Multiscale Vehicle Traffic Air Pollutant Exposure and Equity Analysis in the United States using a Novel Emissions Exposure Surrogate

Brittany Antonczak
Department of Civil and Environmental Engineering, Transportation Research Center
University of Vermont, Burlington, VT, 05405
Email: Brittany.Antonczak@uvm.edu

Tammy M. Thompson
Environmental Defense Fund
Boulder, CO, 80302
Email: tthompson@edf.org

Mindi W. DePaola
Environmental Defense Fund
Boulder, CO, 80302
Email: mdepaola@edf.org

Gregory Rowangould
Department of Civil and Environmental Engineering, Transportation Research Center
University of Vermont, Burlington, VT, 05405
Email: Gregory.Rowangould@uvm.edu

ABSTRACT

We estimate the emission density of directly emitted (primary) nitrogen oxides (NO_X) and fine particulate matter ($PM_{2.5}$) from on-road vehicle traffic for each census block in the United States (U.S.) and use these data as a new spatially refined and computationally efficient exposure surrogate. Our analysis using block level emission density estimates reveals in new detail the widespread extent of vehicle traffic emission exposure hotspots, the large impact of medium- and heavy-duty truck traffic on exposure, and environmental justice concerns that encompass nearly every county in the U.S. We find that emissions from trucks contribute to 46% of NO_X and 50.4% of $PM_{2.5}$ exposure from vehicle traffic in the U.S. We also find statistically significant associations between where greater proportions of people of color or people with lower incomes and higher traffic emission exposures in over 88% of the counties in the U.S. The magnitude of these disparities is often substantial. Our findings are notable in that traffic related emission exposure hotspots and related exposure inequalities are not limited to just the large metropolitan areas that have been the focus of much of the prior transportation and air quality literature. They are in fact much more widespread than previously shown.

Keywords: Environmental Justice, Equity, Air Quality, Vehicle Emissions, Vehicle Traffic, Public Health

INTRODUCTION

On-road vehicle traffic is a major source of hazardous air pollutant emissions in the United States (U.S.), disproportionately affecting communities of color and those with lower incomes. Numerous studies have shown that these populations are exposed to higher levels of traffic-related air pollution (TRAP), particularly within a few hundred meters of major roadways, where TRAP emission hotspots have been shown to occur.[1,2] Proximity to high-traffic roads is associated with increased risks of adverse health outcomes, including respiratory and cardiovascular diseases, as evidenced by numerous health effect studies.[3–6] A systematic review by the Health Effects Institute (2022) underscores strong evidence of TRAP exposure leading to increased mortality and health issues such as asthma and lung cancer.[7] Racial, ethnic, and socioeconomic disparities in TRAP exposure in the U.S. are well-documented[8–11] and persist despite overall reductions in vehicle emissions[12–14], exacerbating health disparities in underserved communities.

Recent research also highlights the significant contributions of medium- and heavy-duty vehicle (MDV and HDV) traffic to TRAP exposure and exposure disparities. Despite making up a smaller proportion of vehicle traffic, MDV and HDV traffic disproportionately contributes to TRAP exposure because their fine particulate matter ($PM_{2.5}$) and nitrogen oxides (NO_X) emission rates are much higher than those from light-duty vehicles (LDVs).[15–19] In addition, HDV traffic tends to be concentrated in urban and freight corridors, which further deepens exposure disparities in disadvantaged communities.[9,20,21]

In epidemiological studies and exposure equity and environmental justice (EJ) screening tools such as EJScreen[22], proximity to high-traffic roads and traffic density are commonly used as surrogates to estimate TRAP exposure[8,11,23], given the challenges of directly measuring these emissions. While these surrogates offer practical advantages for large-scale assessments, they fail to capture critical factors that influence vehicle emission rates. Air quality models—including chemical transport models (CTMs) and dispersion models—can provide more accurate estimates of pollutant concentrations by incorporating meteorological conditions and the photochemical processes that drive the formation of secondary pollutants. However, these models are computationally intensive and often produce estimates at spatial resolutions that are too coarse to identify near-roadway exposure hotspots, limiting their utility in large-scale studies of near-roadway exposure to TRAP and associated exposure disparities.[24–28]

The existing literature consistently shows racial, ethnic, and income-based disparities in TRAP exposure. Studies report that Black, Hispanic, and Asian populations experience both higher levels of traffic-related pollution[29–31] and worse health outcomes[7,32] when compared to White populations. A recent review by Mustansar et al. (2025), which examines 55 studies on air pollution exposure by ethnic groups in high-income countries, finds that minority ethnic groups in the U.S. are more exposed to air pollutants, including $PM_{2.5}$ and NO_2.[30] Despite clear evidence of exposure disparities and the important role of truck traffic, few national-scale studies quantify the contributions of different types of vehicle traffic to exposure and equity.[9,10] Furthermore, many studies rely on spatially coarse resolution data, such as county-level aggregates from the U.S. Environmental Protection Agency (EPA) National Emissions Inventory (NEI). While useful for identifying broad trends, this resolution is too coarse to evaluate exposure to TRAP hotspots that drive public health and EJ concerns, especially near roads with high traffic volume. Moreover, few studies evaluate and statistically assess exposure disparities across racial, ethnic, and socioeconomic groups at subnational scales in national scale studies.

This study aims to: (1) develop a refined primary (directly emitted) vehicle emission exposure surrogate to improve national-scale vehicle emissions exposure assessments; (2) evaluate near-roadway TRAP exposure equity, with a focus on historically underserved populations; and (3) quantify the contributions of different vehicle types to TRAP exposure and exposure disparities. To achieve this, we introduce a novel "vehicle emission density" approach, which provides a continuous, fine-scale metric with nationwide coverage. This method overcomes key limitations of existing approaches, offering a more comprehensive analysis of near-roadway emissions exposure while reducing computational complexity and burden. By leveraging a unique national traffic dataset that provides average traffic volumes for most roads in the U.S. and the EPA's Motor Vehicle Emission Simulator (MOVES), we estimate emission density values for every census block in the U.S., enabling a more precise evaluation of exposure to emissions from LDVs, MDVs, and HDVs. This approach improves upon previous methods, which often rely on coarser proximity-based or traffic density measures, by offering greater spatial resolution in exposure assessments. Our focus on primary emissions—NO_X and $PM_{2.5}$—is crucial, as these pollutants create localized hotspots near roadways, posing significant health risks, especially in communities with higher concentrations of lower-income populations and people of color. NO_X and $PM_{2.5}$ are linked to a range of adverse health effects and are major contributors to pollution in urban and freight corridors.

This research refines near-roadway emission exposure surrogates, balancing between spatial precision and computational efficiency. The vehicle emission density method captures variations in emission rates driven by factors such as climate, vehicle maintenance, and traffic patterns. It also differentiates emissions from LDV, MDV, and HDV traffic on individual roadway segments. By calculating emission densities at the census block level, this approach enables a more nuanced understanding of exposure and highlights disparities across national, state, and local levels, offering key insights to assess equity in TRAP exposure and inform policies to reduce these disparities.

