Environmental Science & Technology

pubs.acs.org/est

Article

Intercomparison of Modeled Urban-Scale Vehicle NO_x and $PM_{2.5}$ Emissions—Implications for Equity Assessments

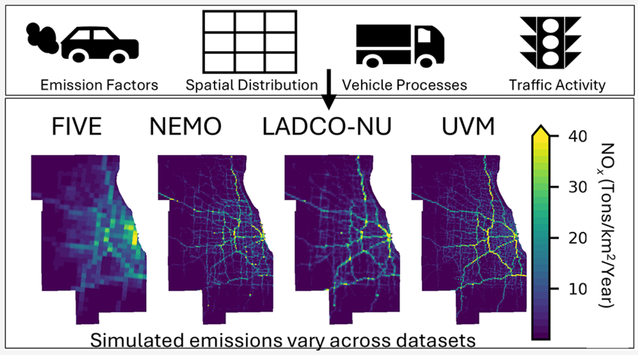
Victoria A. Lang,* Sara F. Camilleri, Suzan van der Lee, Gregory Rowangould, Brittany Antonczak, Tammy M. Thompson, Maria H. Harris, Colin Harkins, Daniel Q. Tong, Mark Janssen, Zachariah E. Adelman, and Daniel E. Horton

Cite This: *Environ. Sci. Technol.* 2025, 59, 4560−4570

Read Online

ACCESS | Metrics & More | Article Recommendations | Supporting Information

ABSTRACT: Accurate characterization of emissions is essential for understanding spatiotemporal variations of air pollutants and their societal impacts, including population exposure, health outcomes, and environmental justice implications. Characterizing emissions from the transportation sector is challenging due to uncertainties in emission-producing processes and in fleet composition and activity—factors that lead to differences across modeled vehicle emissions data sets. Here, we compare four data sets—Fuel-Inventory Vehicle Emissions, Neighborhood Emission Mapping Operation, Lake Michigan Air Director Consortium-Northwestern University, and University of Vermont—over the Greater Chicago region at three shared spatial resolutions (1.0, 1.3, and 4 km^2). While domain-level data set agreement is strongest at the coarsest resolution, at finer resolutions we find notable inconsistencies, particularly at local scales. At 1 km^2, simulated domain total NO_x emissions across the four data sets differ up to 82% (~32−58 k tons/year), while grid cell maximum $PM_{2.5}$ emissions vary up to 272% (~1.5−5.5 tons/km^2/year). Intercompared emissions data sets share similar inputs; however, divergent outcomes arise from differences in emission factors, simulated vehicle processes, and characterization of traffic data. While domain-level emission burdens among racial/ethnic subgroups are generally ranked similarly across data sets, the magnitude of relative disparities can vary up to 11%—a potentially consequential factor to consider in downstream impact analyses.



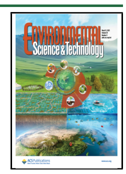
KEYWORDS: *vehicle emissions, emission modeling, fine particulate matter, nitrogen oxides, equity, distributional impacts*

1. INTRODUCTION

In the U.S., on-road vehicle emissions, including tailpipe exhaust, evaporative vapors from refueling and leaks, and nonexhaust sources such as brake, clutch, tire, and road wear, contribute ~23% of total greenhouse gas emissions, ~29% of nitrogen oxide (NO_x; NO + NO_2) emissions, and ~1.3% of primary fine particulate matter ($PM_{2.5}$) emissions.[1,2] Exposure to pollutants associated with vehicle emissions has been linked with numerous adverse health outcomes.[3−10] Nearly a quarter of the U.S. population—primarily nonwhite and low-income—resides near heavily trafficked roadways (i.e., within 500 m of roads with more than 25,000 vehicles passing daily); a proportion that has increased nearly 5 percentage points over the past decade.[11,12] Consequently, nonwhite and low-income populations are disproportionately impacted by traffic-related pollution.[13−15]

Efforts to assess vehicle emission impacts rely heavily on modeled vehicle emissions data sets. However, accurately characterizing vehicle emissions is challenging as models must account for numerous vehicle processes as well as dynamic fleet compositions and activities.[16,17] This complexity requires vehicle emission modelers to make assumptions and choices regarding model processes and input data which introduces uncertainties to simulated products. As such, it is crucial to characterize similarities and differences among simulated vehicle emission data sets, as these data sets are foundational inputs for estimating air pollution concentrations, which in turn inform assessments of population exposure and public health outcomes. Variations in vehicle emission modeling approaches introduce uncertainties that can propagate through air quality models,[18] and as these models advance to finer, and more equity-relevant spatial resolutions (i.e., ~1 km),[19,20] data set differences could lead to divergent environmental equity findings.

Received: September 13, 2024
Revised: February 1, 2025
Accepted: February 3, 2025
Published: February 27, 2025



With greater understanding of vehicle processes and advances in traffic data collection, computational resources, and modeling frameworks, the sophistication and spatiotemporal resolution of vehicle emission models has increased.[21] Among the most comprehensive vehicle emissions models is the U.S. EPA motor vehicle emission simulator (MOVES), which simulates on- and off-road emissions for 13 distinct vehicle classes, 6 road types, and 6 fuel types at the national-level, county-level, or along individual roadways.[22] The granularity of MOVES allows for detailed characterization of vehicle emission sources, albeit at a high computational cost when used to evaluate roadway-level impacts. Alternatively, MOVES can be used in reduced-complexity emission modeling frameworks, such as that from the University of Vermont (UVM) where emission factors (EFs) are aggregated by fewer vehicle classes and omit some vehicle processes for computational efficiency, enabling the simulation of emissions along individual roadways across broader spatial domains.

Modeled vehicle emission data sets rely on EFs empirically derived from observations. EFs quantify the mass of a pollutant emitted per distance or time for specific vehicle processes,[23] such as tailpipe exhaust, evaporative emissions, brake and tire wear, cold starts, and idling. EFs vary based on attributes such as vehicle age, engine load, speed, acceleration, road grade, and meteorology (ambient temperature, humidity).[17,24] EFs vary across different driving conditions within the same vehicle class. As such, EFs developed for emissions modeling aggregate and average across observations. An alternative EF development method uses fuel-sales records, i.e., fuel consumption, to normalize EFs for use in fuel-based emission models (e.g., the Fuel-Inventory Vehicle Emissions model), which express EFs per unit of fuel consumed rather than per distance traveled.[25] Regardless of method, EFs change over time as emission control technologies advance, necessitating regular updates to emission modeling frameworks.

Vehicle emission models also need detailed traffic activity data, which characterizes vehicle fleets, traffic conditions, and traffic volumes on individual roadways. Fleet characteristics (e.g., model, make, age) are primarily obtained from county-level vehicle registration data, while traffic conditions, traffic volume, and vehicle miles traveled (VMT) are supplied by the U.S. Federal Highway Administration (FHWA) Highway Statistics and Highway Performance Monitoring System (HPMS). The FHWA requires states to gather traffic data for public roads, excluding local or rural minor collector roads, within a margin of error of 5−10% for major roadways, large urban cores, and rural interstates,[26] but are only obligated to provide a random sample of medium-duty vehicle (MDV) and heavy-duty vehicle (HDV) traffic activity on unsampled roadways. This poses a potential challenge for emission models, as HDVs are the largest on-road contributor of NO_x emissions, despite comprising just ∼5% of the total population of on-road vehicles.[27,28] Emission models fill such data gaps using techniques such as population weighting, linear regression, or machine learning algorithms, introducing the potential for divergent model outcomes. Overall, an emission model's performance is intrinsically linked to the accuracy of EFs and the representation of traffic activity and vehicle fleet composition.

