National and Intraurban Air Pollution Exposure Disparity Estimates in the United States: Impact of Data-Aggregation Spatial Scale

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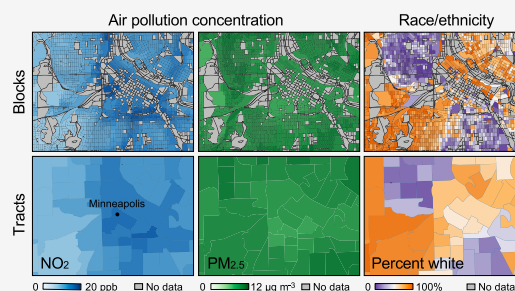
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ABSTRACT: Air pollution exposure disparities by race/ethnicity and socioeconomic status have been analyzed using data aggregated at various spatial scales. Our research question is this: To what extent does the spatial scale of data aggregation impact the estimated exposure disparities? We compared disparities calculated using data spatially aggregated at five administrative scales (state, county, census tract, census block group, census block) in the contiguous United States in 2010. Specifically, for each of the five spatial scales, we calculated national and intraurban disparities in exposure to fine particles ($PM_{2.5}$) and nitrogen dioxide (NO_2) by race/ethnicity and socioeconomic characteristics using census demographic data and an empirical statistical air pollution model aggregated at that scale. We found, for both pollutants, that national disparity estimates based on state and county scale data often substantially underestimated those estimated using tract and finer scales; in contrast, national disparity estimates were generally consistent using tract, block group, and block scale data. Similarly, intraurban disparity estimates based on tract and finer scale data were generally well correlated for both pollutants across urban areas, although in some cases intraurban disparity estimates were substantially different, with tract scale data more frequently leading to underestimates of disparities compared to finer scale analyses.

KEYWORDS: *air quality, spatial resolution, environmental justice, distributional justice, spatial inequality, inequity*

INTRODUCTION

Air pollution exposure disparities by race/ethnicity and socioeconomic status are a major environmental justice[1] issue in the United States (US). Researchers, public agencies, and communities are grappling with how to quantify air pollution exposure disparities. There is an urgent need for guidance on quantifying air pollution exposure disparities, due to rapid evolution of data (e.g., from satellites, models, and low-cost sensors) and to growing momentum in efforts to measure, track, and address such disparities (e.g., from US state environmental justice policies[2,3] and screening tools[4,5]). Analytic challenges[6] in doing so include the definition of disparity metrics, the collection of air pollution and demographic data, the method of exposure assessment, and the spatial scale of data aggregation.

Here, we investigate the *spatial scale of data aggregation*, i.e., the spatial resolution at which demographic data and air pollution data are combined to quantify air pollution exposure disparities. In such analyses, demographic data (e.g., race/ethnicity from the census) and air pollution data (e.g., predicted pollutant concentrations from models) are often aggregated to common spatial references, such as administrative boundaries (e.g., census tracts) or model grids (e.g., 10 km grids), with varying spatial resolution. For example, researchers have aggregated data at various air pollution model grid resolutions (e.g., 1 km to 288 km)[7] and at the county,[8]

census tract,[9−11] and block group[12,13] scales to quantify air pollution exposure disparities in the US. Similarly, US public agencies have aggregated data at the census tract[5] and block group[4] scales in environmental justice screening tools.

The spatial scale of data aggregation may impact the analysis of disparities.[14] Both air pollution concentrations and demographic characteristics can vary substantially within US cities at fine spatial scales. For example, contrasts in air pollution concentrations[15] as well as patterns of racial/ethnic residential segregation[16,17] can be observed at the census block level in US cities. Aggregating data at coarser spatial scales may mask these finer variations and lead to inaccurate estimates of air pollution exposure disparities.

The extent to which the spatial scale of data aggregation impacts analysis of air pollution exposure disparities has not been studied in detail, for example, across pollutants, disparity metrics, spatial scales, and data sources. Prior studies, based on mechanistic air pollution models in the US, found that coarser spatial grid resolutions resulted in substantial underestimates of

Table 1. Spatial Scales of Data Aggregation

Spatial scale	Total number of units		Population-weighted median (IQR[a]) length[b] per unit (km)	
	National[c]	Urban[d]	National[c]	Urban[d]
State	49[e]	–	390 (350−520)	–
County	3109	–	45 (36−59)	–
Census tract	72,043	46,612	2.5 (1.5−6.4)	1.7 (1.2−2.5)
Census block group	215,491	137,312	1.4 (0.80−3.3)	1.0 (0.65−1.5)
Census block	6,182,882	2,477,876	0.26 (0.15−0.63)	0.20 (0.14−0.39)