METHODS

To assess exposure to near-roadway hotspots and evaluate exposure equity, we first estimate the emission density for primary NO_X and $PM_{2.5}$ emissions at the census block level, stratified by vehicle type (LDV, MDV, and HDV). This approach builds upon and refines the traffic density methodologies used in our previous studies.[8,11,33] Emission factors are derived from the U.S. EPA's MOVES, and vehicle activity data are obtained from the Federal Highway Administration's (FHWA) Highway Performance Monitoring System (HPMS).

The emission density metric sums the emissions from vehicle traffic on roadway links that fall within each U.S. census block, including a 250-meter buffer surrounding the block. Emissions are then normalized by the block area to obtain a density value in grams per square kilometer (g/km²). We compute separate emission densities for LDV, MDV, and HDV traffic to capture the distinct contributions of each vehicle class to local air quality.

We define emission exposure as the population-weighted mean emission density within a defined geographic area. To evaluate exposure equity, we compare average emission exposure levels across demographic groups, group blocks into deciles based on emission density, and apply ordinary least squares (OLS) regression models to assess the relationship between emission density and census block demographics at the county level. These methods enable us to evaluate disparities in TRAP exposure across the U.S. by integrating high-resolution spatial data with demographic information, providing a robust assessment of both exposure levels and equity.

HPMS Data

We use vehicle activity data from the 2018 HPMS managed by the U.S. FHWA.[34] This publicly accessible and comprehensive dataset is based on annual traffic counts collected by states across highways, arterials, and collector roadways. While the HPMS provides valuable insights into national transportation patterns, it lacks comprehensive coverage for MDVs and HDVs, particularly on lower-volume road not included in the U.S. highway system. Approximately 28% of HPMS road links, representing 47% of total lane-kilometers, do not have MDV and HDV annual average daily traffic (AADT) data, with availability varying across states due to differences in traffic counting technologies and reporting practices. To address these gaps, we developed a random forest regression model to estimate MDV and HDV traffic volumes on roadways where these data were missing. Details of the model development, fitting procedure, and validation of the estimated MDV and HDV traffic data are provided in our prior work.[33]

Emission Modeling and Exposure Analysis

We use version 3 of the MOVES[35], developed by the U.S. EPA, to construct county-specific emission factor look-up tables. Given the substantial computational requirements for modeling annual average daily emissions at the road link level across the U.S. using MOVES, we develop a streamlined approach. This approach involves selectively running MOVES for representative counties that represent unique combinations of model parameters for January and July, following a method similar to that used in the 2017 NEI by the EPA.[36] January and July are selected to represent winter and summer conditions , and the resulting emission factors are averaged to reflect annual conditions.

We develop MOVES modeling scenarios for representative counties by integrating multiple datasets. First, we extract county-level average temperature and humidity values for January and July from the MOVES default database. These values are derived from the National Climatic Data Center's average temperature records spanning 2001 to 2011, ensuring comprehensive coverage across U.S. counties. We also gather data on county-specific MOVES fuel regions and vehicle inspection and maintenance (I/M) programs, which vary considerably between urban and rural areas—particularly in regions designated as air quality nonattainment areas. Across the U.S., we identify 117 unique combinations of fuel types and I/M programs. Subsequently, we merge these datasets to identify distinct Climate-Fuel-I/M combinations. We round temperature and humidity values to the nearest 10°F and 10%, respectively, to reduce the number of unique combinations while retaining key meteorological variation.

In total, we identify 444 unique Climate-Fuel-I/M combinations. For combinations that include only one or two counties, we model each county individually. For all other combinations, we model two representative counties—one urban and one rural—to account for minor differences in model parameters that vary with the level of urbanization. To select representative counties, we use 2020 U.S. Census population data[37] and identify the most populous county and the county closest to the 25th percentile in population size within each Climate–Fuel–I/M group. This selection process results in 479 counties modeled in total, representing approximately 15% of all U.S. counties. The modeling process takes about 50 hours to complete on a desktop workstation.

We run MOVES in inventory mode for the year 2018 using default data inputs for all 479 counties modeled. We model primary NO_X and $PM_{2.5}$ emissions from running exhaust and $PM_{2.5}$ emissions from brake and tire wear. We derive distance-based emission factors (g/m) by dividing the total county-level emissions by the corresponding vehicle distance traveled for each combination of emission source type (i.e., vehicle type) and road type (i.e., urban or rural, restricted or unrestricted). This yields a database of average daily NO_X and $PM_{2.5}$ emission factors by MOVES Climate–Fuel–I/M group, road type, and vehicle class.

Emission factors from our database are matched to each roadway segment in the HPMS dataset and used to estimate annual average daily emissions from each segment. We first classify all U.S. counties as urban or rural using the 2013 USDA County-level Rural-Urban Continuum Codes (RUCC).[38] Counties with a RUCC of 8 or 9 are classified as rural; all others are classified as urban. Next, we align MOVES source types with HPMS vehicle traffic categories. MOVES includes 13 source types (See Table 4-1 in *MOVES3 Technical Guidance*[39]), while HPMS classifies traffic into three broader categories. We aggregate MOVES emission factors accordingly (see **Table S.1** for the full mapping of source types to vehicle traffic categories). We then assign a single MOVES road type to each HPMS roadway segment based on its urban/rural classification and HPMS functional classification code (see **Table S.2** for the mapping between MOVES road types and HPMS functional classifications). Emission factors are mapped to each roadway segment based on its Climate-Fuel-I/M group and road type. Finally, we calculate the annual average daily emission rate (g/m/day) for each roadway segment by multiplying the corresponding emission factor by the vehicle kilometers traveled (VKT) on that segment and dividing by the segment's length, separately for each vehicle type and pollutant.

Next, we estimate emission densities (in g/km²) for each pollutant and vehicle type for each U.S. census block. This process begins by creating a 250-meter spatial buffer around each census block using GIS software. The buffer is intended to capture emissions from traffic on nearby roadways that contribute to emissions exposure, even if the roadways do not directly intersect the census block. Emissions from roadway segments within the buffered area (including portions of segments that cross the buffer boundary) are summed and then divided by the area of the census block. These block-level emission densities are then used as surrogates for evaluating emissions exposure.

Equity Analysis

We use 2020 Census block-level population data on race and ethnicity[37], along with 2016-2020 American Community Survey (ACS) 5-Year data on median household income at the block group level and poverty status at the census tract level.[40] In our analysis, individuals identifying as "White" are those who reported their race as White alone in the 2020 Census, while "non-White" encompasses all other racial identities. The "other race" category includes individuals who self-identify as American Indian and Alaska Native alone, Native Hawaiian and Other Pacific Islander alone, or another race not categorized as Black or Asian alone. The Hispanic or Latino category includes individuals of Hispanic or Latino origin, regardless of race. Median household income for each census block is assigned from its corresponding block group, while poverty status (i.e., population living below the federal poverty level) is assigned from its corresponding census tract.

To assess emission exposure equity, we classify each census block into deciles based on its emission density for each pollutant. These deciles range from blocks with the lowest emission density (decile 1) to the highest (decile 10), with each decile containing an equal number of census blocks. For each decile, we calculate the proportion of the population by race, ethnicity, and poverty level, as well as the population-weighted average median household income. This comparative analysis allows us to examine disparities in vehicle emission exposure across demographic groups.