Analyzing simulated emissions from diverse modeling platforms is essential for identifying similarities and differences between emission data sets and for characterizing uncertainties in exposure and impact studies. Herein, we compare four distinct on-road vehicle emission data sets: (1) Fuel-Inventory Vehicle Emissions (FIVE);[14] (2) Neighborhood Emission Mapping Operation (NEMO);[29] (3) Lake Michigan Air Director Consortium-Northwestern University (LADCO-NU);[30] and (4) University of Vermont (UVM).[31] Each data set offers a unique combination of modeling inputs, enabling a comprehensive comparison of outputs across methodologies. We assess the variations among the four data sets over the Greater Chicago region—a region selected for its intricate network of nearly 30,000 miles of roads and a demographically diverse population of approximately 8.5 million residents.[32,33] We investigate spatial discrepancies, differences in simulated vehicle emission magnitudes, and the implications of these differences for the distribution of vehicle emissions. Our analysis addresses a critical gap in understanding uncertainties associated with high spatial resolution on-road vehicle emission modeling.

2. MATERIALS AND METHODS

In this section, we describe the methodologies and data inputs used in the FIVE, NEMO, LADCO-NU, and UVM data sets to simulate primary emissions of NO_x and $PM_{2.5}$ over the Greater Chicago region. Each data set was developed at a unique native spatial resolution, ranging from the representation of individual roads (i.e., link-level) to gridded emissions at a 4 km^2 resolution (Supporting Information Table S1). To ensure spatial uniformity for our comparisons, a first-order flux-conservative regridding method (Section 2.5) was applied to each emissions data set. The Greater Chicago region, defined as Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will Counties (Figure S1), contains 68.5% of Illinois' population.[33] The region is a major freight hub, with trucks constituting nearly 1 in 7 vehicles on urban interstates. This high truck presence is in part due to ∼25% of all U.S. freight trains and ∼50% of intermodal trains passing through the region,[34] along with a high concentration of freight establishments per capita.[35] In the main text, we provide NO_x-focused figures, while equivalent $PM_{2.5}$ figures are provided in the Supporting Information.

2.1. NEMO. The George Mason University NEMO[29] simulates hourly and annual average vehicle emissions for the contiguous United States (CONUS) at a resolution of 1 km^2 for the year 2017 (Table S1). NEMO data are developed using the U.S. EPA's emission modeling system, Sparse Matrix Operator Kernel Emissions[36] (SMOKE), and integrates input data from the EPA's 2017 National Emission Inventory (NEI; version 2017gb)[37] which uses county-level vehicle data from the 2017 FHWA Highway Statistics (Supporting Information Section S1.1). County-level, hourly, and meteorologically informed vehicle emissions are generated using MOVESv2014b EFs, with meteorological variables of temperature and relative humidity estimated by the Weather Research Forecast (WRF) model.[37] NEMO simulates emissions from vehicle tailpipe exhaust, evaporative processes, cold starts, brake wear, tire wear, and hotelling.[38] Hotelling is a process unique to long-haul trucks, representing emissions that occur while drivers take federally mandated breaks in which air conditioning, heating, or other devices are powered by prolonged engine idling, auxiliary power units, or alternative electrical sources.[38] To spatially allocate county-level vehicle emissions to a subcounty, 1 km^2 fixed grid, SMOKE uses spatial surrogates. Spatial surrogates quantify the proportion of a geographic attribute within a grid cell, relative to a

https://doi.org/10.1021/acs.est.4c09777
Environ. Sci. Technol. 2025, 59, 4560−4570

corresponding attribute's distribution across a given county. NEMO's modeling framework incorporates average annual daily traffic (AADT) from the 2016 HPMS, categorized by restricted and unrestricted road types to spatially distribute vehicle emissions. This approach allocates county-level emissions to fixed model grid cells, assigning a higher proportion of county-level vehicle emissions to road segments with greater traffic volumes, and ensuring that emissions from HDV processes are distributed only to roads where HDVs are present. Hotelling emissions are spatially allocated to grid cells that contain truck or rest stops. The spatial distribution of cold start emissions is informed by the National Land Cover Data set's (NLCD) "Medium and High Development Intensity" and "All Development".

2.2. LADCO-NU. LADCO-NU simulates hourly vehicle emissions at 1.3 km^2 resolution across a Chicago-centric, midwestern domain (Table S1). Emissions are generated for four seasonal months (August and October 2018, January and April 2019) and hourly emissions have been averaged to derive an annualized mean. LADCO-NU uses the EPA's 2016 V2[39] emission modeling platform, which incorporates MOVESv3 EFs and vehicle activity data from the 2017 NEI (version 2016fj). The 2016fj activity data is developed similarly to that of NEMO but projected back one year using the 2016 HPMS Highway Statistics.[39] Hourly, gridded meteorological inputs were developed using WRFv3.8,[40] whose performance is evaluated and outlined in Montgomery et al. (2023).[41] MOVESv3 simulates vehicle emissions originating from tailpipe exhaust, evaporative processes, cold starts, brake wear, tire wear, hotelling, and off-network idling (ONI) processes. ONI simulates emissions arising from vehicles idling off roadways for durations of less than 1 h, such as those parked in driveways, waiting in pick-up lines, or loading and unloading freight. LADCO-NU incorporates spatial surrogates generated by the LADCO, which spatially distributes on-road vehicle emissions using 2013 HPMS data. Emissions for cold starts and hoteling use similar spatial surrogates as NEMO. ONI, however, is spatially distributed to subcounty grid cells using "Medium and High Development Intensity" attributes from the NLCD.

2.3. UVM. UVM includes CONUS-wide annual average on-road vehicle emissions at a link-level resolution for 2018 (Table S1). UVM integrates county-level monthly average temperature and humidity for January and July, MOVES fuel regions, and vehicle inspection programs, resulting in 444 unique combinations. Representative counties are selected from each combination based on population size to capture varying urbanization levels. Emissions modeling is performed using MOVESv3 for 701 county−month combinations, encompassing 479 counties and representing 15.2% of U.S. counties. Annual average vehicle EFs (i.e., the annual average emissions produced per vehicle per unit of distance traveled) for on-road running rate emissions (i.e., tailpipe exhaust, evaporative emissions, brake, and tire wear) are calculated for each road type and source (vehicle) type. EFs are classified using MOVES road types with FHWA roadway functional classifications, allowing for their association with road links in the HPMS. EFs are aggregated by light-duty vehicles (LDV), MDVs, and HDVs, following MOVES vehicle definitions derived from HPMS vehicle types. Counties not modeled in MOVES are assigned EFs corresponding to their specific model parameters.[31] To estimate traffic volumes for MDVs and HDVs where FHWA does not provide AADT estimates, UVM developed a random forest regression model that was trained on links with available data using several predictors (i.e., total roadway segment AADT, functional classification, lane count, state and county indicators) to estimate the missing MDV and HDV traffic volume estimates. County-specific EFs are then applied to the augmented 2018 HPMS traffic data to calculate annual average daily emissions for NO_x and $PM_{2.5}$ for each roadway link.

2.4. FIVE. FIVE includes CONUS-wide hourly vehicle emissions, which are aggregated to represent weekday and weekend emissions for each month at 4 km^2 resolution for 2018 (Table S1). FIVE EFs, unlike the previous three data sets, use fuel-based EFs which have been derived from tunnel and near-road remote sensing studies for LDV (<or equal to 8500 lbs.) and HDV (>8500 lbs.) for winter and summer.[16,17,42,43] Brake wear, tire wear, and cold start EFs are provided by the U.S. EPA's MOVESv2014a. FIVE simulates vehicle emissions from tailpipe exhaust, evaporative processes, and cold starts (gasoline vehicles only). The 2018 Highway Statistics taxable fuel sales are then used to scale EFs, assuming gasoline and diesel consumption patterns for LDV and HDV, respectively.[17] Traffic activity data from the 2018 HPMS and fleet composition is used to spatially distribute on-road emissions for 82% and 71% LDV and HDV, respectively, to individual roadways based on available data. Emissions for traffic activity not available from the HPMS, such as that on local residential roads and minor collectors, are spatially allocated using population density.[44]

2.5. Regridding. With the exception of UVM, the emissions data sets are regridded to three common resolutions (1.0, 1.3, and 4 km^2) using first-order flux-conservation[45] from the xESMF python package[46] (Supporting Information Section S1.2). Conservative regridding is not performed on the UVM data set as it is provided at link-level. As such, we aggregate link-level data to the three compared grid resolutions (Supporting Information Section S1.3). We present 1.0 km^2 comparisons in the results, while 1.3 and 4 km^2 analyses are provided in the Supporting Information (Figures S11−S22).