[a]IQR is the population-weighted interquartile range (25th−75th percentile). [b]Length calculated as the square root of area. [c]All nonzero-population units within the contiguous United States in the 2010 Decennial Census. [d]All nonzero-population units within the 481 urban areas in the contiguous United States in the 2010 Decennial Census. [e]48 states and the District of Columbia.

national race/ethnicity-based disparities in fine particulate matter exposure,[7] minor impacts on estimates of regional income-based disparities in ozone exposure,[18] and variable impacts across three cities on estimates of intraurban race/ethnicity-based disparities in fine particulate matter exposure.[19] Thus, our research question is this: To what extent does the spatial scale of data aggregation impact estimates of air pollution exposure disparities in the US?

■ MATERIALS AND METHODS

To quantify the impact of the spatial scale of data aggregation, we calculated and compared national and intraurban air pollution exposure disparities for two pollutants in a consistent manner using data aggregated at five census geographies (and corresponding spatial scales) in 2010 for the contiguous US.

Data Aggregation. *Spatial Scales of Data Aggregation and Analysis.* Our exposure disparity analyses have two distinct spatial scales: the *scale of input data aggregation* (i.e., the scale at which demographic and air pollution data are combined; data are typically assumed to be spatially uniform within each spatial unit) and the *scale of analysis* (i.e., the scale at which exposure disparity metrics between groups are then analyzed).

We aggregated the inputs (air pollution and demographic data) at five spatial scales (from coarsest to finest: state, county, tract, block group, block; Table 1), representing administrative boundaries with variable spatial resolution. The census boundaries (tract, block group, and block) scale with population density (i.e., areas with higher population density have higher spatial resolution). We used spatial boundaries from IPUMS[20] for the 2010 Decennial Census geographies.

We then calculated and compared air pollution exposure disparities at two spatial scales of analysis: (1) national (contiguous US) and (2) intraurban (within 481 census-defined urban areas in the contiguous US; details are in the Supporting Information [SI]). National analyses include all five spatial scales of data aggregation; intraurban analyses include the three spatial scales with intraurban spatial resolution: tract, block group, and block.

Air Pollution Data. We used year 2010 annual average ambient pollution levels for two US Environmental Protection Agency (EPA) criteria pollutants, nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$), from the CACES national empirical statistical models.[21,22] CACES models are based on EPA air pollution monitoring data, land use data, and satellite-derived air pollution and land cover data. These estimates cover the contiguous US with block level spatial resolution. CACES provides the model prediction at the centroid location of each nonzero-population block in the 2010 Decennial Census. For other scales, CACES provides the population-weighted mean model predictions based on all block centroids located within each block group, tract, county, or state.

Demographic Data. We used demographic data from the 2010 Decennial Census and from the 2008−2012 American Community Survey (ACS) accessed via IPUMS[20] at each spatial scale of data aggregation for the following self-reported demographic characteristics: race/ethnicity, housing tenure, income, poverty, and language. The Decennial Census provides public demographic data down to the block level (race/ethnicity and housing tenure), and the ACS provides data down to the block group level (income, poverty, and language). Details for the demographic data are in SI.

Exposure Metrics. We estimate a person's exposure as the annual average ambient concentration for the specific geographic unit (i.e., state, county, tract, block group, or block) in which that person lives. Our focus on outdoor, residential-based exposures is consistent with recent US-based environmental justice policy[2,3] and screening tools.[4,5] We estimated exposures for groups of people defined using two distinct approaches: *population based* and *location based*. *Population-based groups* are defined based on demographic characteristics of individual people, regardless of where they live. An example of a population-based group is the low-income population (across all states, counties, tracts, etc.). In contrast, *location-based groups* are defined based on overall demographic characteristics of locations (geographic units). An example of a location-based group is the population living within a geographic unit (e.g., states, counties, tracts, etc.) with a greater than 35% low-income population (i.e., all people [regardless of their own income level] who live in the geographic units matching that condition). The *population-based* approach is consistent with common approaches in national health disparities research (e.g., comparing exposures for different racial/ethnic groups). The *location-based* approach is consistent with common approaches in environmental justice screening tools (e.g., assessing exposures for people who live in specific neighborhoods or locations defined as environmental justice communities).