We also estimate ordinary least squares (OLS) regression models to evaluate the direction, strength, and statistical significance of the relationship between emission density (exposure) and two demographic indicators: the percentage of the population that is non-White and the median household income. Separate models are fit for each U.S. county (excluding a few counties with few populated areas) for each vehicle type and pollutant, resulting in a total of 49,824 individual models.

RESULTS AND DISCUSSION

The geographic distribution of NO_X and $PM_{2.5}$ emission densities across the U.S. in 2018 reveals substantial variations by emission source. As shown in **Figure 1**, distinct patterns emerge in census block-level NO_X and $PM_{2.5}$ emissions originating from LDV, MDV, and HDV traffic across the U.S. Emissions density from LDV traffic is most concentrated in urban areas, where greater population density results in higher LDV traffic volume. Emission density from HDV traffic, on the other hand, is more dispersed, with high emission densities observed in both urban areas and along highway corridors connecting urban centers, extending into rural regions. The geographic distribution of emission density from MDV traffic falls between the patterns seen for LDV and HDV traffic, with higher emission density values generally concentrated in urban areas and along select highway corridors.

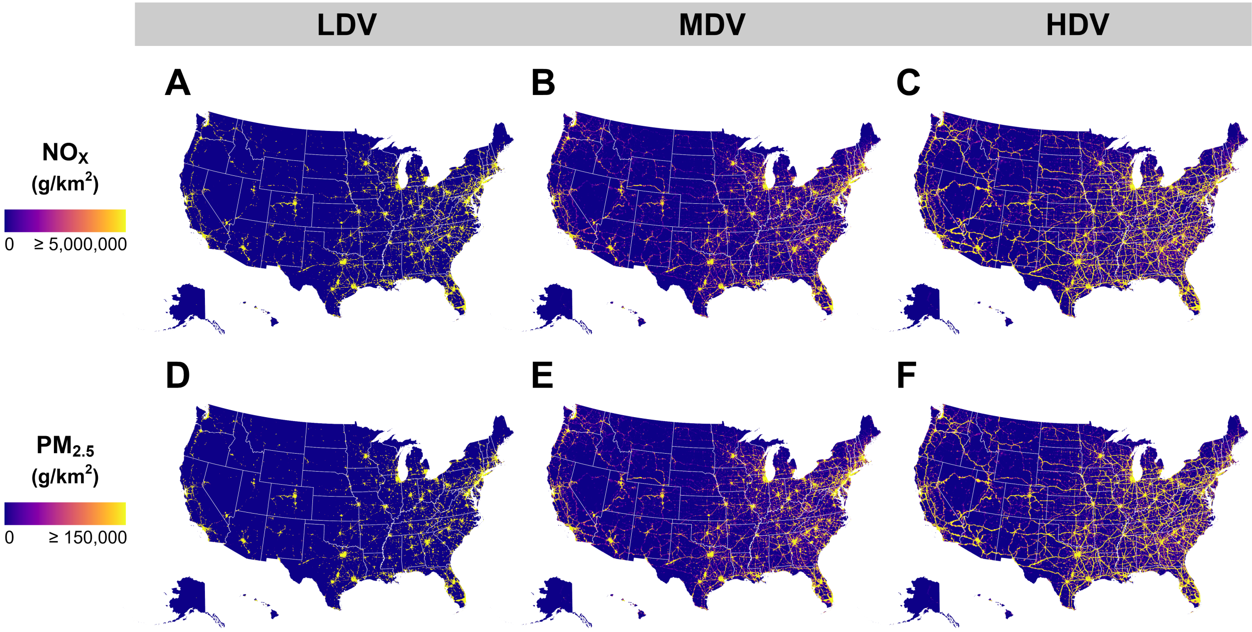

Figure 1. Census block-level emission density across the U.S. categorized by type of vehicle traffic. Panels (A-C) display NO_X emissions density (g/km^2) from light-duty vehicles (LDV), medium-duty vehicles (MDV), and heavy-duty vehicles (HDV), respectively. Panels (D-F) show $PM_{2.5}$ emissions density (g/km^2) from LDV, MDV, and HDV traffic, respectively.

Next, we evaluate population exposure to NO_X and $PM_{2.5}$ from vehicle traffic. Population exposure is defined as the population-weighted mean emission density and is estimated for each county and for the U.S. using the 2018 block-level emission densities shown in **Figure 1**, along with block-level population data from the 2020 Census.

Exposure estimates at the national level reveal that MDV and HDV traffic have a disproportionately large impact on primary NO_X and $PM_{2.5}$ exposure relative to their traffic volume. For example, while MDVs and HDVs account for only 4.3% and 6.5% of average daily VKT in the U.S., respectively, they contribute 19.6% and 26.8% of average NO_X exposure, and 24.7% and 25.7% of average $PM_{2.5}$ exposure (**Table 1**). Together, emissions from MDV and HDV traffic contribute to approximately half of primary NO_X and $PM_{2.5}$ vehicle emissions exposure in the U.S.

Table 1. Average daily exposure to NO_X and $PM_{2.5}$ emissions from vehicle traffic and average daily vehicle-kilometers traveled by vehicle traffic type in the U.S.

	LDV	MDV	HDV
Average NO_X Exposure	102,602 (53.6%)	37,488 (19.6%)	51,407 (26.8%)
Average $PM_{2.5}$ Exposure	3,020 (49.5%)	1,507 (24.7%)	1,570 (25.7%)
Exhaust Emissions	1,585 (36.8%)	1,306 (30.3%)	1,414 (32.8%)
Brake Wear Emissions	1,038 (78.4%)	167 (12.6%)	118 (8.9%)
Tire Wear Emissions	396 (84.8%)	33 (7.2%)	37 (8.0%)
VKT (millions)	11,054 (89.1%)	533 (4.3%)	801 (6.5%)

Note. NO_X = nitrogen oxides; $PM_{2.5}$ = fine particulate matter with aerodynamic diameter ≤ 2.5 micrometers; VKT = vehicle-kilometers traveled; LDV = light-duty vehicle; MDV = medium-duty vehicle; HDV = heavy-duty vehicle. Average exposure values represent the population-weighted mean emission density for each pollutant expressed in grams per square kilometer per day (g/km²/day). Percentages represent the share of average exposure and VKT attributed to each vehicle traffic type.

While LDV and truck traffic (MDVs and HDVs) on average contribute about equally to $PM_{2.5}$ exposure in the U.S., the dominant emission processes differ significantly. LDVs have relatively low $PM_{2.5}$ exhaust emission rates, which results in brake and tire wear accounting for a relatively large share (48%) of $PM_{2.5}$ emissions exposure attributable to LDV traffic (**Table 2**). Overall, LDV traffic is responsible for 78.4% of exposure to $PM_{2.5}$ from brake wear and 84.8% from tire wear in the U.S. (**Table 1**). In contrast, exhaust emissions account for 86.7% of $PM_{2.5}$ exposure attributable to MDV traffic and 90.1% of HDV traffic (**Table 2**). Despite truck traffic accounting for just 10.1% of VKT in the U.S. it is responsible for 63.1% of primary $PM_{2.5}$ exposure from vehicle exhaust (**Table 1**).

Table 2. Relative contributions of exhaust, brake wear and tire wear emissions to $PM_{2.5}$ exposure by vehicle traffic type in the U.S.