3. RESULTS

3.1. Simulated Vehicle Emissions of NO_x. Our analysis highlights similarities and differences in simulated NO_x emissions (Figure 1). All data sets indicate the highest emissions (>40.00 tons/km^2/year) along major highways, particularly I-90, I-290, and I-294. Elevated emissions are also consistently found in downtown Chicago's "Loop" area, where six major highways (I-55, I-57, I-90, I-94, I-290, and I-294) converge. Beyond downtown, heightened emissions are observed along I-294 west of the city. Suburban (Lake, DuPage, Will Counties) and rural (McHenry, Kendall Counties) areas exhibit lower emissions (<2.00 tons/km^2/year).

Notable differences exist, with FIVE and UVM simulating higher NO_x emissions (30.00−85.43 tons/km^2/year) along I-294 southwest and south of Chicago, while NEMO, LADCO-NU, and UVM model higher emissions (>50.00 tons/km^2/year) in Lake County (Figure 1). LADCO-NU and UVM also show higher emissions (>40.00 tons/km^2/year) along I-55 in Will County and I-80 near Joliet, whereas FIVE and NEMO simulate lower emissions (<25.00 tons/km^2/year) in these areas. Maximum localized emissions range from 43.36 tons/km^2/year (FIVE) to 188.90 tons/km^2/year (NEMO), with localized hotspots in NEMO and LADCO-NU corresponding

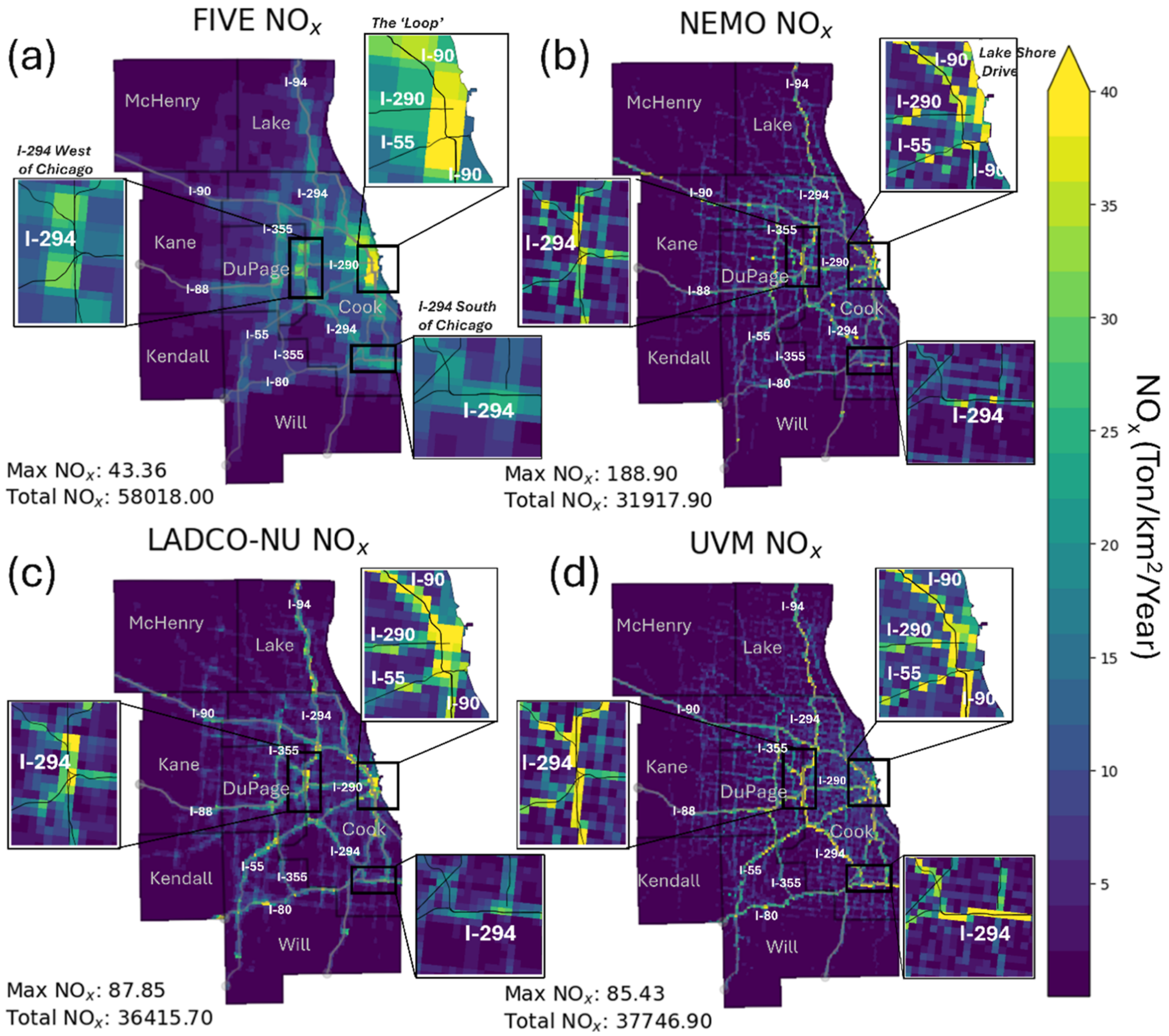


Figure 1. Simulated NO_x emissions from (a) FIVE, (b) NEMO, (c) LADCO-NU, and (d) UVM at 1 km^2 spatial resolution shown over the Greater Chicago region including Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will counties. Insets are centered on the "Loop", and segments of I-294 west, and south of downtown Chicago. "Max NO_x" refers to the maximum grid cell value (tons/km^2/year) within the domain, while "Total NO_x" refers to the sum of gridded emissions (tons/year) over the entire study domain. The corresponding figure for $PM_{2.5}$ emissions is S4.

to hoteling activity from truck stops and rest areas. Grid cells containing hotelling activity contribute approximately 4.9% (~1570 tons/year) and 2.2% (~800 tons/year) to the total NO_x emissions for NEMO and LADCO-NU, respectively. The total sum of simulated emissions ranges from 31,918.90 to 58,018.00 tons/year, with FIVE emissions 1.5 times higher than the other data sets—a pattern also observed in the 1.3 and 4 km^2 intercomparisons (Figures S11 and S17).

We calculate Pearson correlation coefficients to assess the degree of similarity/difference between simulated NO_x emissions and find a strong correlation between MOVES-based models: NEMO and UVM (r = 0.79), LADCO-NU and NEMO (r = 0.72), LADCO-NU and UVM (r = 0.73) (Figure S2). The weakest correlation is between FIVE and NEMO (r = 0.53), in part due to the conservative regridding method, which subdivides FIVE's native grid cells into 16 smaller cells with similar values, resulting in clusters of points with similar emission magnitudes (see Supporting Information Section S1.2). When comparing data sets at coarser resolutions, the similarity increases. For example, at 4 km^2, correlation between FIVE and NEMO increases to r = 0.92 (Figure S17).