We calculated exposure metrics to represent the average (mean, median) and high-end (90th percentile) concentrations experienced for each group of people. We applied population weighting in calculations so that exposure metrics reflect the air pollution levels experienced by people (rather than by geographic units or by land area), consistent with a focus on potential public health impacts of air pollution. Details for calculating exposure metrics are in the SI.

Exposure Disparity Metrics. For each group, we calculated exposure disparities compared to the total population, on an absolute basis (units: ppb [NO_2]; $\mu g\ m^{-3}$ [$PM_{2.5}$]) and on a relative basis (units: %). Absolute metrics
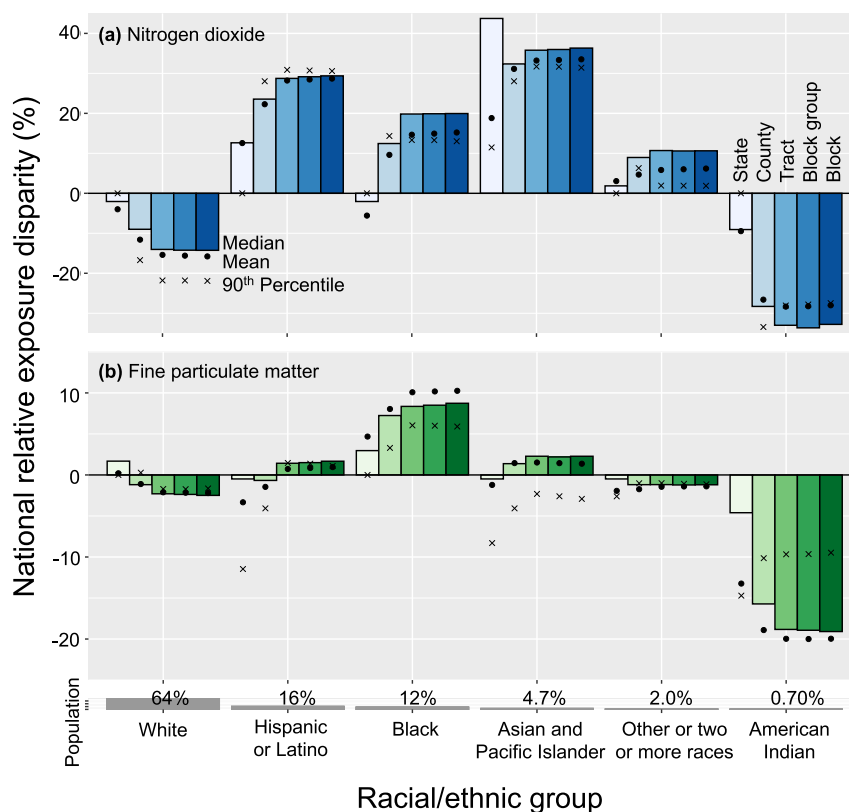
Figure 1. National relative exposure disparity (%) in 2010 calculated using five different spatial scales of data aggregation (state, county, tract, block group, and block) for six racial/ethnic groups compared to the total population for (a) nitrogen dioxide (NO_2) and (b) fine particulate matter ($PM_{2.5}$). The color of the bar indicates the spatial scale of data aggregation, with the lightest color indicating the coarsest spatial scale (state) and the darkest color indicating finest spatial scale (block). The bar indicates the relative percent difference in median exposure for each racial/ethnic group compared to the median exposure for the total population. The circle indicates the relative percent difference in population-weighted mean exposures, and the "x" indicates the relative percent difference in 90th percentile exposures. Positive values indicate that the racial/ethnic group experiences higher levels of air pollution exposure compared to the total population. The population for each racial/ethnic group in 2010 is listed at the bottom of panel (b). Racial/ethnic groups do not include Hispanic or Latino populations, except for the "Hispanic or Latino" group.

for exposure disparities are relevant for understanding pollutant-specific health impacts; relative metrics are relevant for understanding disproportionality in exposures and for comparing exposure disparities across pollutants.[23] We calculated the absolute and relative exposure disparities based on three statistics: differences in the population-weighted mean, median, and 90th percentile exposures. Details for calculating exposure disparity metrics are in the SI.

■ RESULTS AND DISCUSSION

This section focuses on the impact of the spatial scale of data aggregation on estimated exposure disparities. Liu et al.[24] describe the exposure disparities in detail. In summary, exposure disparities across demographic groups were generally larger for NO_2 than for $PM_{2.5}$ (on a relative basis), and exposure disparities were generally larger by racial/ethnic group than by income, across all scales of data aggregation.

Additionally, this section focuses on exposure disparities by race/ethnicity; exposure disparities by other socioeconomic characteristics (income, poverty, housing tenure, language) are in the SI.

National Results. *Population Based.* We found that analyzing national population-based exposure disparities using the coarsest versus finest data often yielded inconsistent results. For example, Figure 1 shows large differences in estimated national relative exposure disparities by race/

ethnicity based on *coarser-than-tract* (i.e., state and county) versus *tract-and-finer* data (i.e., tract, block group, block). In some cases, the state and/or county data yielded national exposure disparity estimates in the *opposite direction* of the tract and finer data. In the remaining cases, state and county data often led to substantial underestimation of national exposure disparities compared to the tract and finer data. For example, county data led to underestimation of national exposure disparities calculated using tract data by 20% (0.3 ppb) for NO_2 and 20% (0.1 $\mu g\ m^{-3}$) for $PM_{2.5}$, on average across six racial/ethnic groups shown in Figure 1.

In contrast, for *tract-and-finer data*, increasing the spatial resolution had a relatively minor impact on the estimated national exposure disparities. For example, Figure 1 shows minor differences among the three finest spatial scales relative to the exposure disparities themselves. The impact of spatial scale (i.e., tract versus block data) accounted for 3% (0.04 ppb) of the national exposure disparity estimate (i.e., based on block data) for NO_2 and 7% (0.01 $\mu g\ m^{-3}$) for $PM_{2.5}$, on average across six racial/ethnic groups (Figure 1). In most cases, tract data led to minor underestimation of national exposure disparities compared to block data.

We found similar patterns by spatial scale of data aggregation for the other national population-based exposure disparity metrics as shown in Figures S1–S11.
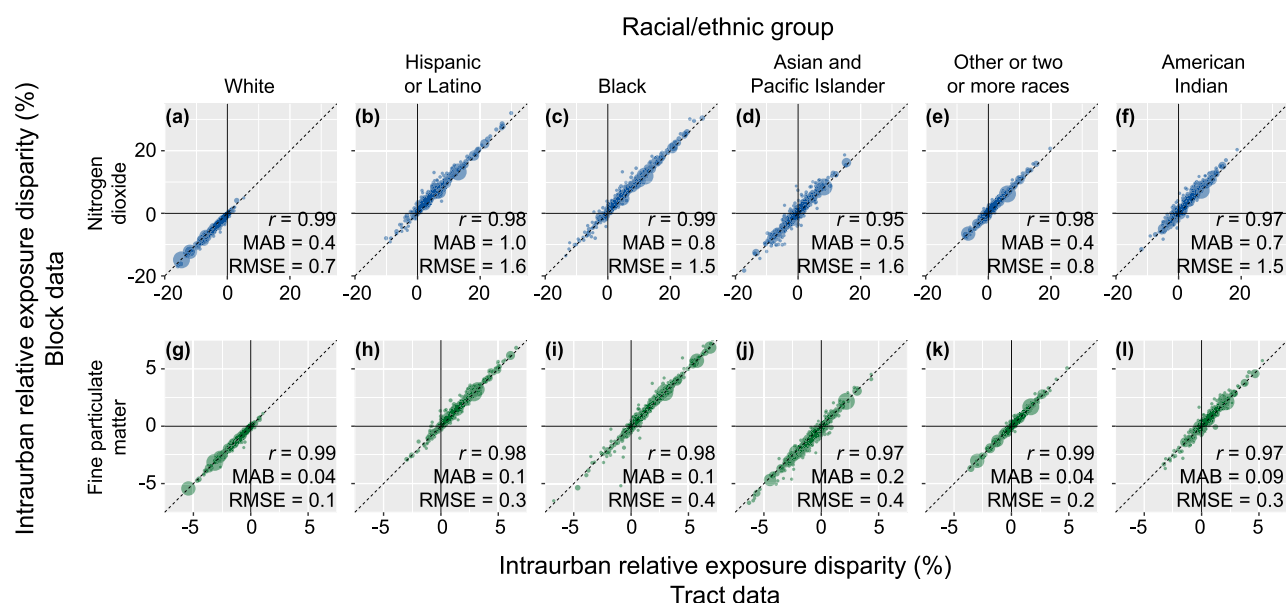
Figure 2. Intraurban relative disparity (%) in mean exposure in 2010 calculated using block versus tract data for six racial/ethnic groups compared to the total population in that urban area for (a−f) nitrogen dioxide (NO_2) and (g−l) fine particulate matter ($PM_{2.5}$) for 481 urban areas in the contiguous United States. The area of circle indicates the relative total population of the urban area. Positive values indicate that the population-weighted mean concentration is higher for that racial ethnic group than for the total population within that urban area. The dashed line (1:1) represents perfect agreement between disparities calculated using block versus tract data. Racial/ethnic groups do not include Hispanic or Latino populations, except for the "Hispanic or Latino" group. RMSE is root-mean-square error (units: percentage points). MAB is the mean absolute bias (calculated as the mean of the differences in the absolute values of the block-based and tract-based intraurban exposure disparity estimates; units: percentage points; positive values indicate lower tract-based estimates on average), and r is Pearson's correlation coefficient.

Location Based. We also found that analyzing national location-based exposure disparities using coarser-than-tract data often yielded inconsistent results, whereas using tract-and-finer data generally yielded consistent results (Figures S12−S27).

Intraurban Results. *Population Based.* We found that rankings of intraurban exposure disparities across the 481 US urban areas were generally consistent by spatial scale of data aggregation. For example, Figure 2 shows intraurban exposure disparities by racial/ethnic group based on tract versus block data were well-correlated ($r > 0.95$). Other intraurban population-based exposure disparity metrics based on tract versus finer data were similarly well correlated ($r > 0.93$; Figures S28−S32). However, we also identified exceptions to this overall pattern (i.e., specific urban areas for which estimated intraurban exposure disparities differ substantially based on tract versus finer data); such outliers can be observed in Figure 2 and Figures S28−S32. For example, Table S1 lists urban area outliers from Figure 2 (complete data set is in SI).

The impact of increasing spatial resolution from tract to block was generally similarly minor for intraurban exposure disparities as for national exposure disparities, on an *absolute* basis. However, because intraurban exposure disparities were generally smaller than national exposure disparities, the impact of increasing spatial resolution was more substantial for intraurban exposure disparities on a *relative* basis. For example, the impact of spatial scale (i.e., tract versus block data) accounted for 80% (0.07 ppb) of the intraurban exposure disparity estimate (i.e., based on block data) for NO_2 and 80% (0.02 $\mu g\ m^{-3}$) for $PM_{2.5}$, on average across the six racial/ethnic groups and 481 urban areas (Table S2). Across the six racial/ethnic groups and 481 urban areas in Figure 2, the absolute difference in the intraurban relative exposure disparity between

tract and block data was greater than 1 percentage point in 34% of cases for NO_2 and 1% of cases for $PM_{2.5}$.

Tract data led to underestimates of intraurban exposure disparities in most, but not all, cases, relative to finer data. For example, tract data led to underestimation of intraurban exposure disparities calculated using block data in 79% of cases for NO_2 and 66% of cases for $PM_{2.5}$, across the six racial/ethnic groups and 481 urban areas in Figure 2. Of cases in Figure 2 in which the difference in the intraurban relative exposure disparity between tract and block data was greater than 1 percentage point, tract data led to lower (i.e., under) estimates in 85% of cases for NO_2 and 87% of cases for $PM_{2.5}$. Mean absolute bias in intraurban relative exposure disparities based on block versus tract data ranged from 0.4 to 1.0 percentage points across racial/ethnic groups in Figure 2 for NO_2 and 0.04 to 0.2 percentage points for $PM_{2.5}$.

Location Based. For intraurban location-based exposure disparity metrics based on tract versus block data, correlations across US urban areas were moderately high, although comparatively lower than for the population-based exposure disparity metrics ($r > 0.79$). We found that the impact of spatial scale had similar magnitude as the exposure disparities themselves in many cases, and coarser data led to under-predictions relative to finer data in most cases (Figures S33 and S34).

Discussion. Results demonstrate the importance of fine spatial scale data for identifying and quantifying air pollution exposure disparities, across a variety of exposure disparity metrics, for $PM_{2.5}$ and NO_2, at national and intraurban scales. In national analyses, the coarsest data (state and county scale) generally substantially underestimated exposure disparities based on the finer data (tract, block group, and block scale) and, in a few cases, led to exposure disparity estimates in the opposite direction. In intraurban analyses, the impacts of

spatial scale for the coarsest (tract scale) versus finest (block scale) data were often similar in magnitude to the intraurban exposure disparities themselves—again, emphasizing the importance of finest-scale spatial resolution.

Increasing spatial resolution from the tract to finer scales (i.e., block group, block) generally had only a minor impact on estimated *national* exposure disparities between groups. Those findings are consistent with a recent mobile-monitoring air pollution study[25] in one US metropolitan region, which reported that between-neighborhood differences (rather than finer between-block differences) in pollution and in segregation were a main contributor to between-group racial/ethnic disparities in exposure.

Intraurban exposure disparities calculated using tract versus finer data were generally well correlated across all urban areas, although, in some cases, the impact of spatial scale on intraurban exposure disparity estimates was substantial, with tract data leading to lower estimates in most, but not all cases, relative to block scale data. The finding that the impact of spatial scale varied across urban areas is consistent with a modeling study[19] that reported that the impact of spatial scale on $PM_{2.5}$ exposures by race/ethnicity varied across three US cities. Future studies could investigate the underlying reasons for this variation in impact of spatial scale of data aggregation across urban areas using the outliers identified here.

The impact of analyzing exposure disparities using data with finer than tract scale resolution was greater for intraurban analyses than for national analyses. This finding could be explained in part by differences in spatial variability of demographic patterns and/or air pollution levels at national versus intraurban scales. Our analysis (Figure S35; methods in SI) revealed substantially greater levels of variability in residential patterns of race/ethnicity (i.e., higher levels of racial/ethnic segregation, at finer spatial scales) at the intraurban scale compared to at the national scale. In contrast, variability in air pollution by spatial scale was relatively consistent at the national and intraurban scales (Figure S35). These findings demonstrate the potential importance of aggregating data at the spatial scale of finest available *demographic* data for intraurban analyses of exposure disparities.

Limitations of this study include the following: (1) The results are based on national air pollution models, which do not account for all local sources of air pollution or within-block differences in air pollution. (2) The exposure assessment is based on at-residence, ambient air pollution levels and does not account for other sources of exposure (e.g., during travel, at work, etc.). (3) The analysis focuses on between-group exposure disparities. Future studies could address these limitations by incorporating other types of air pollution data (e.g., from other empirical statistical models,[13] chemical transport models,[26] reduced complexity models,[27] satellite-based observations,[9,28] mobile monitoring,[25] low-cost sensor networks[29]), accounting for mobility[30] and indoor[31] environments in exposure assessment, and analyzing other spatial scales (e.g., postal codes, parcels, etc.[32]) and metrics (e.g., within-group disparities, inequality metrics[23,33]). Additionally, future studies could investigate the impact of uncertainty in air pollution and demographic estimates on exposure disparity estimates by spatial scale of data aggregation.

ASSOCIATED CONTENT

Ⓢ Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.estlett.2c00403.

> Details for methods, results for additional exposure disparity metrics, and results for analysis of spatial variability in air pollution versus demographic data (PDF)
>
> Data set with results for Figure 2 (XLSX)

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Notes

The authors declare no competing financial interest.

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REFERENCES

(1) Bullard, R. D. Introduction: Environmental Justice–Once a Footnote, Now a Headline. *Harvard Environ. Law Rev.* **2021**, *45* (2), 243−248.

(2) New Jersey Law. *An Act Concerning the Disproportionate Environmental and Public Health Impacts of Pollution on Overburdened Communities, and Supplementing Title 13 of the Revised Statutes*; Acts of 2020, Chapter 92, Section C.13:1D-158, 2020.

(3) Massachusetts Law. *An Act Creating a Next-Generation Roadmap for Massachusetts Climate Policy*; Acts of 2021, Chapter 8, Section 56, 2021.

(4) U.S. Environmental Protection Agency (EPA). EJSCREEN: EPA's Environmental Justice Screening and Mapping Tool (Version 2.0). https://ejscreen.epa.gov/mapper/ (accessed Apr 1, 2022).

(5) California Office of Environmental Health Hazard Assessment (OEHHA). CalEnviroScreen 3.0. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30 (accessed Aug 20, 2021).

(6) Gardner-Frolick, R.; Boyd, D.; Giang, A. Selecting Data Analytic and Modeling Methods to Support Air Pollution and Environmental Justice Investigations: A Critical Review and Guidance Framework. *Environ. Sci. Technol.* **2022**, *56* (5), 2843−2860.

(7) Paolella, D. A.; Tessum, C. W.; Adams, P. J.; Apte, J. S.; Chambliss, S.; Hill, J.; Muller, N. Z.; Marshall, J. D. Effect of Model Spatial Resolution on Estimates of Fine Particulate Matter Exposure and Exposure Disparities in the United States. *Environ. Sci. Technol. Lett.* **2018**, *5* (7), 436−441.

(8) Fann, N.; Coffman, E.; Hajat, A.; Kim, S.-Y. Change in Fine Particle-Related Premature Deaths among US Population Subgroups between 1980 and 2010. *Air Qual. Atmos. Heal.* **2019**, *12* (6), 673−682.

(9) Demetillo, M. A. G.; Harkins, C.; McDonald, B. C.; Chodrow, P. S.; Sun, K.; Pusede, S. E. Space-Based Observational Constraints on NO_2 Air Pollution Inequality From Diesel Traffic in Major US Cities. *Geophys. Res. Lett.* **2021**, *48* (17), 1−12.

(10) Colmer, J.; Hardman, I.; Shimshack, J.; Voorheis, J. Disparities in $PM_{2.5}$ Air Pollution in the United States. *Science* **2020**, *369* (6503), 575−578.

(11) Kerr, G. H.; Goldberg, D. L.; Anenberg, S. C. COVID-19 Pandemic Reveals Persistent Disparities in Nitrogen Dioxide Pollution. *Proc. Natl. Acad. Sci. U. S. A.* **2021**, *118* (30), e2022409118.

(12) Clark, L. P.; Millet, D. B.; Marshall, J. D. Changes in Transportation-Related Air Pollution Exposures by Race-Ethnicity and Socioeconomic Status: Outdoor Nitrogen Dioxide in the United States in 2000 and 2010. *Environ. Health Perspect.* **2017**, *125* (9), 097012.

(13) Rosofsky, A.; Levy, J. I.; Zanobetti, A.; Janulewicz, P.; Fabian, M. P. Temporal Trends in Air Pollution Exposure Inequality in Massachusetts. *Environ. Res.* **2018**, *161*, 76−86.

(14) Baden, B. M.; Noonan, D. S.; Turaga, R. M. R. Scales of Justice: Is There a Geographic Bias in Environmental Equity Analysis? *J. of Environ. Plann. Man.* **2007**, *50* (2), 163−185.

(15) Apte, J. S.; Messier, K. P.; Gani, S.; Brauer, M.; Kirchstetter, T. W.; Lunden, M. M.; Marshall, J. D.; Portier, C. J.; Vermeulen, R. C. H.; Hamburg, S. P. High-Resolution Air Pollution Mapping with Google Street View Cars: Exploiting Big Data. *Environ. Sci. Technol.* **2017**, *51* (12), 6999−7008.

(16) Reardon, S. F.; Matthews, S. A.; O'Sullivan, D.; Lee, B. A.; Firebaugh, G.; Farrell, C. R.; Bischoff, K. The Geographic Scale of Metropolitan Racial Segregation. *Demography* **2008**, *45* (3), 489−514.

(17) Lane, H. M.; Morello-Frosch, R.; Marshall, J. D.; Apte, J. S. Historical Redlining Is Associated with Present-Day Air Pollution Disparities in U.S. Cities. *Environ. Sci. Technol. Lett.* **2022**, *9* (4), 345−350.

(18) Saari, R. K.; Thompson, T. M.; Selin, N. E. Human Health and Economic Impacts of Ozone Reductions by Income Group. *Environ. Sci. Technol.* **2017**, *51* (4), 1953−1961.

(19) Parvez, F.; Wagstrom, K. Impact of Regional versus Local Resolution Air Quality Modeling on Particulate Matter Exposure Health Impact Assessment. *Air Qual. Atmos. Heal.* **2020**, *13* (3), 271−279.

(20) Manson, S.; Schroeder, J.; Van Riper, D.; Ruggles, S. IPUMS NHGIS (National Historical Geographic Information System): Version 14.0 [Database]. https://www.ipums.org/projects/ipums-nhgis/d050.v14.0 (accessed Jul 16, 2021).

(21) Kim, S.-Y.; Bechle, M.; Hankey, S.; Sheppard, L.; Szpiro, A. A.; Marshall, J. D. Concentrations of Criteria Pollutants in the Contiguous U.S., 1979 − 2015: Role of Prediction Model Parsimony in Integrated Empirical Geographic Regression. *PLoS One* **2020**, *15* (2), e0228535.

(22) Center for Air Climate & Energy Solutions (CACES). V1 empirical models [Database]. https://www.caces.us/data (accessed Jul 16, 2021).

(23) Harper, S.; Ruder, E.; Roman, H. A.; Geggel, A.; Nweke, O.; Payne-Sturges, D.; Levy, J. I. Using Inequality Measures to Incorporate Environmental Justice into Regulatory Analyses. *Int. J. Environ. Res. Public Health* **2013**, *10* (9), 4039−4059.

(24) Liu, J.; Clark, L. P.; Bechle, M. J.; Hajat, A.; Kim, S.-Y.; Robinson, A. L.; Sheppard, L.; Szpiro, A. A.; Marshall, J. D. Disparities in Air Pollution Exposure in the United States by Race-Ethnicity and Income, 1990 - 2010. *Environ. Health Perspect.* **2021**, *129* (12), 1−14.

(25) Chambliss, S. E.; Pinon, C. P. R.; Messier, K. P.; LaFranchi, B.; Upperman, C. R.; Lunden, M. M.; Robinson, A. L.; Marshall, J. D.; Apte, J. S. Local- And Regional-Scale Racial and Ethnic Disparities in Air Pollution Determined by Long-Term Mobile Monitoring. *Proc. Natl. Acad. Sci. U. S. A.* **2021**, *118* (37), e2109249118.

(26) Nguyen, N. P.; Marshall, J. D. Impact, Efficiency, Inequality, and Injustice of Urban Air Pollution: Variability by Emission Location. *Environ. Res. Lett.* **2018**, *13* (2), 024002.

(27) Tessum, C. W.; Paolella, D. A.; Chambliss, S. E.; Apte, J. S.; Hill, J. D.; Marshall, J. D. $PM_{2.5}$ Polluters Disproportionately and Systemically Affect People of Color in the United States. *Sci. Adv.* **2021**, *7* (18), 1−7.

(28) Demetillo, M. A. G.; Navarro, A.; Knowles, K. K.; Fields, K. P.; Geddes, J. A.; Nowlan, C. R.; Janz, S. J.; Judd, L. M.; Al-Saadi, J.; Sun, K.; McDonald, B. C.; Diskin, G. S.; Pusede, S. E. Observing Nitrogen Dioxide Air Pollution Inequality Using High-Spatial-Resolution Remote Sensing Measurements in Houston, Texas. *Environ. Sci. Technol.* **2020**, *54* (16), 9882−9895.

(29) Tanzer, R.; Malings, C.; Hauryliuk, A.; Subramanian, R.; Presto, A. A. Demonstration of a Low-Cost Multi-Pollutant Network to Quantify Intra-Urban Spatial Variations in Air Pollutant Source Impacts and to Evaluate Environmental Justice. *Int. J. Environ. Res. Public Health* **2019**, *16* (14), 2523.

(30) Kim, J.; Kwan, M.-P. Assessment of Sociodemographic Disparities in Environmental Exposure Might Be Erroneous Due to Neighborhood Effect Averaging: Implications for Environmental Inequality Research. *Environ. Res.* **2021**, *195*, 110519.

(31) Rosofsky, A.; Levy, J. I.; Breen, M. S.; Zanobetti, A.; Fabian, M. P. The Impact of Air Exchange Rate on Ambient Air Pollution Exposure and Inequalities across All Residential Parcels in Massachusetts. *J. Expo. Sci. Environ. Epidemiol.* **2019**, *29* (4), 520−530.

(32) Clark, L. P.; Tabory, S.; Tong, K.; Servadio, J. L.; Kappler, K.; Xu, C. K.; Lawal, A. S.; Wiringa, P.; Kne, L.; Feiock, R.; Marshall, J. D.; Russell, A.; Ramaswami, A. A Data Framework for Assessing Social Inequality and Equity in Multi-Sector Social, Ecological, Infrastructural Urban Systems: Focus on Fine-Spatial Scales. *J. Ind. Ecol.* **2022**, *26* (1), 145−163.

(33) Boyce, J. K.; Zwickl, K.; Ash, M. Measuring Environmental Inequality. *Ecol. Econ.* **2016**, *124*, 114−123.