Emission Process	LDV	MDV	HDV
Exhaust	52.5%	86.7%	90.1%
Brake Wear	34.4%	11.1%	7.5%
Tire Wear	13.1%	2.2%	2.4%

Note. LDV = light-duty vehicle; MDV = medium-duty vehicle; HDV = heavy-duty vehicle.

At the county level, the dominant source of vehicle emissions exposure varies considerably. While LDV traffic generally contributes more significantly to emissions exposure compared to

MDV or HDV traffic, there are large regions of the country where HDV traffic is the dominant source of exposure (**Figure 2**). Notably, counties in states across the central U.S., from North Dakota to Texas, as well as Nevada and Utah, exhibit considerably larger proportions of emissions exposure from HDV traffic. This occurs primarily in areas where highways carry high volumes of truck traffic through rural counties with small populations and relatively low LDV traffic volumes. In contrast, more urbanized regions with higher population densities also have highways with high HDV traffic volumes. However, the higher LDV and MDV traffic volumes on these roads reduce the significance of HDV traffic in explaining overall exposure levels at the county level. It is important to note that for individual communities (e.g., those located adjacent to truck corridors) within urban counties, MDV and HDV vehicle traffic can still dominate emissions exposure, even if LDV traffic is shown to be the largest source of exposure at the county level in **Figure 2**. For example, the maps in **Figure S.1** show the census blocks in the Los Angeles, California and New York-New Jersey regions where truck traffic (combined MDV and HDV traffic) accounts for more than 50% of NO_X and $PM_{2.5}$ emission density.

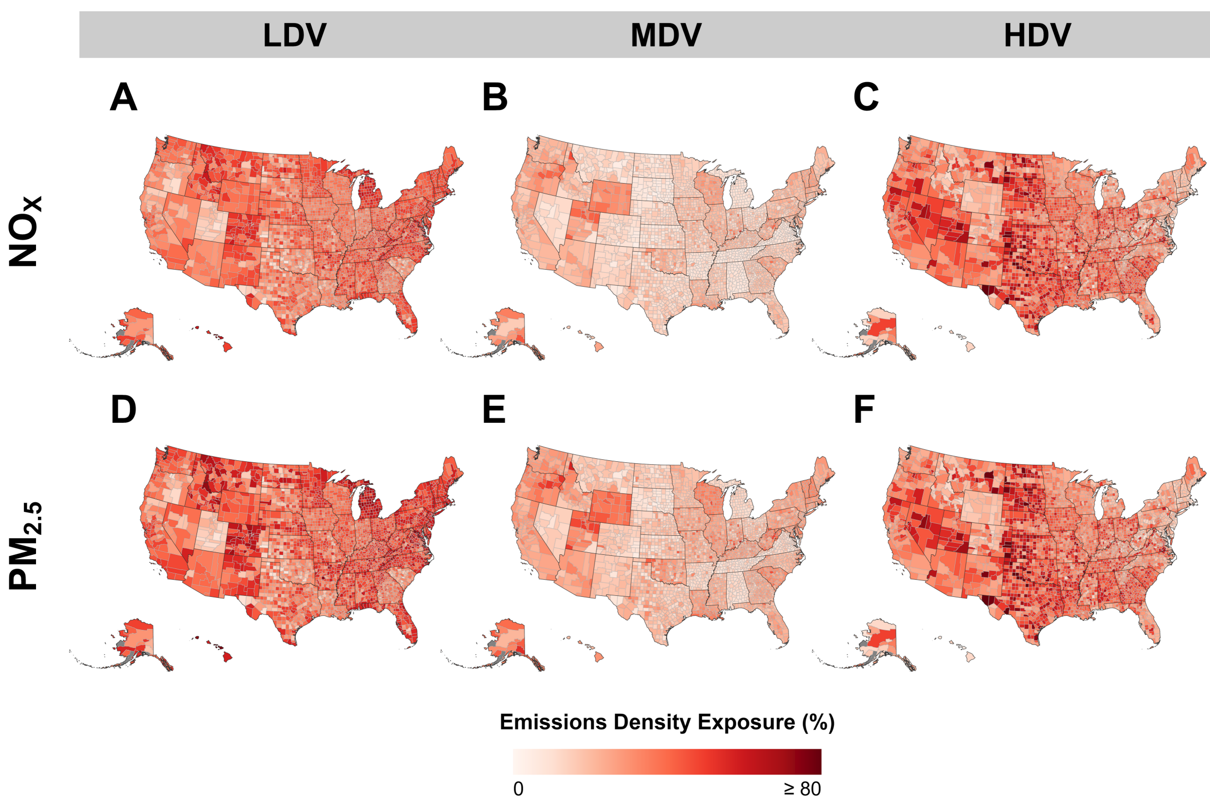

Figure 2. Percentage contribution of light-duty vehicles (LDVs), medium-duty vehicles (MDVs), and heavy-duty vehicles (HDVs) to primary (A–C) NO_X and (D–F) $PM_{2.5}$ emissions exposure in each U.S. county. County-level emissions exposure represents the population-weighted mean of block-level emission density.

We now evaluate exposure equity across different population groups defined by race, ethnicity, and income. On average, people of color and those living in poverty face disproportionately high levels of exposure to primary NO_X (**Figure 3**) and $PM_{2.5}$ (**Figure S.2**) emissions from vehicle traffic in the U.S. in 2020. On average, people of color in the U.S. are exposed to approximately twice the amount of NO_X and $PM_{2.5}$ emissions from vehicle traffic compared to the White population. This trend holds across all non-White population groups examined. Among racial groups, the Asian population experiences the highest average exposure from LDV and MDV traffic, while the Black population faces the greatest exposure from HDV traffic.

Individuals living in poverty are also exposed to significantly higher levels of vehicle emissions. On average, they experience roughly twice the exposure to primary NO_X and $PM_{2.5}$ emissions from LDV and MDV traffic compared to the population that is above the poverty level in the U.S. in 2020 (**Figure 3** and **Figure S.2**). This disparity is even more pronounced for HDV traffic, with individuals living in poverty experiencing roughly three times the primary NO_X and $PM_{2.5}$ emissions compared to the population above the poverty level. On average, a person living in poverty is exposed to 200% (three times) more primary NO_X and $PM_{2.5}$ emissions from HDV traffic, and about 80% to 100% (approximately twice as much) more from MDV and LDV traffic, than the average person in the U.S.

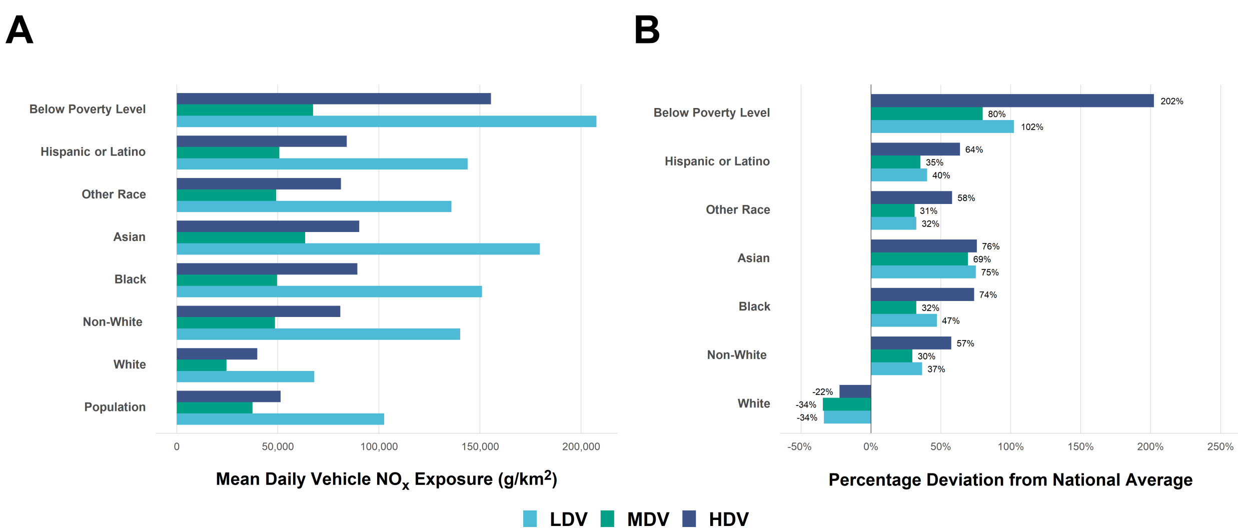

Figure 3. Comparison of average daily vehicle NO_X emission exposure in the U.S. (A) Bar plots showing exposure (g/km^2) by vehicle traffic type, categorized by the overall population, race, ethnicity, and poverty status. (B) Bar plots showing the ratio of exposure from each vehicle type relative to the national average, categorized by race, ethnicity, and poverty status. National exposure values reflect the population-weighted mean of census block level emission density estimates. Vehicle traffic types include light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) traffic. For detailed exposure values, refer to Table S.3.

Next, we delve deeper into exposure equity by examining how the demographic characteristics of populations vary across areas with different levels of primary NO_X and $PM_{2.5}$ emission densities from LDV, MDV, and HDV traffic. We sort U.S. census blocks into ten equally sized bins (i.e., deciles) based on their emission densities for each vehicle type. The first decile contains census blocks with the lowest emission density values, while the tenth decile contains those with the highest (**Figure 4 and Figure S.3).** Emission densities vary widely across deciles, with the median census block NO_X and $PM_{2.5}$ emission densities within each decile spanning several orders of magnitude, as shown in **Table S.4**.

The results shown in **Figure 4** and **Figure S.4** reveal substantial disparities across exposure deciles. For instance, in the lowest NO_X emission density decile, non-White individuals constitute only 17% of the population, whereas in the highest decile they make up 56% of the population—a 39 percentage point increase (**Figure 4.B**). Similar trends are evident when we disaggregate the non-While population into specific race and ethnicity groups (**Figure 4.C-F**). For example, in the highest NO_X emission density decile, the proportion of Black individuals is 3.3 times, Asian individuals 6.1 times, and Hispanic or Latino individuals 4.0 times greater than in the lowest decile.

Disparities are also notable with respect to income and poverty (**Figure 4.G-H**). The poverty rate increases from 12.2% in the lowest NO_X decile to 17.1% in the highest—a 4.9 percentage point (40.5%) increase. While the relationship between median household income and emission density deciles is non-linear (households in very low emission density areas often have lower incomes, attributable to lower earning in very rural areas but not necessarily greater poverty) the results clearly indicate a strong association between lower median income and higher emissions exposure.

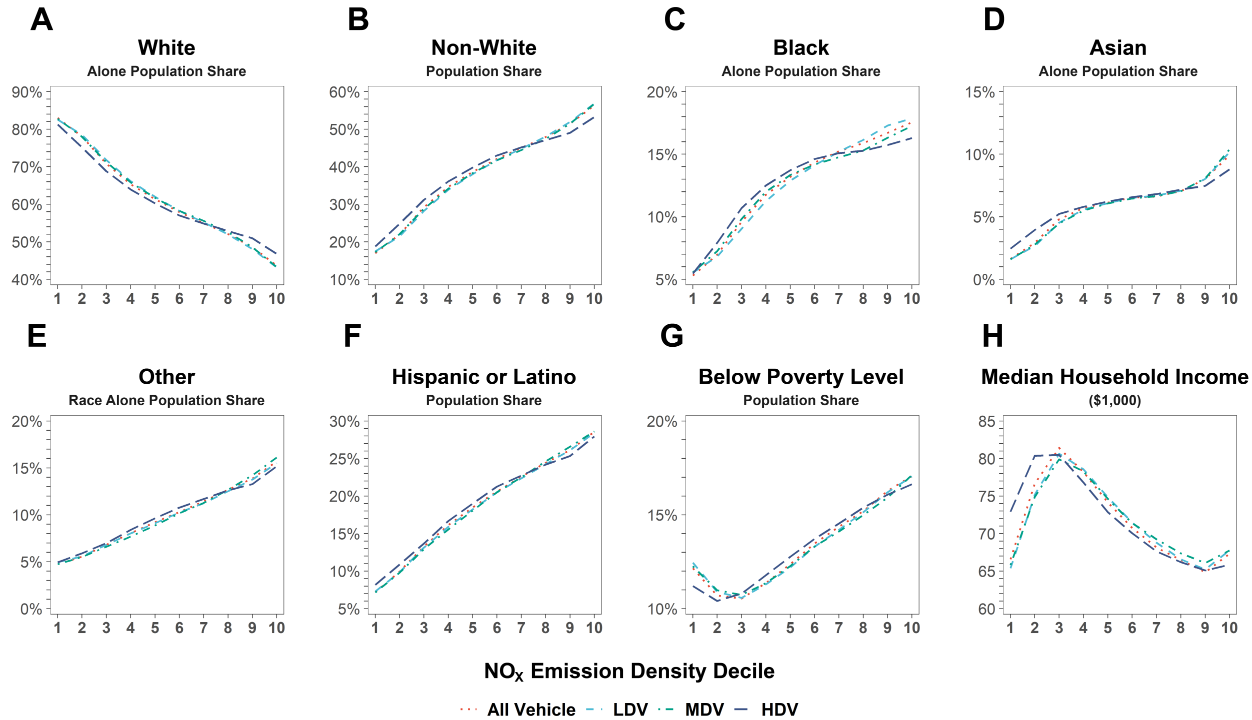

Figure 4. The relationship between race, ethnicity, poverty status, income, and NO_X emission density by type of vehicle traffic in the U.S. Panels (A) through (G) illustrate the percentage of the population residing within each emission density decile, categorized as White alone, non-White alone, Black alone, Asian alone, some other non-White race alone (not Black or Asian), Hispanic or Latino, and living below the federal poverty level. Panel (H) displays the population-weighted average median household income (in $1,000s) of the population residing within each emission density decile. Vehicle traffic types include light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) traffic. For median census block emission densities (VKT/km^2) by decile and type of vehicle traffic, refer to Table S.4.

These disparities are also observed—and of similar magnitude—when evaluated by vehicle traffic type (LDV, MDV, and HDV), as shown in **Figure 4**. It is important to note that the census blocks within each exposure decile vary by vehicle traffic type. For example, a particular census block may fall into decile 3 based on emission density from LDV traffic but into decile 6 based on HDV traffic emissions. Trends very similar to those described for NO_X are also observed for $PM_{2.5}$ and are shown in **Figure S.3**.

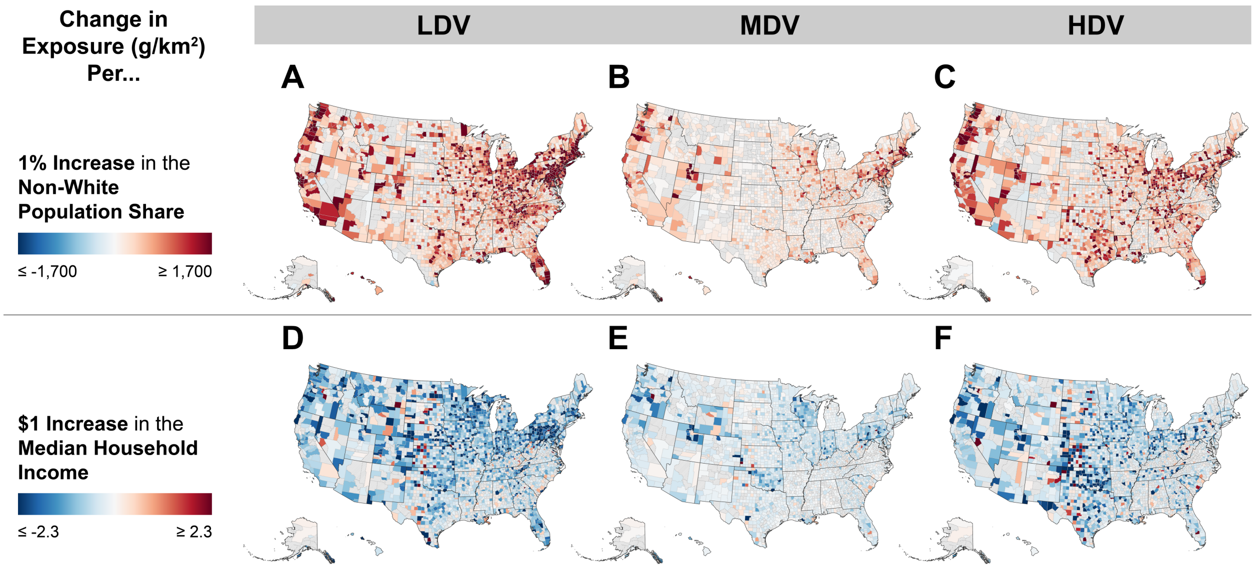

Figure 5. Linear regression model slope coefficients for NO_X emission density as a function of U.S. census block level (A-C) non-White population share and (D-F) median household income by vehicle traffic type for each U.S. county. Vehicle traffic types include light-duty vehicle (LDV), medium-duty vehicle (MDV), and heavy-duty vehicle (HDV) traffic. Hatched areas indicate counties where slope estimates are statistically insignificant at the 95% confidence level ($p > 0.05$).

Next, we examine how exposure disparities by race and income vary across the U.S. **Figure 5** displays the coefficient estimates (i.e., slope) from county-level linear regression models where block-level emission density is modeled as a function of either the percentage of the block population this is non-White or the block's median household income. The coefficient estimates indicate the change in emission density (g/km^2) associated with a 1% increase in the non-White population share or a $1 increase in median household income. For example, counties shaded red in **Figure 5.A-C** indicate a statistically significant positive association between a higher proportion of non-White residents and higher NO_X emission densities. In contrast, counties shaded blue in **Figure 5.D-F** indicate a statistically significant negative association between higher median household incomes and NO_X emission densities. Counties with statistically insignificant coefficient estimates ($p > 0.05$, based on a 95% confidence interval) are shown with hatching in **Figure 5**. For the corresponding analysis of $PM_{2.5}$ emissions, refer to **Figure S.4**.

We find that 78.9% of counties exhibit a statistically significant relationship between total NO_X emission density and the percentage of the population that is non-White based on all vehicle traffic (LDV 79.9%, MDV 79.1%, and HDV 74.3%). Similarly, 77.6% of counties demonstrate a statistically significant relationship between total NO_X emission density and median household income (LDV 79.5%, MDV 79.4%, and HDV 71.9%). Similar patterns are observed for $PM_{2.5}$ emission density, non-white population, and median household income. See **Figure S.5** in the Supplemental Information for a detailed presentation of the box plots illustrating the distribution of linear regression model coefficient estimates and coefficients of determination (R^2) for NO_x and $PM_{2.5}$ across U.S. counties.

The maps in **Figure 5** and **Figure S.4** reveal significant and widespread disparities in exposure to NO_X and $PM_{2.5}$ emissions from vehicle traffic across the U.S. in 2020. Across all regions, there is a positive and statistically significant association between the share of non-White people and NO_X and $PM_{2.5}$ emission density (red shading), with very few instances of a negative association (blue shading) (**Figure 5.A-C** and **Figure S.4.A-C**). Similarly, there is a negative and statistically significant association between median household income and NO_X and $PM_{2.5}$ emission density (blue shading) throughout the U.S., with few counties showing a positive association (red shading) (**Figure 5.D-F** and **Figure S.4.D-F**). Counties with no statistically significant association ($p > 0.05$) are generally rural areas with very small populations (shown with hatching).

The disparities displayed in **Figure 5** are striking, as they are observed in the majority of U.S. counties, including those that do not contain large cities or are predominantly rural. LDV and HDV traffic are the primary drivers of the most pronounced inequities (indicated by the darker shading on the maps), though MDV traffic also contributes significantly in some areas. One of the most notable differences across the various maps in Figure 5 lies between those illustrating racial and income-based disparities. Emission exposure disparities affecting non-White populations are generally largest in the most urbanized areas of the U.S. (e.g., the Northeast and West Coast regions), whereas disparities related to lower income populations are more commonly observed outside of the largest urban centers.

Table 3. Percentages of U.S. counties with race and/or income disparity based on emission density analysis.

Pollutant	Vehicle Traffic Type	Race Disparity (%)	Income Disparity (%)	Race or Income Disparity (%)	Race and Income Disparity (%)
NO_X	All	78	70	88	60
	LDV	79	72	89	62
	MDV	79	72	89	61
	HDV	74	64	85	53
$PM_{2.5}$	All	78	71	89	61
	LDV	79	73	89	63
	MDV	79	72	89	61
	HDV	74	65	85	54

Note. NO_X = nitrogen oxides; $PM_{2.5}$ = fine particulate matter with an aerodynamic diameter less than or equal to 2.5 micrometers; All = all vehicle traffic; LDV = light-duty vehicle; MDV = medium-duty vehicle; HDV = heavy-duty vehicle. Race disparity is defined as counties with a statistically significant ($p < 0.05$) and positive correlation between census block emission density and the non-White population share. Income disparity is defined as counties with a statistically significant ($p < 0.05$) and negative correlation between census block traffic density and the median household income. Percentages are calculated out of the total number of counties, parishes, and county equivalents across all 50 U.S. states and Washington, D.C. (n = 3,143).

Table 3 quantifies the prevalence of disparities in exposure to NO_X and $PM_{2.5}$ emissions from vehicle traffic by race and income in U.S. counties in 2020. A race disparity is defined as a statistically significant ($p < 0.05$), positive correlation between census block emission density and the non-White population share. An income disparity is defined as a statistically significant, negative correlation between emission density and median household income.

Overall, we find that statistically significant disparities in exposure to NO_X and $PM_{2.5}$ emissions from vehicle traffic are present across racial and income groups in a large majority of U.S. counties. Specifically, race-based disparities in exposure to both pollutants are observed in 78% of counties (see **Table 3**). Income-based disparities are observed in 70% of counties for NO_X and 71% for $PM_{2.5}$ (**Table 3**). Disparities based on either race or income are evident in nearly all counties—88% and 89%, respectively. Similar patterns hold when disaggregating emissions by vehicle type (LDV, MDV, and HDV).

In this study, we introduce a refined surrogate for assessing exposure to primary (direct) vehicle traffic emissions near roadways. The emission density surrogate enables a more spatially detailed and source-specific evaluation of near-roadway emissions exposures, revealing in new detail the widespread extent of exposure hotspots, the large impact of medium- and heavy-duty truck traffic, and environmental justice concerns that affect nearly every county in the U.S. This approach also allows for rapid analysis of flexible user-defined areas, such as individual neighborhoods. Our findings are notable in that exposure hotspots and associated inequalities are not limited to large metropolitan areas, which have historically been the focus of transportation and air quality research. High levels of exposure and significant environmental justice concerns are present in all types of communities. Additionally, the significant role of truck traffic is an important finding, as mitigating these emissions (e.g., through fleet electrification) is expected to be more challenging for trucks than for light-duty passenger vehicles.

It is important to note that this analysis is limited to roadways with functional classifications 1 through 6. Residential streets in urban areas and low volume roadways in rural areas (functional classification 7 in the HPMS dataset) are excluded due to the lack of available HPMS traffic data for these roadways. This omission may lead to underestimation of exposure in specific contexts. For example, intermodal freight facilities, warehouses and port facilities that are embedded within residential neighborhoods may generate high volumes of truck traffic on local streets used to access them. For example, the Chicago Truck Counts initiative[41], found high volumes of truck activity on local streets near freight facilities in the Chicago, Illinois region. As such, our findings on exposure disparities are likely conservative in these areas, and actual exposure burdens—particularly those relevant to environmental justice—may be even more pronounced.

The surrogate approach developed in this study can also inform future research and policy decisions. While we have conducted a cross-sectional evaluation of current conditions, emission density can be used to track exposure changes over time and adapted for planning and forecasting applications. For example, it is relatively straightforward and computationally minimal to recalculate block-level emission density values to represent future scenarios where vehicle emission rates or traffic volumes are different from current levels. Our block-level emission density estimates can also serve as more spatially refined inputs for chemical transport and photochemical air quality modeling.

REFERENCES

(1) Karner, A. A.; Eisinger, D. S.; Niemeier, D. A. Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data. Environmental Science & Technology 2010, 44 (14), 5334–5344. https://doi.org/10.1021/es100008x.

(2) Zhou, Y.; Levy, J. Factors Influencing the Spatial Extent of Mobile Source Air Pollution Impacts: A Meta-Analysis. BMC Public Health 2007, 7 (89). https://doi.org/10.1186/1471-2458-7-89.

(3) Brugge, D.; Durant, J. L.; Rioux, C. Near-Highway Pollutants in Motor Vehicle Exhaust: A Review of Epidemiologic Evidence of Cardiac and Pulmonary Health Risks. Environ Health 2007, 6 (23). https://doi.org/10.1186/1476-069X-6-23.

(4) Gan, W. Q.; Tamburic, L.; Davies, H. W.; Demers, P. A.; Koehoorn, M.; Brauer, M. Changes in Residential Proximity to Road Traffic and the Risk of Death From Coronary Heart Disease. Epidemiology 2010, 21 (5), 642–649. https://doi.org/10.1097/EDE.0b013e3181e89f19.

(5) Hoffmann, B.; Moebus, S.; Möhlenkamp, S.; Stang, A.; Lehmann, N.; Dragano, N.; Schmermund, A.; Memmesheimer, M.; Mann, K.; Erbel, R.; Jöckel, K.-H. Residential Exposure to Traffic Is Associated With Coronary Atherosclerosis. Circulation 2007, 116 (5), 489–496. https://doi.org/10.1161/CIRCULATIONAHA.107.693622.

(6) McConnell, R.; Berhane, K.; Yao, L.; Jerrett, M.; Lurmann, F.; Gilliland, F.; Künzli, N.; Gauderman, J.; Avol, E.; Thomas, D.; Peters, J. Traffic, Susceptibility, and Childhood Asthma. Environ Health Perspect 2006, 114 (5), 766–772. https://doi.org/10.1289/ehp.8594.

(7) HEI. Systematic Review and Meta- Analysis of Selected Health Effects of Long-Term Exposure to Traffic-Related Air Pollution. Special Report 23; HEI Panel on the Health Effects of Long-Term Exposure to Traffic-Related Air Pollution: Boston, MA, 2022. https://www.healtheffects.org/system/files/hei-special-report-23_2.pdf.

(8) Rowangould, G. A Census of the US Near-Roadway Population: Public Health and Environmental Justice Considerations. Transportation Research Part D: Transport and Environment 2013, 25, 59–67. https://doi.org/10.1016/j.trd.2013.08.003.

(9) Tessum, C. W.; Paolella, D. A.; Chambliss, S. E.; Apte, J. S.; Hill, J. D.; Marshall, J. D. PM2.5 Polluters Disproportionately and Systemically Affect People of Color in the United States. Science Advances 2021, 7 (18), eabf4491. https://doi.org/10.1126/sciadv.abf4491.

(10) Wang, Y.; Apte, J. S.; Hill, J. D.; Ivey, C. E.; Patterson, R. F.; Robinson, A. L.; Tessum, C. W.; Marshall, J. D. Location-Specific Strategies for Eliminating US National Racial-Ethnic PM2.5 Exposure Inequality. Proc Natl Acad Sci U S A 2022, 119 (44), e2205548119. https://doi.org/10.1073/pnas.2205548119.

(11) Antonczak, B.; Thompson, T. M.; DePaola, M. W.; Rowangould, G. 2020 Near-Roadway Population Census, Traffic Exposure and Equity in the United States. Transportation Research Part D: Transport and Environment 2023, 125, 103965. https://doi.org/10.1016/j.trd.2023.103965.

(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. Environmental Health Perspectives 2017, 125 (9), 097012. https://doi.org/10.1289/EHP959.

(13) Colmer, J.; Hardman, I.; Shimshack, J.; Voorheis, J. Disparities in PM2.5 Air Pollution in the United States. Science 2020, 369 (6503), 575–578. https://doi.org/10.1126/science.aaz9353.

(14) 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. Environmental Health Perspectives 2021, 129 (12), 127005. https://doi.org/10.1289/EHP8584.

(15) Anenberg, S. C.; Miller, J.; Minjares, R.; Du, L.; Henze, D. K.; Lacey, F.; Malley, C. S.; Emberson, L.; Franco, V.; Klimont, Z.; Heyes, C. Impacts and Mitigation of Excess Diesel-Related NOx Emissions in 11 Major Vehicle Markets. Nature 2017, 545 (7655), 467–471. https://doi.org/10.1038/nature22086.

(16) Dallmann, T. R.; Kirchstetter, T. W.; DeMartini, S. J.; Harley, R. A. Quantifying On-Road Emissions from Gasoline-Powered Motor Vehicles: Accounting for the Presence of Medium- and Heavy-Duty Diesel Trucks. Environ. Sci. Technol. 2013, 47 (23), 13873–13881. https://doi.org/10.1021/es402875u.

(17) Haugen, M. J.; Bishop, G. A. Long-Term Fuel-Specific NOx and Particle Emission Trends for In-Use Heavy-Duty Vehicles in California. Environ. Sci. Technol. 2018, 52 (10), 6070–6076. https://doi.org/10.1021/acs.est.8b00621.

(18) Xiang, S.; Yu, Y. T.; Hu, Z.; Noll, K. E. Characterization of Dispersion and Ultrafine-Particle Emission Factors Based on Near-Roadway Monitoring Part II: Heavy Duty Vehicles. Aerosol Air Qual. Res. 2019, 19 (11), 2421–2431. https://doi.org/10.4209/aaqr.2019.08.0386.

(19) Xiang, S.; Hu, Z.; Zhai, W.; Wen, D.; Noll, K. E. Concentration of Ultrafine Particles near Roadways in an Urban Area in Chicago, Illinois. Aerosol Air Qual. Res. 2018, 18 (4), 895–903. https://doi.org/10.4209/aaqr.2017.09.0347.

(20) Demetillo, M. A. G.; Harkins, C.; McDonald, B. C.; Chodrow, P. S.; Sun, K.; Pusede, S. E. Space-Based Observational Constraints on NO2 Air Pollution Inequality From Diesel Traffic in Major US Cities. Geophysical Research Letters 2021, 48 (17), e2021GL094333. https://doi.org/10.1029/2021GL094333.

(21) 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. https://doi.org/10.1021/acs.est.0c01864.

(22) US EPA, O. Overview of Environmental Indicators in EJScreen. https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen (accessed 2024-06-24).

(23) Tian, N.; Xue, J.; Barzyk, T. M. Evaluating Socioeconomic and Racial Differences in Traffic-Related Metrics in the United States Using a GIS Approach. J Expos Sci Environ Epidemiol 2013, 23 (2), 215–222. https://doi.org/10.1038/jes.2012.83.

(24) Hatzopoulou, M.; Miller, E. J. Linking an Activity-Based Travel Demand Model with Traffic Emission and Dispersion Models: Transport's Contribution to Air Pollution in Toronto.

Transportation Research Part D: Transport and Environment 2010, 15 (6), 315–325. https://doi.org/10.1016/j.trd.2010.03.007.

(25) Lefebvre, W.; Vercauteren, J.; Schrooten, L.; Janssen, S.; Degraeuwe, B.; Maenhaut, W.; de Vlieger, I.; Vankerkom, J.; Cosemans, G.; Mensink, C.; Veldeman, N.; Deutsch, F.; Van Looy, S.; Peelaerts, W.; Lefebre, F. Validation of the MIMOSA-AURORA-IFDM Model Chain for Policy Support: Modeling Concentrations of Elemental Carbon in Flanders. Atmospheric Environment 2011, 45 (37), 6705–6713. https://doi.org/10.1016/j.atmosenv.2011.08.033.

(26) Poorfakhraei, A.; Tayarani, M.; Rowangould, G. Evaluating Health Outcomes from Vehicle Emissions Exposure in the Long Range Regional Transportation Planning Process. Journal of Transport & Health 2017. https://doi.org/10.1016/j.jth.2017.05.177.

(27) Rowangould, G. A New Approach for Evaluating Regional Exposure to Particulate Matter Emissions from Motor Vehicles. Transportation Research Part D: Transport and Environment 2015, 34, 307–317. https://doi.org/10.1016/j.trd.2014.11.020.

(28) Tayarani, M.; Rowangould, G. Estimating Exposure to Fine Particulate Matter Emissions from Vehicle Traffic: Exposure Misclassification and Daily Activity Patterns in a Large, Sprawling Region. Environmental Research 2020, 182, 108999. https://doi.org/10.1016/j.envres.2019.108999.

(29) Di Fonzo, D.; Fabri, A.; Pasetto, R. Distributive Justice in Environmental Health Hazards from Industrial Contamination: A Systematic Review of National and near-National Assessments of Social Inequalities. Social Science & Medicine 2022, 297, 114834. https://doi.org/10.1016/j.socscimed.2022.114834.

(30) Mustansar, T.; van den Brekel, L.; Timmermans, E. J.; Agyemang, C.; Vaartjes, I. Air Pollution Exposure Disparities among Ethnic Groups in High-Income Countries: A Scoping Review. Environmental Research 2025, 267, 120647. https://doi.org/10.1016/j.envres.2024.120647.

(31) Clark, L. P.; Millet, D. B.; Marshall, J. D. National Patterns in Environmental Injustice and Inequality: Outdoor NO2 Air Pollution in the United States. PLOS ONE 2014, 9 (4), e94431. https://doi.org/10.1371/journal.pone.0094431.

(32) Liu, M.; Meijer, P.; Lam, T. M.; Timmermans, E. J.; Grobbee, D. E.; Beulens, J. W. J.; Vaartjes, I.; Lakerveld, J. The Built Environment and Cardiovascular Disease: An Umbrella Review and Meta-Meta-Analysis. European Journal of Preventive Cardiology 2023, 30 (16), 1801–1827. https://doi.org/10.1093/eurjpc/zwad241.

(33) Antonczak, B.; Fay, M.; Chawla, A.; Rowangould, G. Estimated Roadway Segment Traffic Data by Vehicle Class for the United States: A Machine Learning Approach. arXiv February 7, 2025. https://doi.org/10.48550/arXiv.2502.05161.

(34) U.S. FHWA. Highway Performance Monitoring System (HPMS) 2018. U.S. Department of Transportation. https://data-usdot.opendata.arcgis.com/search?q=hpms.

(35) U.S. EPA. MOtor Vehicle Emission Simulator (MOVES), 2020. https://www.epa.gov/moves.

(36) U.S. EPA, O. National Emissions Inventory (NEI), 2017. https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei (accessed 2024-06-24).

(37) U.S. Census Bureau. Census 2020, Redistricting Data, Tables P1 and P2, 2021.

(38) U.S. Department of Agriculture, Economic Research Service. Rural-Urban Continuum Codes (RUCC), 2013, 2013. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/.

(39) U.S. EPA. MOVES3 Technical Guidance: Using MOVES to Prepare Emission Inventories for State Implementation Plans and Transportation Conformity; EPA-420-B-20-002; 2020. https://www.epa.gov/moves.

(40) U.S. Census Bureau. American Community Survey, 2020 American Community Survey 5-Year Estimates, Tables B17001 and B19013. U.S. Census Bureau. https://www.census.gov/programs-surveys/decennial-census/about/census-acs.html.

(41) Little Village Environmental Justice Organization; Center for Neighborhood Technology. Chicago Truck Counts. https://chicagotruckcounts.cnt.org (accessed 2025-04-29).