Our evaluation of each data set's distribution shows that median simulated NO_x emissions range from 0.78 to 2.85 tons/km^2/year (Figure S3). The highest emissions occur along major roadways, which represent a small subset of the study area, resulting in a positively skewed distribution, with 95th percentiles ranging from 12.75 to 19.09 tons/km^2/year. Simulated NO_x emissions from NEMO, LADCO-NU, and UVM show similar distributions, with means of 2.95, 3.36, and 3.48 tons/km^2/year, and medians of 0.92, 1.25, and 0.78 tons/km^2/year, respectively. FIVE exhibits the highest magnitude of simulated emissions, with a mean of 5.35, median of 2.85, and a 95th percentile of 19.08 tons/km^2/year. FIVE also exhibits the greatest variability with an interquartile range of 0.64−7.83 tons/km^2/year.

To highlight differences between data sets and identify data set anomalies, we subtract each individual data set from the mean of the four data sets (Figure 2). NEMO generally simulates lower emissions (−0.04−5.25 tons/km^2/year) across most of the study domain, except along highways, grid cells containing hotelling activity, and along Lake Shore Drive, where emissions exceed the four-data set mean by up to 112.30

https://doi.org/10.1021/acs.est.4c09777
Environ. Sci. Technol. 2025, 59, 4560−4570

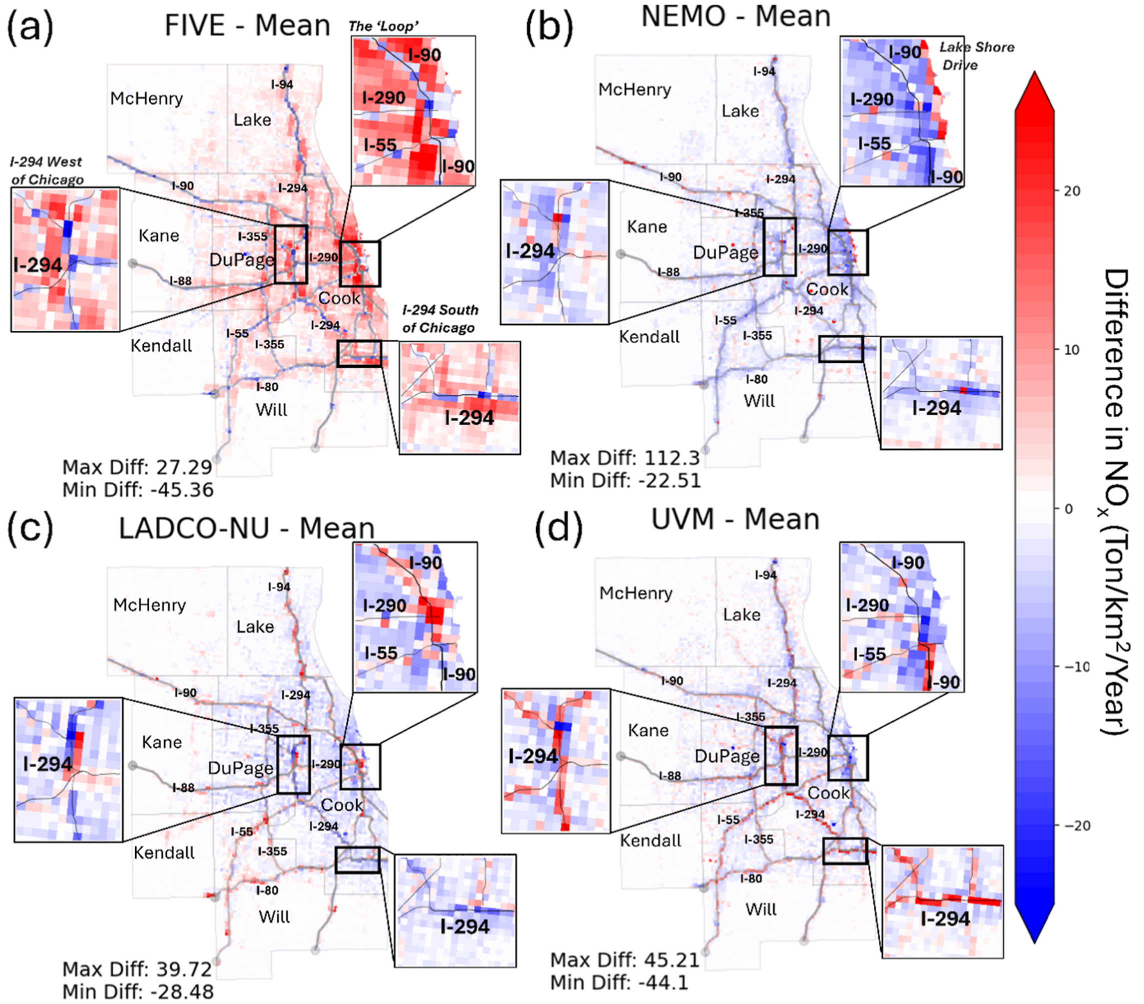


Figure 2. Spatial distribution of simulated NO_x emission differences from the four-data set mean (data set minus mean) across the Greater Chicago region: (a) FIVE, (b) NEMO, (c) LADCO-NU, and (d) UVM at 1 km^2 spatial resolution. Insets are centered on the "Loop", and segments of I-294 west, and south of downtown Chicago. The corresponding figure for $PM_{2.5}$ emissions is S7.

tons/km^2/year higher. This aligns with a recent study that found NEMO overestimated emissions relative to satellite NO_2 observations along Lake Shore Drive.[47] FIVE simulates higher NO_x emissions (up to 27.29 tons/km^2/year) across most of the Greater Chicago region, except for along interstates where emissions are up to −5.29 tons/km^2/year below the mean, driven in part by the conservative regridding process and FIVE's native resolution. Differences from the mean for MOVES-based (i.e., NEMO, LADCO-NU, UVM) data sets occur predominantly along interstates, where UVM simulates higher emissions along southwestern and southern portions of I-294 and LADCO-NU simulates higher emissions along interstates in Will and Lake counties, as well as within the Loop.

3.2. Simulated Vehicle Emission of $PM_{2.5}$. Our analysis reveals variations in the magnitude and spatial distribution of simulated $PM_{2.5}$ emissions among the four data sets (Figure S4). All data sets show similar spatial patterns, with the highest $PM_{2.5}$ emissions (>1.50 tons/km^2/year) along interstates like I-90, I-290, and I-294, and near the Loop. Within the Loop, FIVE, NEMO, and LADCO-NU simulate the highest $PM_{2.5}$ emissions: 1.48, 5.52, and 4.36 tons/km^2/year, respectively. Suburban and rural areas (Kane, Kendall, McHenry, Will Counties) consistently exhibit lower emissions (<0.15 tons/km^2/year). While FIVE, NEMO, and LADCO-NU simulate maximum emissions near the Loop, UVM simulates a localized maximum of 2.33 tons/km^2/year along I-294 south of Chicago (Figure S4). NEMO uniquely simulates higher emissions along interstates and highways (up to 3.00 tons/km^2/year), as well as along Lake Shore Drive (up to 5.52 tons/km^2/year). Localized hotspots associated with hotelling activity are discernible in both NEMO and LADCO-NU due to the presence of truck and rest stops along interstates. The sum of $PM_{2.5}$ emissions within the domain ranges from 1.213.30−1.996.40 tons/year, with UVM total emissions 44% lower (540 tons/year) than that of the next lowest data set, LADCO-NU (1756.2 tons/year). Differences in NO_x and $PM_{2.5}$ estimates among the four data sets are discussed in detail in Section 4.

In considering the similarities/differences between data sets, Pearson correlation coefficients show NEMO and UVM have the strongest correlation (r = 0.84), with NEMO presenting a high bias in one-to-one plots (Figure S5). NEMO and UVM also show a strong agreement with the LADCO-NU data set, with correlation coefficients of 0.76 and 0.74, respectively. The data sets with the weakest correlation are FIVE and NEMO (r = 0.56), partly due to our conservative regridding methods. Correlation coefficients improve at coarser resolutions, for example, correlation of FIVE and NEMO increases to r = 0.90

https://doi.org/10.1021/acs.est.4c09777
Environ. Sci. Technol. 2025, 59, 4560−4570

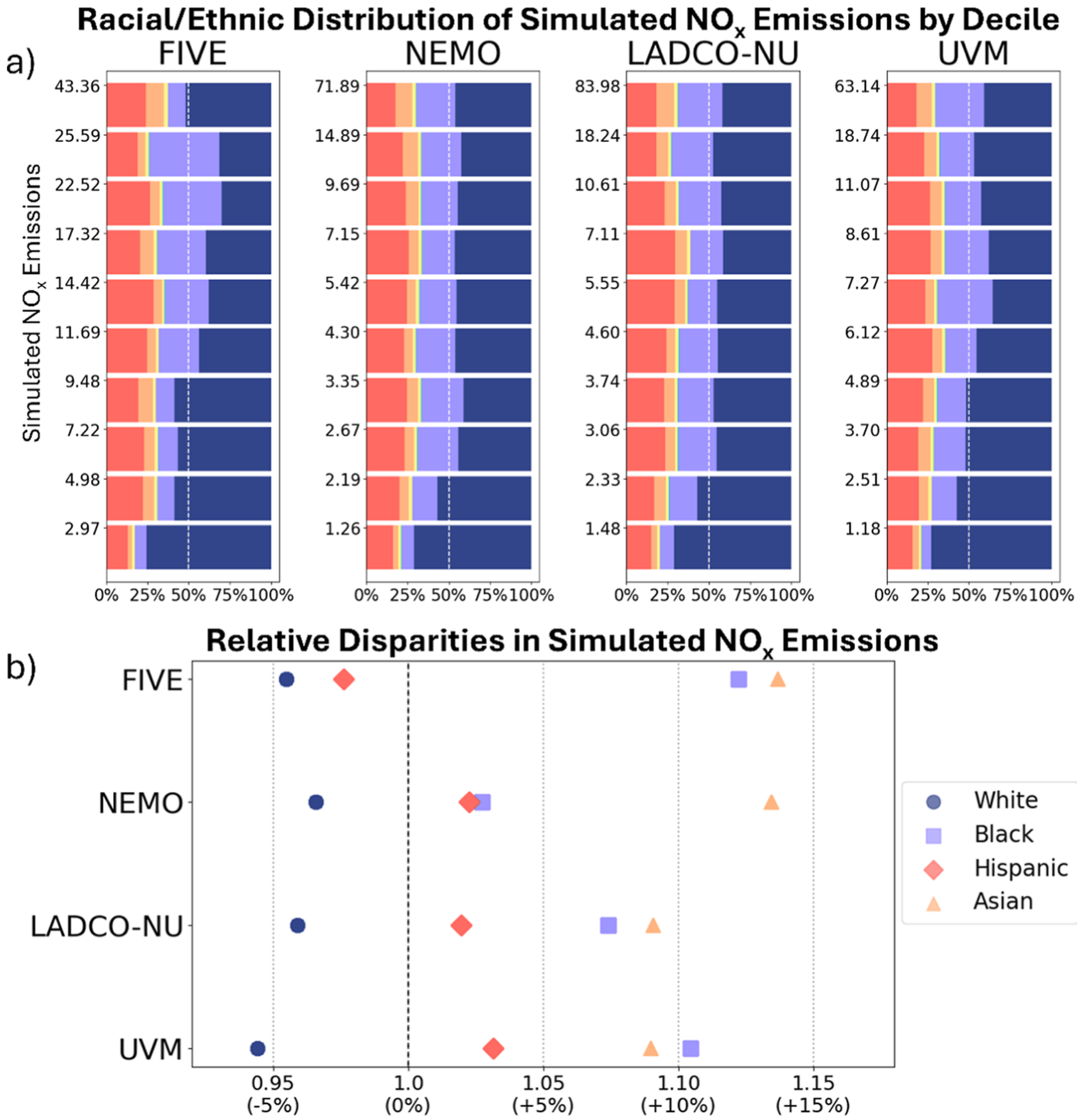


Figure 3. (a) Relative race/ethnicity composition of the population for deciles of area-weighted average NO*x* emissions (tons/km^2/year) across census tracts. The *Y*-axis shows the range of emission magnitudes within each decile, and the *X*-axis represents population percentages, with the vertical dashed line marking the 50th percentile. The legend in panel (b) corresponds to the same racial/ethnic groups as panel (a), with yellow representing "Two or more races" and green representing "Other". (b) Relative NO_x emission disparities for racial and ethnic subgroups, calculated using the FIVE, NEMO, LADCO-NU, and UVM data sets for the Greater Chicago Region. Disparities are expressed as the ratio of subgroup population-weighted emissions to the domain-wide population-weighted average. Values above 1 (black dashed line) indicate higher-than-average emissions, while values below 1 indicate lower-than-average emissions. The corresponding figure for $PM_{2.5}$ emissions is S9.

at 4 km^2 resolution (Figure S19). $PM_{2.5}$ distributions are generally similar across data sets, with means ranging from 0.11−0.18 and medians from 0.02−0.10 tons/km^2/year, showing a positive skew from higher emissions along roadways (Figure S6).

To identify $PM_{2.5}$ emission anomalies and distinctive patterns, we compute differences between individual data sets and the mean of the four data sets (Figure S7). FIVE simulates higher $PM_{2.5}$ emissions across the domain (0.07−0.95 tons/km^2/year), but lower emissions (−0.18−1.49 tons/km^2/year) along interstates. UVM simulates lower $PM_{2.5}$ emissions than the four-data set mean, except along I-294 west and south of Chicago where emissions are up to 0.89 tons/km^2/year higher. NEMO simulates higher emissions along highways (>2.00 tons/km^2/year), in grid cells that contain hotelling (>1.00 tons/km^2/year), and along Lake Shore Drive (up to 3.17 tons/km^2/year). LADCO-NU simulates $PM_{2.5}$ emissions up to 2.33 tons/km^2/year higher near the Chicago Loop area, but outside downtown and interstates, LADCO-NU emissions are generally lower than the mean within Cook and DuPage Counties.

3.3. Implications of Simulated Emission Uncertainties for Equity Analyses. Previous studies have overlaid emission estimates with demographic data to explore emission distribution inequities.[48,49] Here, using the four different emissions data sets, we perform similar analyses to demonstrate the impact of emissions uncertainties on distributional analyses, i.e., studies that stratify impact by income, race/ethnicity, etc.[50] However, it is important to recognize that the following analyses only quantify the distribution of traffic-related emissions simulated near populations and do not explicitly consider pollutant concentration exposure or public health impacts—measures that are a product of emissions, meteorology, atmospheric chemistry, pollutant lifetimes, and, in the case of health, population susceptibilities.[51]

First, to investigate the demographic composition of the full range of simulated emissions, we follow the methods of Chambliss et al.[15] by using area-weighted averages of emissions within each census tract and stratifying the domain-wide results by decile and demographic group (i.e., not population-weighted). Demographic data is sourced from the American Community Survey 2015−2019.[33] Despite the domain's majority white population (51%) (Figure S8), the highest simulated traffic-related NO_x and $PM_{2.5}$ emissions are found in areas with higher proportions of nonwhite residents (Figures 3a, S9 and S10). This disparity is particularly pronounced when examining census tracts with the highest emissions (i.e., 10th decile), where nonwhite residents collectively represent over 50% of the population in three of the four data sets: NEMO, LADCO-NU, and UVM. In the remaining data set, FIVE, the 10th decile is not comprised of a majority of nonwhite residents, but rather is ∼52% white in both the NO_x and $PM_{2.5}$ analyses.

Nest, to examine relative emission disparities, we calculate racial and ethnic subgroup population-weighted average emissions within the study domain. We define relative emission disparities following the methods of Kerr et al.,[14] by computing the ratio of each subgroup's population-weighted emissions to the domain-average. Relative emission burdens among population subgroups are generally ranked similarly, with higher relative NO_x and $PM_{2.5}$ emissions simulated in census tracts with larger Black and Asian populations (Figures 3b and S9). UVM simulates the largest relative disparities for the Black population, whereas the other three data sets consistently show the highest disparities for the Asian population. Despite general agreement in ranking, relative NO_x disparities vary widely: Black: +2.7% to +12.2%; Asian: +9.0% to +13.7%; Hispanic: −2.4% to +3.1%. Conversely, lower relative emissions are simulated for the White population in all data sets.

4. DISCUSSION

In the above intercomparison, we find similarities and differences in modeled vehicle emissions data sets. As emission models advance in sophistication and spatiotemporal resolution, allowing for the simulation of vehicle emissions from neighborhood to link-level spatial scales, it is critical to evaluate emission model uncertainties and associated implications. Diverse emissions estimates have downstream ramifications for applications that use traffic-related emissions data such as models that assess air pollutant exposure, health outcomes, environmental justice, and policy impacts. While many vehicle emission model inputs are shared and/or similar across emissions models, variability in input data is primarily driven by choices related to EFs, traffic activity, and the inclusion/exclusion of specific vehicle emission processes. Despite the challenges posed by divergent data inputs in developing the four emission data sets, which limits direct comparisons and our ability to pinpoint specific factors leading to observed similarities and differences, below we highlight methodological commonalities and distinctions that help to explain divergent outcomes.

4.1. Emission Factors. Each vehicle emissions model data set considered here uses EFs consistent with their technical formulation or model generation. In our intercomparison, FIVE is the one model that uses fuel-based EFs. FIVE's on-road NO_x emissions have been found to be within ∼8% of the EPA's 2017 NEI nationwide estimates.[52] However, our analysis indicates that over our regional domain, FIVE's NO_x emissions are substantially higher than those simulated by the 2017 NEI-informed, MOVES-based NEMO and LADCO-NU data sets. This discrepancy is likely, in part, attributable to differences in fuel-specific EFs, as FIVE's national estimates of NO_x emissions for diesel vehicles are nearly twice as high as those in MOVESv2014.[53] FIVE's EFs, derived from near-road observations, suggest that HDV selective catalytic reduction systems may not be as effective as assumed by regulatory models like MOVES, which tend to be more optimiztic about downward trends in HDV NO_x emissions.[54] Consequently, in the Chicago region, where HDV activity is substantial, this discrepancy may have a more pronounced impact on vehicle emission estimates. A recent comparison of simulated vehicle emissions from the MOVES and FIVE data sets, used as inputs in a chemical transport model (CTM) at 12 km^2 resolution, found that Greater Chicago area NO_2 concentrations in FIVE-based simulations were more than 2 ppb higher than MOVES-based.[18] While pollutant concentration differences varied regionally, the CTM's coarse spatial resolution did not capture hotspots along subgrid-scale features like roadways, suggesting that differences in NO_2 concentrations could be even higher if assessed at finer spatial resolutions. Conversely, FIVE's simulated $PM_{2.5}$ is more aligned with the other three data sets, all of which utilize various versions of MOVES EFs for brake and tire wear—a large source of vehicle $PM_{2.5}$ emissions.

Model version differences in emission model EFs can also explain differences between data sets, even if emission models use a similar modeling framework. For example, NEMO and LADCO-NU use different versions of the EPA's MOVES, with NEMO using MOVESv2014b and LADCO-NU using MOVESv3. In MOVESv3, the EPA increased HDV running rate EFs for NO_x, reduced HDV tailpipe exhaust EFs for $PM_{2.5}$, and reduced hotelling hours.[55] These changes have led to a nationwide decrease in simulated vehicle emissions of NO_x and $PM_{2.5}$ by 8% and 20%, respectively, when comparing nationwide simulated emissions from MOVESv2014 to MOVESv3.[55] Although reduced hotelling activity contributes to lower nationwide NO_x levels, urban areas with congested roads may still experience NO_x increases,[55] which contributes to differences we observe in overall domain totals and spatial variations in simulated NO_x and $PM_{2.5}$ along major roadways, e.g., I-80 and I-55. These examples illustrate how EFs can lead to diverging model outputs, even within data sets developed using similar modeling frameworks.

4.2. Traffic Activity. To constrain traffic activity, each emissions model considered here relies on HPMS data, but they differ in the vintages used and methods used for spatial distribution. FIVE and UVM use 2018 HPMS data, while NEMO and LADCO-NU rely on older data sets—2017 and 2016, respectively. Traffic activity in the HPMS data set is categorized by single unit (HPMS class 4−7), combination truck (HPMS class 8+), and total AADT.[26] FIVE and UVM emissions are estimated using this categorized AADT paired with EFs for specific vehicle classes (e.g., LDV, HDV). In contrast, NEMO and LADCO-NU first disaggregate traffic data to MOVES vehicle types to calculate county-level emissions. County-level emissions are then spatially distributed to a fixed grid using spatial surrogates based on total AADT and road type, where road type (e.g., unrestricted) determines which road segments to allocate HDV emissions.

While NEMO and LADCO-NU's disaggregation approach provides detailed emission data, the spatial distribution methods may introduce uncertainties by potentially leading to high bias on unrestricted roadways where total AADT primarily consists of LDV traffic, or vice versa for roadways experiencing additional HDV traffic such as known freight corridors. Given that HDVs are disproportionately responsible for on-road emissions, accurate spatial representation of HDVs is critical for policy and equity applications. Satellite observations have found that the EPA's MOVES modeling framework may not adequately capture elevated pollution near areas of dense warehousing,[47] which are often located in nonwhite neighborhoods.[56,57] This finding may be amplified by the spatial distribution methods addressed in this analysis and the limited traffic data for low-volume roads near freight hubs—highlighting the need for future emission models to better account for HDV activity and assessments to quantify impacts of unaccounted for HDV activity.

4.3. Vehicle Processes. During the development of vehicle emission models, a crucial decision revolves around whether to solely address on-road emissions or to include off-road processes such as cold starts and idling. Our intercomparison shows that the choice to include off-road processes results in localized variability. UVM primarily focuses on on-road running rate emissions, whereas FIVE integrates both running rate emissions and cold start emissions. NEMO and LADCO-NU encompass a broader spectrum of vehicle emission processes, including on-road running rates, cold starts, and idling activity. In NEMO and LADCO-NU, cold starts are distributed across the study domain as area emissions, contributing to domain totals without creating localized hotspots. However, differences in simulated vehicle emissions are observed in areas known for hoteling activity. Although idling activity constitutes a small portion of vehicle emissions, it impacts localized emission maximums. As simulated vehicle emissions are modeled at higher spatial resolutions and used for air pollution exposure assessments, accurately representing all off-road vehicle emission processes becomes increasingly important.

4.4. Recommendations. Highlighting potential factors that lead to discrepancies in simulated vehicle emission data sets at equity-relevant spatial resolutions is necessary for identifying uncertainties and increasing data set accuracy, which in turn can support the design of policies that can more effectively mitigate traffic-related pollution and promote environmental equity. Although emissions data sets developed using different methodologies yield divergent outcomes, each data set considered here has limitations that warrant consideration when used in equity-focused analyses. For example, MOVES-based models, including NEMO and LADCO-NU, are particularly advantageous for regulatory applications due to their granular outputs, such as emissions estimates stratified by vehicle class and fuel type. However, we recommend utilizing the most up-to-date MOVES-based modeling platforms and considering local HPMS data for both combination trucks and total AADT to better evaluate the spatial distribution of simulated emissions, particularly in urban areas with substantial HDV activity. The UVM data set, while offering higher spatial resolution and potentially greater accuracy for localized on-road traffic emissions, requires Supporting Information to account for contributions of off-road processes and cannot be used as input in chemical transport models. As a result, the UVM data set may be better suited for applications such as urban planning and local policy development. FIVE, in contrast, provides a complementary perspective by employing remote-sensed fuel-based EFs, offering an alternative characterization of emissions—particularly from diesel vehicles—that diverges from MOVES-based methodologies. A more apt intercomparison could be achieved if FIVE data were prepared at a higher-spatial resolution,[58,59] however it was unavailable for this domain. To fully leverage data set intercomparisons, improved access to emission models is needed as is formalized collaboration across modeling groups. Such an effort would enable cross-model spatiotemporal sensitivity analyses, improved uncertainty quantification, and refined methodologies that could increase the accuracy and reliability of vehicle emission data sets for applications in air quality, health, and policy assessments.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.4c09777.

NEMO emissions development, regridding methodologies, and intercomparison results for NOx and $PM_{2.5}$ at 1.3 km^2 and 4 km^2 resolutions (PDF)

AUTHOR INFORMATION

Corresponding Author

Victoria A. Lang – *Department of Earth, Environmental, and Planetary Sciences, Northwestern University, Evanston, Illinois 60208, United States;* orcid.org/0000-0002-9545-6822; Email: VictoriaLang2027@u.northwestern.edu

Authors

Sara F. Camilleri – *Department of Earth, Environmental, and Planetary Sciences, Northwestern University, Evanston, Illinois 60208, United States;* orcid.org/0000-0002-4299-8644

Suzan van der Lee – *Department of Earth, Environmental, and Planetary Sciences, Northwestern University, Evanston, Illinois 60208, United States*

Gregory Rowangould – *Department of Civil and Environmental Engineering, University of Vermont, Burlington, Vermont 05405, United States*

Brittany Antonczak – *Department of Civil and Environmental Engineering, University of Vermont, Burlington, Vermont 05405, United States*

Tammy M. Thompson – *Environmental Defense Fund, New York, New York 10010, United States*

Maria H. Harris – *Environmental Defense Fund, New York, New York 10010, United States*

Colin Harkins – *NOAA Chemical Sciences Laboratory, Boulder, Colorado 80305, United States; Cooperative Institute for Research in Environmental Sciences, Boulder, Colorado 80309, United States;* orcid.org/0000-0001-5692-3427

Daniel Q. Tong – *Department of Atmospheric, Oceanic and Earth Sciences, George Mason University, Fairfax, Virginia 22030, United States*

Mark Janssen – *Lake Michigan Air Directors Consortium, Chicago, Illinois 60624, United States*

https://doi.org/10.1021/acs.est.4c09777
Environ. Sci. Technol. 2025, 59, 4560−4570

Zachariah E. Adelman − *Lake Michigan Air Directors Consortium, Chicago, Illinois 60624, United States*
Daniel E. Horton − *Department of Earth, Environmental, and Planetary Sciences, Northwestern University, Evanston, Illinois 60208, United States;* orcid.org/0000-0002-2065-4517

Complete contact information is available at:
https://pubs.acs.org/10.1021/acs.est.4c09777

Author Contributions

V.A.L., S.F.C., S.L., T.M.T., M.H.H., and D.E.H. designed the study. V.A.L. performed the analysis and wrote the manuscript. All coauthors contributed editorial suggestions.

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This research was supported by the U.S. National Science Foundation CAREER award (CAS-Climate-2239834) and an Environmental Defense Fund grant to D.E.H. Environmental Defense Fund acknowledges support for this research from the Robertson Foundation and Signe Ostby and Scott Cook, Valhalla Foundation. Development of NEMO was funded by NOAA Weather Program Office and NASA Health and Air Quality Program. We thank the teams behind the FIVE dataset (https://csl.noaa.gov/groups/csl7/measurements/2020covid-aqs/data/emissions/FIVE/), NEMO dataset (http://www.emissionnow.org/), and UVM dataset for their contributions.

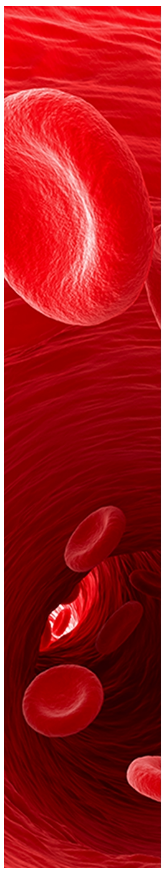
■ REFERENCES

(1) U.S. Environmental Protection Agency.*2017 National Emissions Inventory (NEI) Data*, 2017. https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-data (accessed 2024 01 04).
(2) U.S. Environmental Protection Agency. *Fast Facts on Transportation Greenhouse Gas Emissions*. https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions (accessed 2023 01 15).
(3) Faustini, A.; Rapp, R.; Forastiere, F. Nitrogen Dioxide and Mortality: Review and Meta-Analysis of Long-Term Studies. *Eur. Respir. J.* **2014**, *44* (3), 744−753.
(4) Di, Q.; Wang, Y.; Zanobetti, A.; Wang, Y.; Koutrakis, P.; Choirat, C.; Dominici, F.; Schwartz, J. D. Air Pollution and Mortality in the Medicare Population. *N. Engl. J. Med.* **2017**, *376* (26), 2513−2522.
(5) Khreis, H.; Kelly, C.; Tate, J.; Parslow, R.; Lucas, K.; Nieuwenhuijsen, M. Exposure to Traffic-Related Air Pollution and Risk of Development of Childhood Asthma: A Systematic Review and Meta-Analysis. *Environ. Int.* **2017**, *100*, 1−31.
(6) Davidson, K.; Fann, N.; Zawacki, M.; Fulcher, C.; Baker, K. R. The Recent and Future Health Burden of the U.S. Mobile Sector Apportioned by Source. *Environ. Res. Lett.* **2020**, *15* (7), 075009.
(7) Khomenko, S.; Cirach, M.; Pereira-Barboza, E.; Mueller, N.; Barrera-Gómez, J.; Rojas-Rueda, D.; de Hoogh, K.; Hoek, G.; Nieuwenhuijsen, M. Premature Mortality Due to Air Pollution in European Cities: A Health Impact Assessment. *Lancet Planet Health.* **2021**, *5* (3), e121−e134.
(8) Boogaard, H.; Patton, A. P.; Atkinson, R. W.; Brook, J. R.; Chang, H. H.; Crouse, D. L.; Fussell, J. C.; Hoek, G.; Hoffmann, B.; Kappeler, R.; Kutlar Joss, M.; Ondras, M.; Sagiv, S. K.; Samoli, E.; Shaikh, R.; Smargiassi, A.; Szpiro, A. A.; Van Vliet, E. D. S.; Vienneau, D.; Weuve, J.; Lurmann, F. W.; Forastiere, F. Long-Term Exposure to Traffic-Related Air Pollution and Selected Health Outcomes: A Systematic Review and Meta-Analysis. *Environ. Int.* **2022**, *164*, 107262.
(9) Weuve, J.; Kaufman, J. D.; Szpiro, A. A.; Curl, C.; Puett, R. C.; Beck, T.; Evans, D. A.; Mendes De Leon, C. F. Exposure to Traffic-Related Air Pollution in Relation to Progression in Physical Disability among Older Adults. *Environ. Health Perspect.* **2016**, *124* (7), 1000−1008.
(10) Andrews, R. M.; Adar, S. D.; Szpiro, A. A.; Kaufman, J. D.; Christopher, C. N.; Beck, T. L.; Dhana, K.; Wilson, R. S.; Rajan, K. B.; Evans, D.; Weuve, J. Association of Tailpipe-Related and Non-tailpipe−Related Air Pollution Exposure with Cognitive Decline in the Chicago Health and Aging Project. *Environ. Health Perspect.* **2024**, *132* (12), 127002.
(11) Rowangould, G. M. A Census of the US Near-Roadway Population: Public Health and Environmental Justice Considerations. *Transp. Res. D* **2013**, *25*, 59−67.
(12) Antonczak, B.; Thompson, T. M.; DePaola, M. W.; Rowangould, G. 2020 Near-Roadway Population Census, Traffic Exposure and Equity in the United States. *Transp. Res. D* **2023**, *125*, 103965.
(13) Castillo, M. D.; Kinney, P. L.; Southerland, V.; Arno, C. A.; Crawford, K.; van Donkelaar, A.; Hammer, M.; Martin, R. V.; Anenberg, S. C. Estimating Intra-Urban Inequities in PM2.5-Attributable Health Impacts: A Case Study for Washington, DC. *GeoHealth* **2021**, *5* (11), No. e2021GH000431.
(14) Kerr, G. H.; Goldberg, D. L.; Harris, M. H.; Henderson, B. H.; Hystad, P.; Roy, A.; Anenberg, S. C. Ethnoracial Disparities in Nitrogen Dioxide Pollution in the United States: Comparing Data Sets from Satellites, Models, and Monitors. *Environ. Sci. Technol.* **2023**, *57*, 19532.
(15) 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), No. e2109249118.
(16) McDonald, B. C.; Gentner, D. R.; Goldstein, A. H.; Harley, R. A. Long-Term Trends in Motor Vehicle Emissions in U.S. Urban Areas. *Environ. Sci. Technol.* **2013**, *47* (17), 10022−10031.
(17) McDonald, B. C.; McKeen, S. A.; Cui, Y. Y.; Ahmadov, R.; Kim, S.-W.; Frost, G. J.; Pollack, I. B.; Peischl, J.; Ryerson, T. B.; Holloway, J. S.; Graus, M.; Warneke, C.; Gilman, J. B.; de Gouw, J. A.; Kaiser, J.; Keutsch, F. N.; Hanisco, T. F.; Wolfe, G. M.; Trainer, M. Modeling Ozone in the Eastern U.S. Using a Fuel-Based Mobile Source Emissions Inventory. *Environ. Sci. Technol.* **2018**, *52* (13), 7360−7370.
(18) Ma, S.; Tong, D.; Harkins, C.; McDonald, B. C.; Wang, C.; Li, Y.; Baek, B. H.; Woo, J.; Zhang, Y. Impacts of On-Road Vehicular Emissions on U.S. Air Quality: A Comparison of Two Mobile Emission Models (MOVES and FIVE). *J. Geophys. Res.:Atmos.* **2024**, *129* (20), No. e2024JD041494.
(19) Mohegh, A.; Goldberg, D.; Achakulwisut, P.; Anenberg, S. C. Sensitivity of Estimated NO_2-Attributable Pediatric Asthma Incidence to Grid Resolution and Urbanicity. *Environ. Res. Lett.* **2021**, *16* (1), 014019.
(20) Clark, L. P.; Harris, M. H.; Apte, J. S.; Marshall, J. D. National and Intraurban Air Pollution Exposure Disparity Estimates in the United States: Impact of Data-Aggregation Spatial Scale. *Environ. Sci. Technol. Lett.* **2022**, *9* (9), 786−791.
(21) Forehead, H.; Huynh, N. Review of Modelling Air Pollution from Traffic at Street-Level - The State of the Science. *Environ. Pollut.* **2018**, *241*, 775−786.
(22) U.S. Environmental Protection Agency. *Population and Activity of On-Road Vehicles in MOVES3*, 2020. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjNkbaAl-78AhWyjIkEHZ7EBB4QFnoECCEQAQ&url=%3A%2F%2Fcfpub.epa.gov%2Fsi%2Fsi_public_file_download.cfm%3Fp_download_id%3D541844%26Lab%3DOTAQ&usg=AOvVaw3ZcRhl5p7HIvj67qhGobon (accessed 2023 01 25).
(23) U.S. Environmental Protection Agency. *Air Emissions Factors and Quantification*. https://www.epa.gov/air-emissions-factors-and-quantification (accessed 2023 05 16).

(24) Franco, V.; Kousoulidou, M.; Muntean, M.; Ntziachristos, L.; Hausberger, S.; Dilara, P. Road Vehicle Emission Factors Development: A Review. *Atmos. Environ.* **2013**, *70*, 84−97.
(25) Singer, B. C.; Harley, R. A. A Fuel-Based Motor Vehicle Emission Inventory. *J. Air Waste Manage. Assoc.* **1996**, *46* (6), 581−593.
(26) Office of Highway Policy Information. *Highway Performance Monitoring System Field Manual*. https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/(accessed 2023 12 22).
(27) U.S. Department of Transportation. *Highway Statistics* 2020. https://www.fhwa.dot.gov/policyinformation/statistics/2020/vm1.cfm.
(28) U.S. Environmental Protection Agency. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990−2020*. U.S. Environmental Protection Agency, 2022. https://www.epa.gov/system/files/documents/2022-04/us-ghg-inventory-2022-main-text.pdf (accessed 2023 01 25).
(29) Ma, S.; Tong, D. Q. Neighborhood Emission Mapping Operation (NEMO): A 1-Km Anthropogenic Emission Dataset in the United States. *Sci. Data* **2022**, *9* (1), 680.
(30) *Lake Michigan Air Directors Consortium*. https://www.ladco.org/(accessed 2023 01 23).
(31) Antonczak, B.; Rowangould, R. Multiscale Vehicle Traffic Air Pollutant Exposure and Equity Analysis in the United States Using a Novel Emissions Exposure Surrogate. In *103rd Annual Meeting of the Transportation Research Board of the National Academies*, 2024, Washington, D.C.
(32) CMAP. Chicago Metropolitan Agency for Planning: *Highway System Performance Trends*; FY18−0031; 2017. https://www.cmap.illinois.gov/documents/10180/71423/Highway+Performance_FINAL_9-15-17.pdf.
(33) Manson, S.; Schroeder, J.; Van Riper, D.; Kugler, T.; Ruggles, S. *IPUMS National Historical Geographic Information System*: Version 17.0 [5-Year Data [2015−2019, Block Groups & Larger Areas]], 2023.
(34) CMAP. Chicago Metropolitan Agency for Planning: *Data: The Freight System*, 2017. https://www.cmap.illinois.gov/documents/10180/517119/FY17-0095+Freight+Snapshot/3ae1174d-d8f4-4005-8a9f-e02eb87eeac2 (accessed 2024 03 11).
(35) Cidell, J. Concentration and Decentralization: The New Geography of Freight Distribution in US Metropolitan Areas. *J. Transp. Geogr.* **2010**, *18* (3), 363−371.
(36) Baek, B. H.; Seppanen, C. Sparse Matrix Operator Kernel Emissions (SMOKE) Modeling System. Technical Report 2018.
(37) U.S. Environmental Protection Agency. *2017 National Emissions Inventory: January 2021 Updated Release, Technical Support Document*; EPA-454/R-21−001, 2021. https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-technical-support-document-tsd.
(38) U.S. Environmental Protection Agency. *Population and Activity of On-Road Vehicles in MOVES2014*; EPA-420-R-16−003a, 2016.
(39) Eyth, A.; Vukovich, J.; Farkas, C.; Godfrey, J. *Technical Support Document (TSD): Preparation of Emissions Inventories for the 2016v2 North American Emissions Modeling Platform*; US Environmental Protection Agency, Office of Air Quality Planning and Standards, 2022.
(40) Skamarock, W. C.; Klemp, J. B.; