U.S. ambient air monitoring network has inadequate coverage under new $PM_{2.5}$ standard

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Abstract

The Clean Air Act (CAA) in the United States relies heavily on regulatory monitoring networks, yet monitoring sites are sparsely located, especially among historically disadvantaged communities. For ambient fine particulate matter ($PM_{2.5}$), we compare the air quality monitoring data with spatially complete concentrations derived from empirical models to quantify the gaps of existing U.S. monitoring networks in capturing concentration hotspots and exposure disparities. Recently, the U.S. Environmental Protection Agency adopted a more stringent annual-average air quality standard for $PM_{2.5}$ (9 $\mu g/m^3$). Here, we demonstrate that 44% of urban areas exceeding this new standard – encompassing ~ 20 million people – would remain undetected because of gaps in the current $PM_{2.5}$ monitoring network. Crucially, we find that "uncaptured" hotspots, which contain 2.8 million people in census tracts that are misclassified as in attainment of the new $PM_{2.5}$ standard, have substantially higher percentages of minority populations (i.e., people of color, disadvantaged communities, and low-income populations) compared to the overall US population. To address these gaps, we highlight 10 priority locations that could reduce the population in the uncaptured hotspots by 67%. Overall, our findings highlight the urgent need to address gaps in the existing monitoring network.

Keywords: $PM_{2.5}$, Clean Air Act, air quality monitoring, environmental justice, NAAQS

Synopsis: Existing air quality monitoring networks are insufficient to capture concentration hotspots, disproportionately impacting minority populations.

Introduction

Ambient air pollution causes hundreds of billions of dollars in health damages per year in the United States, driven principally by the health effects of fine particulate matter ($PM_{2.5}$). These exposures and health burdens disproportionately affect people of color (POC) and low-income populations.[1–3] The US Environmental Protection Agency (EPA), implementing the Clean Air Act (CAA) over the past five decades, has dramatically reduced exposures to criteria air pollutants for hundreds of millions of Americans, yielding enormous health benefits.[4] Nonetheless, we don't all breathe the same air, and major disparities in exposure remain.[2,5–8]

The CAA relies on State and Local Air Monitoring Station (SLAMS) networks for determining hotspots and background concentrations, the health and welfare impacts of air pollution, and compliance with the National Ambient Air Quality Standards (NAAQS) (see Supporting Information [SI], Section 1)[9]. However, due to the high capital and operational cost of monitoring stations, the existing SLAMS network is sparsely located across the US, often missing localized concentration variations[10,11] and causing millions of high-exposure populations to be undetected and unprotected by the monitors.[12–14]

Moreover, there are disproportionately fewer monitoring sites in communities with higher shares of POC and low-income people.[14–17] While new measurement approaches such as low-cost sensors and mobile monitoring have made denser monitoring networks and high-resolution concentration surfaces feasible,[18–21] such data are still unevenly distributed among those communities[22–24] and have not been incorporated in the NAAQS nonattainment process.

On February 7, 2024, EPA revised the annual primary standard for $PM_{2.5}$, from 12 $\mu g/m^3$ to 9 $\mu g/m^3$.[25] At present, EPA is modifying the $PM_{2.5}$ monitoring network design to include an environmental justice factor[25] and is distributing tens of millions of dollars for enhancing monitoring in overburdened communities.[26,27] However, limited scientific knowledge exists regarding: 1) the effectiveness of the existing monitoring networks under the new standard and 2) how to address the monitoring gaps. Here, we quantify gaps in the SLAMS network's ability to detect concentration hotspots under the new $PM_{2.5}$ standard, particularly for minority populations. We also evaluate approaches for adding monitoring sites to address these gaps. We find that the existing SLAMS are inadequate for capturing concentration hotspots and disparities. Adding monitors can improve the representation of concentration hotspots, but not concentration disparities. This study provides the first quantification of the monitoring gaps under the new and future decreasing standards and informs policies for addressing the monitoring gaps.

Materials and Methods

Air pollution data and attainment status definition

The U.S. EPA uses ambient measurements from SLAMS to determine whether a specific geographical area is in attainment of the NAAQS. Attainment here is assessed for Core-Based Statistical Areas (CBSAs), which each correspond to one or more adjoining counties that encompass a large urban area or population nucleus. We employ CBSAs because they are usually used for determining area-wide air quality levels and planning new monitors (see SI Section S1).[9] There are 894 CBSAs in the contiguous U.S., home to 320 million people: 379 metropolitan statistical areas (MSAs; population ≥ 50,000) and 515 micropolitan statistical areas (μSAs; population 10,000-49,999).

To investigate whether SLAMS are potentially missing areas of elevated $PM_{2.5}$ in excess of the NAAQS, we employ a spatially complete dataset of census-tract level $PM_{2.5}$ estimates for the contiguous U.S. from the empirical model of the Center for Air, Climate and Energy Solutions (CACES, www.caces.us),[28,29] building on partial least squares regressions with universal kriging framework. For the model years we consider here (2017-2019), the predictions have high-fidelity to out-of-sample validation measurements (R^2: 0.77-0.83; standardized root mean square error: 14%-16%).[29] We compute three-year averaged tract-level concentrations from the annual model predictions to match EPA's design values (three-year averaged measurements)[30] and further reduce the influence of model uncertainties and extreme events (see SI Section S2).

Next, we obtain the design values and geographical coordinates of the 2017-2019 active $PM_{2.5}$ monitoring sites (n = 988) from the EPA's Air Quality System and match them with CACES predictions (Figure S1). To further validate the empirical model, we check if model predictions correctly classify monitoring sites exceeding 9 μg/m^3 NAAQS (Figure S2). The model's low bias makes our conclusions slightly conservative in identifying exceeding tracts. As sensitivity tests, we separately employ years 2017, 2018, and 2019 from CACES, and an alternative dataset of remotely-sensed 0.01° × 0.01° resolution (~1.1 km) $PM_{2.5}$ predictions (see SI Section S2).[31]

For each CBSA, we compare $PM_{2.5}$ model predictions at monitoring sites with $PM_{2.5}$ distributions for all census tracts. EPA determines a CBSA as "nonattainment" if any SLAMS monitors' design values exceed the NAAQS. We adapt this by defining nonattainment as having three or more tracts within a CBSA exceeding the standard, allowing us to focus on areas with elevated concentrations that likely affect thousands of people, rather than small-location hotspots. As sensitivity tests, we employ alternative nonattainment definitions (see SI Section 2). Finally, we classify nonattainment CBSAs by whether the $PM_{2.5}$ estimates at monitoring locations exceed the NAAQS (see Table S1). CBSAs are considered to be "captured" if they are correctly identified as nonattainment by monitoring locations; and "uncaptured" if they are misclassified as in attainment by monitoring locations, but have other unmonitored hotspots exceeding the NAAQS. Uncaptured CBSAs are of special concern here. As another sensitivity test, we evaluate nonattainment at the county level (see SI Section S2).

Demographic data and exposure disparities

We consider three demographic groupings: (1) race-ethnicity, (2) disadvantaged community (DAC) status, and (3) median household income, all by Census Tract for 2020. The five racial-ethnic groups based on US Census data are: non-Hispanic White (58%; "White"), Latino or Hispanic (19%; "Hispanic"), non-Hispanic Black or African American (12%; "Black"), non-Hispanic Asian and Pacific Islander (5%; "Asian"), and American Indian, another race, or multiracial (3%; "Other"). All except non-Hispanic White are grouped as People of Color (POC).

Second, DACs are defined by combining six publicly available national screening tools from the federal government (see SI Section S3; Table S2). We identify a census tract as DAC if it surpasses the specified thresholds by three or more tools (~25% of the total US population; Figures S3-S6). The reasons for combining six tools are to avoid the ineffectiveness or uncertainty in any single tool[32] and to highlight locations of highest concern or federal funding.

Third, median household income is from the 2020 American Community Survey. We classify income into tertiles: high (> \$76,164), middle (\$51,168 - \$76,164), and low (<\$51,168).

We calculate $PM_{2.5}$ exposure disparities by race-ethnicity, DAC status, and household income, respectively, as the population-weighted average concentration for POC, DAC, and low-income populations, minus the overall population-average concentration. Disparities are calculated for all census tracts and tracts near monitors (n = 4,360; defined here as centroids within 1-km buffer of a monitoring site).

Results and Discussion

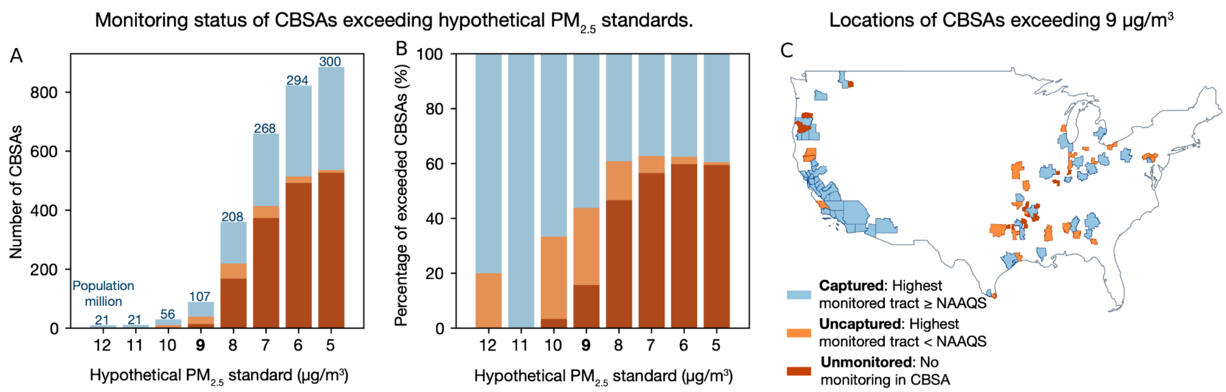

Figure 1. Core-based statistical areas (CBSAs) exceed a hypothetical $PM_{2.5}$ standard, classified by monitoring status. Here, we consider only those CBSAs with three or more census tracts that have modeled $PM_{2.5}$ exceeding a range of hypothetical $PM_{2.5}$ standards, which we thereby consider to be in nonattainment. We classify the (a) number and (b) percentage of CBSAs exceeding the $PM_{2.5}$ standard into three distinct groups. In blue, we present “captured” CBSAs. These CBSAs are correctly identified as exceeding the standard, by virtue of having monitors located in tracts that exceed the standard. In orange, we present “uncaptured CBSAs,” which would be misclassified as in attainment based on present monitoring locations. In these uncaptured CBSAs, the highest monitored tract does not exceed the standard, despite other unmonitored hotspot tracts exceeding the standard. Finally in red, we show CBSAs that exceed a given standard value and have no monitors at all. There are no red or orange bars in (a) and (b) when the standard is set at 11 μg/m³, as the highest concentrations in all nonattainment CBSAs fall between 11 and 12 μg/m³. Therefore, with a standard of 11 μg/m³, there are no “uncaptured” or “unmonitored” CBSAs (see Figure S8 for details). In (c), we illustrate the geographic distribution of CBSAs for the new $PM_{2.5}$ NAAQS of 9 μg/m^3.

The median number of $PM_{2.5}$ monitoring stations in an MSA is 1 (µSA: 0) (population-weighted median: 5 [MSA], 1 [µSA]; Figure S7). On average, there is one site per 250,000 people. For NAAQS attainment status, the results reveal that 89 CBSAs (total population: 107 million) exceed the new $PM_{2.5}$ standard (9 µg/m^3) (Figure 1a). Among the nonattainment CBSAs, 44% (n=39; 20 million people) are not captured by monitoring (Figures 1b and S8), because the CBSA has either no monitoring stations or the existing locations fail to capture the concentration hotspots (see Figure S9 for case studies). Most uncaptured nonattainment CBSAs are in the Midwest and South (Figure 1c). The estimations of monitoring gaps are robust considering model errors, using alternative nonattainment definitions, separate years, alternative concentration data, and at the county level (see SI Section S2; Figures S10-S13; Table S3). Under future decreasing standards (e.g., to the World Health Organization guideline, 5 µg/m^3), ~60% of nonattainment CBSAs would not be captured by existing monitors (Figure 1b).

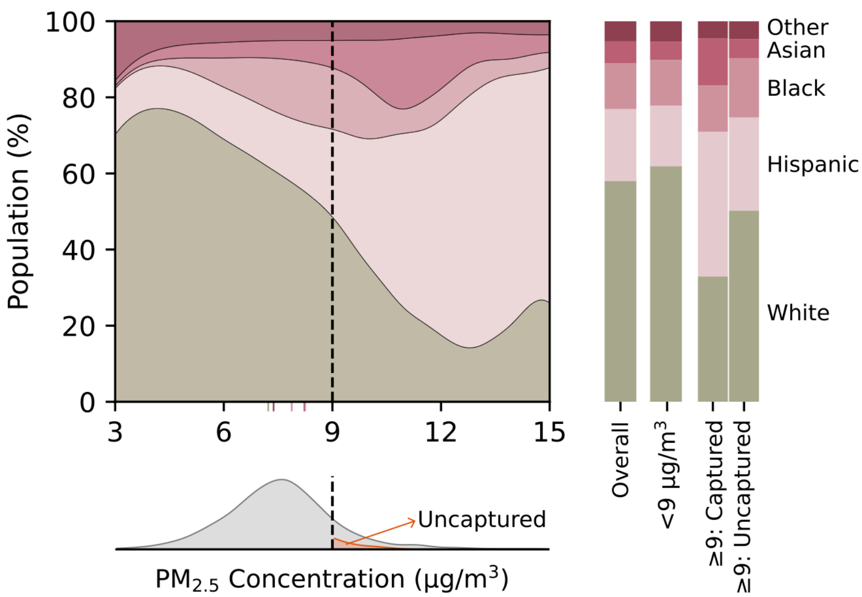

Figure 2. Tract-level racial-ethnic composition under different $PM_{2.5}$ exposure levels. Instead of considering the whole CBSAs (Figure 1), this figure considers the census tracts themselves. If one high-exposure census tract (≥ 9 µg/m^3) is in the captured CBSAs (blue colors in Figure 1 c), then the tract is defined as captured; otherwise, the high-exposure census tract is defined as uncaptured. Left panel: tract-level racial-ethnic composition (White, Hispanic, Black, Asian, or Other; upper row) and concentration distribution (population-weighted; bottom row)

across the concentration range (3-15 μg/m^3). The new standard (9 μg/m^3) is represented as black dashed lines. The uncaptured high-exposure tracts (≥ 9 μg/m^3) are represented by the orange shadow (bottom-left panel). Right panel: racial-ethnic composition for (i) overall census tracts; (ii) census tracts with concentrations < 9 μg/m^3; (iii) census tracts with concentrations ≥ 9 μg/m^3 and located in nonattainment CBSAs that are captured by monitors (blue color in Figure 1c); (iv) census tracts with concentrations ≥ 9 μg/m^3 and not in the captured nonattainment CBSAs. There are three reasons for non capturing: the census tracts are in nonattainment CBSAs that are uncaptured by monitors (orange and red colors in Figure 1c); the CBSAs where the census tracts are located don't have three or more census tracts exceeding the standard; or the census tracts are rural tracts (not within any CBSAs). The latter two reasons include high-exposure tracts that are not located in the blue-, orange-, or red-colored CBSAs in Figure 1c.

Considering only the census tracts exceeding 9 μg/m^3 $PM_{2.5}$ (i.e., only the tracts themselves, rather than the whole CBSAs; "hotspot" tracts), 44 million people (14% of the U.S. population) live in exceeding tracts, of which most (41 million) live in tracts captured by monitors, and the rest (2.8 million) live in tracts not captured by monitors (Figures 2 and S14). The average concentration in the captured hotspots (10.2 μg/m^3) is higher than the uncaptured hotspots (9.2 μg/m^3). Crucially, both captured and uncaptured hotspots contain higher percentages of POC (68% and 50%, respectively) compared to the overall population (42%) (Figure 2). Those hotspots also contain higher percentages of DAC (42% and 41%) and low-income populations (28% and 39%) than the overall population (25% [DAC]; 28% [low-income]; Figures S15-S16). Minority population percentages in the uncaptured hotspots are higher than the state average in most states (Figure S17). This suggests that the existing monitors are insufficient to identify concentration hotspots, disproportionately impacting minority populations. According to the Code of Federal Regulations,[9] regulatory monitors primarily focus on area-wide air quality, not concentration hotspots. However, the EPA is planning new monitors in at-risk communities, including minority communities, to capture source impacts (see SI Section S1). Our results indicate that new monitors are essential for detecting hotspots in those communities.

We also examine whether monitoring locations represent exposure hotspots, average exposure levels, and disparities by demographic group. On average, 23% of the overall population lives in census tracts with higher concentrations than the highest monitored concentrations in the

CBSAs. However, for POC, DAC, and low-income populations, the numbers are 32%, 39% and 36%, respectively, indicating that monitoring is less representative of the upper bounds of the population-concentration distribution for these minority groups (Figure 3a). Comparing the concentration disparities for all census tracts and tracts around monitors, monitored locations underestimate state-level disparities in most states (Figures 3b-3c, S18-S19). For example, the national racial-ethnic relative disparity of $PM_{2.5}$ concentration is 6.1% for all tracts; the relative disparity for tracts around monitors is only 4.3% (a 30% underestimation).

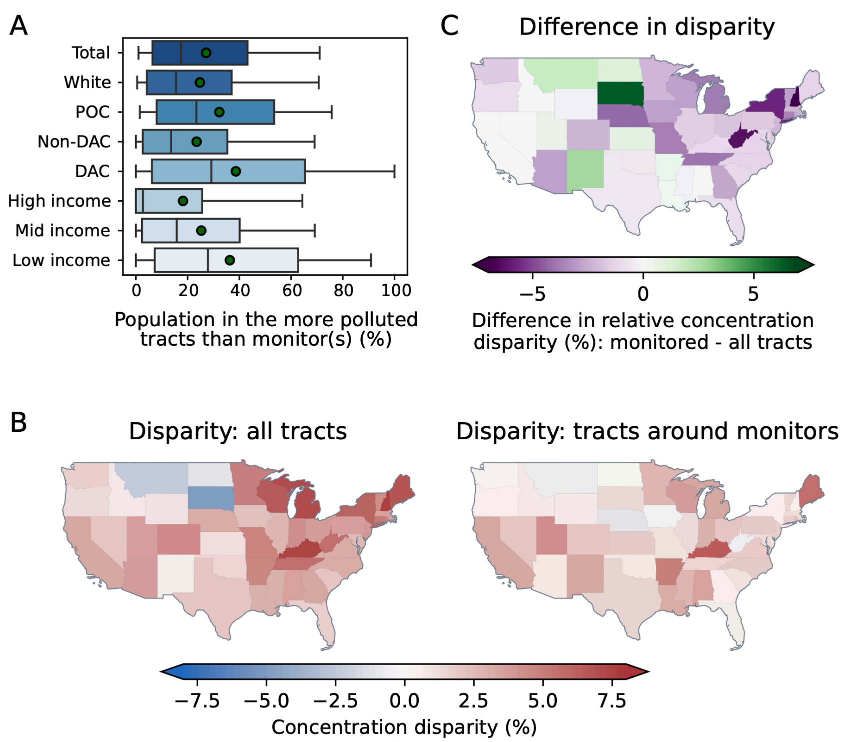

Figure 3. Representativeness of monitoring locations for exposure hotspots and exposure disparities by demographics. (A) Percentages of populations in each CBSA that are exposed to concentrations higher than the maximum concentrations in the monitored tracts. Populations are grouped by race-ethnicity, DAC status, and income levels. The box-and-whisker represents the 10th, 25th, 50th, 75th, and 90th percentiles, and the green circle represents the population-weighted mean. (B) State-level racial-ethnic concentration (relative) disparities in $PM_{2.5}$ for all census tracts and census tracts around (within 1-km circular buffer) monitoring sites. (C) The difference in the two disparities, calculated as disparities for all census tracts minus disparities for tracts around monitors. The purple colors represent that the monitoring locations underestimate racial-ethnic disparities; the green colors represent that monitoring locations overestimate racial-ethnic disparities.

Lastly, we examine approaches for addressing these monitoring gaps and disparities (see SI Section S4), consistent with recent federal and state legislation supporting enhanced monitoring for DACs.[33,34] Here, we present an approach for prioritizing new monitor locations, following a simple scheme that identifies optimal census tracts for monitoring based on the size of the additional population in census tracts that would be newly captured (i.e., correctly reclassified as nonattainment) through the addition of a marginal monitoring site (see SI for full details). Our results imply that adding only 10 new monitor locations could reduce the population in the uncaptured hotspots by 67% (from 2.8 million to 0.9 million; Figure 4). This approach would reduce the percentage of POC population in uncaptured hotspots by 20% (from 50% to 40%; Figure S20), but would provide less benefit to DAC and low-income populations (see Figures S20-S22 for other approaches, which might better target those subpopulations). Nonetheless, although adding a small number of targeted monitor locations could sharply reduce the number of people "uncaptured" by the existing monitoring network, it would not meaningfully improve the ability of the SLAMS to characterize nationwide $PM_{2.5}$ disparities (Figure S23). To accurately evaluate exposure disparities, other methods or tools (instead of regulatory monitoring), with much finer spatial resolution, are likely needed.

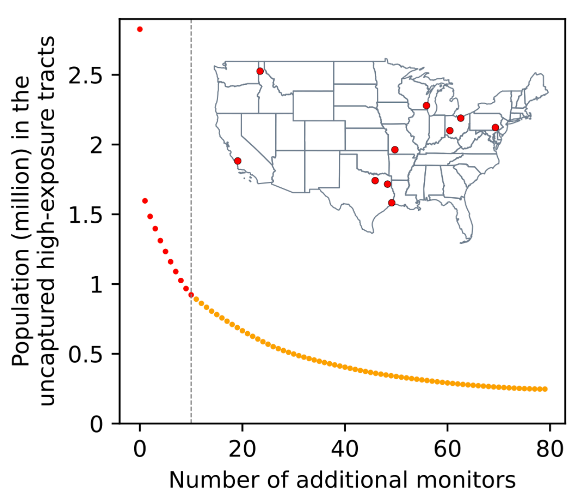

Figure 4. **Number of remaining population residing in high concentration census tracts that are not captured by monitoring (total = 2.8 million people).** By selecting the first 10

CBSAs with the highest number of people residing in uncaptured census tracts (10 red locations), and adding one additional appropriately-sited monitor to each CBSA, the population remaining in uncaptured hotspots would be reduced by 67% to 0.9 million people. The addition of these monitors would result in each of these 10 CBSAs (total population = 13 million) being classified as in non-attainment of the new PM2.5 NAAQS based on the 2017-2019 design value. Note that after all hotspots in the CBSAs are captured, there remains a non-urban high-exposure population of ~ 0.2 million people that is located outside of the CBSAs.

Implications for future policy

Our study comprehensively quantifies gaps and disparities in the existing regulatory monitoring networks, revealing the following key points. First, the existing SLAMS regulatory monitoring network fails to capture 44% of nonattainment CBSA under the new $PM_{2.5}$ NAAQS, providing inadequate protection to tens of millions of highly-exposed people. These uncaptured populations are higher than previously documented under the old $PM_{2.5}$ standards,[12–14] highlighting the urgent need for additional monitors to implement the new standard effectively.

Second, existing monitoring networks have disproportionately less coverage among the high-exposure minority populations. Those populations are already more vulnerable and sensitive to the health effects from air pollution.[35,36] Our findings indicate that adding a small number of additional monitors can noticeably reduce the number of unmonitored exceeding locations; that step will benefit the overall population and help reduce injustices via State Implementation Plans.

Third, the monitoring stations underestimate exposure disparities. Unfortunately, adding a moderate number of monitors would be ineffective at addressing this gap (Figure S23). Indeed, since empirical models may underestimate hotspot concentrations,[2,37] the true underestimation in disparities by the monitoring networks is likely to be even greater than is estimated here. Our results imply that other technologies and tools with higher spatial resolution, such as mobile monitoring,[37–40] well-calibrated low-cost or portable sensors,[22–24,41–44] and satellite-based models,[45–49] could aid in representing exposure hotspots and disparities. Those tools may also be useful for nonattainment designation. Thus, an important open question is whether new data/tools need to be incorporated into the CAA policies (e.g., for identifying at-risk communities, planning new monitors, and determining attainment/nonattainment status).

Our study informs the implementation of the new $PM_{2.5}$ NAAQS, in terms of regulatory monitoring. Our findings reveal that as the "umbrella" to protect the US population, the existing $PM_{2.5}$ SLAMS network has consequential monitoring gaps. Effective and straightforward solutions exist (i.e., adding a small number of monitors) to address the monitoring gaps identified here. Doing so would protect the overall population, but would not substantially change the underestimation of disparities by the monitoring network. Our results use 2017-2019 data, while EPA's nonattainment designations will rely on post-November 2024 measurements. However, air quality trends have been broadly steady since 2016 (Figure S24), suggesting our findings offer insight into near-future attainment status, though actual concentrations may differ.

Previous research indicated that simply tightening NAAQS standards without targeting specific locations will not address disparities.[8,32] Therefore, improvement in monitoring networks, incorporating other high-resolution tools, and more effective location-based strategies are all urgently needed, in addition to stricter NAAQS standards, to address exposure disparities. Future studies could further investigate state-level solutions for reducing pollution levels, eliminating disparities, and designing monitoring networks to support both goals. Our methodologies for investigating monitoring gaps may apply to other pollutants (e.g., nitrogen dioxide).

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Supporting information

Additional methodological details, sensitivity analyses, and supporting information tables and figures.

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