attributed to mobile source primary $PM_{2.5}$ (figure 2(D)). Therefore, each of these sources contribute roughly one-third of the total $PM_{2.5}$ mass exposure disparities.

While primary $PM_{2.5}$ from cooking and mobile source tailpipe emissions account for about two-thirds of $PM_{2.5}$ exposure disparities, figure 2(E) shows that they make relatively minor contributions to the total $PM_{2.5}$ mass concentrations. The majority (88%) of this $PM_{2.5}$ mass concentrations come from other $PM_{2.5}$, which are mainly secondary species, such as sulfate, nitrate, ammonium, and secondary organic aerosols that are relatively uniformly distributed in space.

Urban-rural differences are an important contributor to exposure disparities (figure S2). Nationally, a greater proportion of POC reside in urban compared to rural areas (POC: 82% urban, 18% rural; non-Hispanic White: 60% urban, 40% rural) (figure S3). In addition, concentrations of primary $PM_{2.5}$ from cooking and mobile source tailpipe emissions are significantly higher in urban areas, as demonstrated in figure 1. For example, urban background concentrations of cooking and mobile primary $PM_{2.5}$ are 5–10 times higher than those in rural areas, which highlights the importance of cooking and mobile sources. The combination of these factors creates higher population-weighted exposures of these pollutants among POC compared to Whites. $PM_{2.5}$ in rural areas is mainly secondary, which does not contribute to significant disparities. Industrial and wildfire sources can be important primary $PM_{2.5}$ sources in certain regions [26], but these sources are not as widespread or frequently as close to population centers as traffic and cooking sources.

In the United States, air pollution regulations are frequently implemented at the state level. Figure 3 presents state-average $PM_{2.5}$ exposure disparities. There is considerable state-to-state variability in racial-ethnic exposure disparities, but 42 states have higher total $PM_{2.5}$ exposures for POC group than White population group (figure 3(A)). The largest disparities are in the northeastern and midwestern regions of the United States. For instance, the ten states with the highest $PM_{2.5}$ exposure disparities are Illinois, California, New York, Missouri, Kentucky, Wisconsin, Michigan, New Jersey, Arkansas, and Pennsylvania.

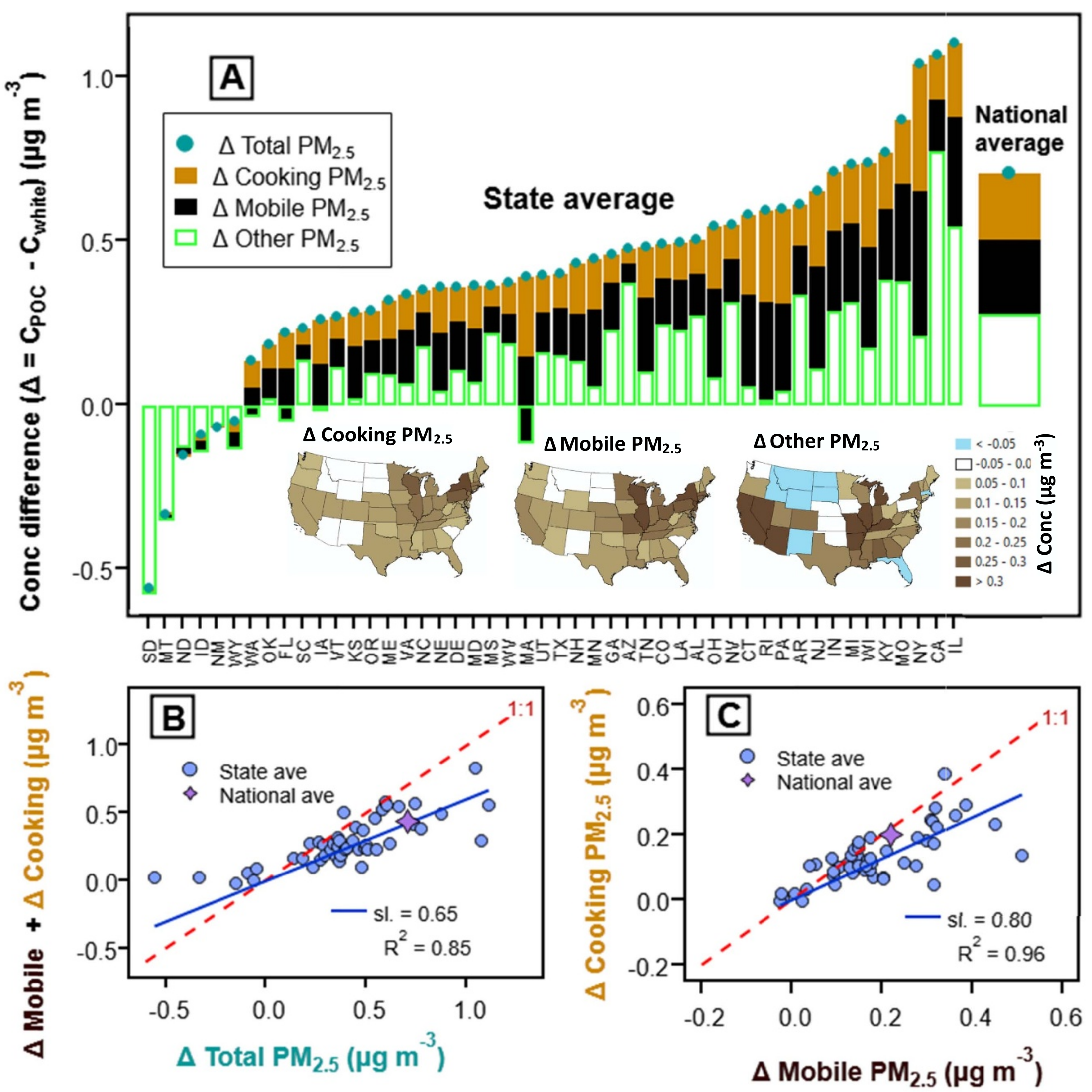

Figure 3. State-level analysis of $PM_{2.5}$ exposure disparities among different racial-ethnic groups. (A) Population-weighted concentration differences between POC and non-Hispanic White population groups, with states ranked by total $PM_{2.5}$ exposure disparities. Contributions of cooking, mobile, and other $PM_{2.5}$ to total $PM_{2.5}$ exposure disparities are shown for each state. Inset maps show the state-level average spatial distribution of cooking and mobile, and other $PM_{2.5}$ exposure disparities between POC and non-Hispanic White groups across the continental US. (B) Scatter plot of exposure disparities between POC and non-Hispanic White population groups from cooking and mobile source primary $PM_{2.5}$ versus total $PM_{2.5}$. (C) Scatter plot of exposure disparities between POC and non-Hispanic White population groups from cooking primary $PM_{2.5}$ versus mobile source primary $PM_{2.5}$.

We investigated the contribution of cooking and mobile-source tailpipe emissions to state-level disparities. Figure 3(B) shows a linear regression of the state-average total $PM_{2.5}$ exposure disparities between POC and White groups versus the disparities from cooking plus traffic $PM_{2.5}$. The slope of this regression is 0.65 (figure 3(B)), which indicates that, on average, approximately two-thirds of the state-average total $PM_{2.5}$ exposure disparities are a result of cooking and mobile primary $PM_{2.5}$ emissions. However, variations in traffic and cooking-related source activity can help explain these state-to-state differences. Road density, restaurants, and commercial activities in proximity to locations with a higher fraction of racial-ethnic minority population are higher in states with higher disparities than in other states (figure S5). The slope of the state-average cooking versus traffic $PM_{2.5}$ disparities is 0.78 (figure 3(C)), indicating nearly similar contributions of mobile-source and cooking emissions to total $PM_{2.5}$ disparities. County-level data show similar trends (figure S6).

Figure 4 summarizes the national population-weighted average exposure disparities among four different racial-ethnic groups: non-Hispanic white, black, Asian, and Hispanic. The data indicates that for POC, cooking emissions contribute ∼30% of the national-average $PM_{2.5}$ exposure disparities, mobile source primary tailpipe emission contribute 33%, and the remaining from other $PM_{2.5}$ sources. Although figure 4(A) indicates there is modest variability among different POC subgroups, all subgroups have higher exposures than the national average.

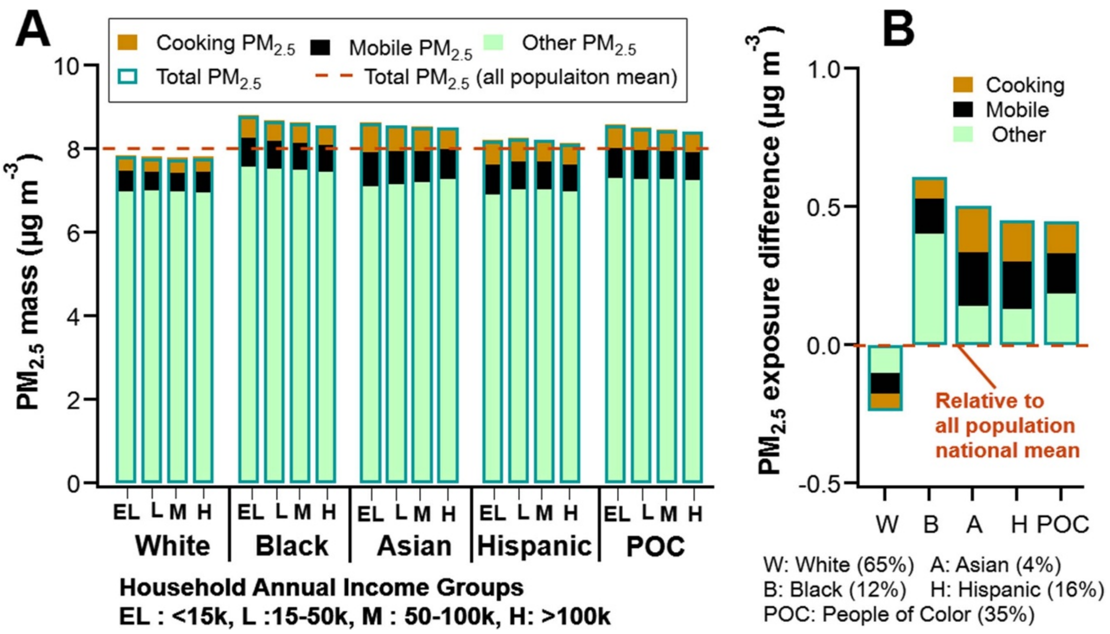

Figure 4. National population weighted average source-resolved $PM_{2.5}$ exposure disparities for different racial-ethnic population and income groups. (A) National population-weighted average concentrations for each combined race-income group. The total height of the bar represents the total $PM_{2.5}$ concentration for each race-income class. The contributions of cooking, mobile, and other $PM_{2.5}$ to the total $PM_{2.5}$ mass concentrations are shown by filled colors. The red dashed line represents the all population-weighted mean total $PM_{2.5}$. (B) Concentration differences for each race-ethnic groups relative to the population-weighted national mean. The total height of the bar represents $PM_{2.5}$ exposure differences. The colors show the contributions of cooking, mobile, and other $PM_{2.5}$ to the total $PM_{2.5}$ exposure difference.

We also examined exposure disparities by income. Figure 4(A) shows that exposure disparities by race-ethnicity are much larger than those based on income. Across all income classes, exposures are higher for POC than Whites. For example, extremely low-income (<15 000 USD per year) Whites have substantially lower exposures than high-income (>100 000 USD per year) POC. However, within a specific demographic group, exposures are only slightly higher for the low-income than for high-income populations. The proportion of POC and Whites living in urban versus rural areas does not vary substantially across income classes (approximately POC: 82% urban and 18% rural; White: 60% urban and 40% rural) (figure S3), which helps explain why variations in household income do not play a significant role in explaining exposure disparities.

The results in figures 2–4 are based on census block-level model estimates for source-specific $PM_{2.5}$ components. The models reasonably captured spatial variabilities of pollutants, as indicated by the cross-validation R^2, which ranged between 0.62 and 0.71. To investigate whether the observed patterns are artifacts of model predictions, we repeated the analyses using directly measured air pollution concentration data from approximately 100–350 locations across the United States (figure S7). The measured data shows similar results to the empirical models. For example, the measured mobile and cooking primary $PM_{2.5}$ concentrations are 80% higher in census block groups with the highest decile of POC fraction, compared to the lowest decile bin. This provides confidence in the conclusions drawn from model predictions. However, as is inherent in any modeling exercise, there is always some degree of uncertainty in model estimates, and future research should consider improvements, such as the incorporation of more observational data and enhanced predictors.

We compared our results to those of Tessum *et al* [15] who used a reduced-complexity chemical transport model to predict source-resolved exposure disparities using emissions data. This is a fundamentally different approach than the land-use regression model estimates shown in figures 2 and 3. It is based on emission inventories and predicted pollutant dispersion versus our land-use regression model that is derived from field measurements.

The two models estimate similar contributions of mobile source emissions. For example, Tessum *et al* [15] estimated that mobile sources contribute about 40% of the national-average exposure disparity for total $PM_{2.5}$, which is similar to our empirical model estimates of 33%. In addition, our analysis is a lower-bound estimate for disparities caused by primary emissions from mobile sources because it does not account non-tailpipe emissions such as brake and tire wear and resuspended road dust [27, 28]. The reasonable agreement between our predictions for mobile source emissions and those presented by Tessum *et al* enhances our confidence in the validity of our approach.

However, our empirical models predict that cooking is a more important source of exposure disparities than the reduced complexity model predictions of Tessum *et al* [15]. We estimate that cooking contributes ∼30% of the $PM_{2.5}$ exposure disparity, which is more than three times that estimated by Tessum *et al* [15]. We believe that this difference is attributable to uncertainty in the county-level National Emissions Inventory (NEI) cooking data; the NEI was used by Tessum *et al* as part of their modeling [15]. We hypothesize that cooking emissions are not widely recognized as a major contributor to air pollution, so they have not received as much attention when developing emission inventories such as the NEI (especially compared to mobile sources) [29, 30].

4. Implications

The important new finding of this study is that nationally, the three emission sources we studied (cooking; tailpipe mobile; all other sources) each are major sources of $PM_{2.5}$ exposure disparities, with the three contributions being similar in magnitude to each other. That means that contributions of cooking emissions are almost comparable to tailpipe emissions from mobile sources in terms of total $PM_{2.5}$ exposure disparities by race-ethnicity. However, cooking as a source is far less recognized compared to mobile source tailpipe emissions. Targeted reductions in cooking emissions may be effective in reducing exposure disparities (figure S8). Some effective $PM_{2.5}$ emission control technologies exist for cooking [31], such as high-efficiency stoves, enhanced filtration systems, and improved usage and maintenance. However, cooking emissions are only regulated in a few locations in the US [32, 33].

While our study underscores the significance of cooking emissions, mobile sources continue to play a substantial role in driving exposure disparities. Our primary analysis focused on tailpipe emissions from mobile sources (HOA and BC). The impact of mobile sources could be even greater than our estimations when considering the non-tailpipe contribution (e.g. tire and brake wear). Nevertheless, mobile source tailpipe emissions have been subjected to stringent controls over decades; it may be that further reductions are more challenging and costly compared to reducing cooking emissions.

Eliminating exposure disparities may require altering the spatial patterns of emissions. Mobile-source regulations often focus on reducing tailpipe emissions, in order to reduce overall average exposure. However, implementing increasingly strict tailpipe emission standards may reduce average exposures but not eliminate disparities, because high-traffic roads are disproportionately located in and near minority communities. Even a dramatic shift towards electric vehicles, which produce no tailpipe emissions, might not eliminate the disparities because electric vehicles still generate non-tailpipe $PM_{2.5}$ (e.g. brake and tire wear; resuspended road dust) [34]. Eliminating disparities may require ambition, 'outside the box' solutions such as selectively relocating urban freeways, redesigning urban centers and transportation infrastructure [35], and creating low-emission zones [36, 37]. Those types of interventions may be more challenging than reducing cooking emissions.

The exposure disparities in the US are structured and systematic. Underlying past policies (e.g. redlining, eminent domain for freeway/industrial siting, etc) created the foundation for many of these systemic disparities [38, 39]. Since the problem is systematic and structured [13, 40], solving these aspects will require systematic and targeted intervention. For instance, emission sources are often located in close proximity to neighborhoods with a higher percentage of POC. Therefore, to effectively address this problem in a city or metropolitan area, interventions should focus on emissions in these specific neighborhoods, rather than imposing policies uniformly for all [13], unless it is possible to ensure a zero-exposure scenario for everyone. However, many of these interventions could be challenging depending on the social perspective and acceptability, and cost for absolute elimination of the disparity. Strong political leadership, community engagement, technological interventional, targeted legislation and regulation, and many other actions may be required in coming decades to eliminate disparities in exposure to air pollution in the United States.

Data availability statements

All data needed to evaluate the findings in the paper are present in the main text and/or the supplementary materials. Additional data related to this paper are available on www.caces.us/ and can be requested from the authors.

All data that support the findings of this study are included within the article (and any supplementary files).

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endorse any products or commercial services mentioned in this publication.

Author contributions

Conceptualization: P K S, A A P, S H, J D M, A L R
Methodology: P K S, A A P, S H, J D M, A L R
Investigation: P K S, A A P, A L R
Visualization: P K S
Supervision: A A P, A L R
Writing—original draft: P K S
Writing—review & editing: P K S, A A P, S H, J D M, A L R

Conflict of interest

Authors declare that they have no competing interests.

ORCID iD

Allen L Robinson https://orcid.org/0000-0002-1819-083X

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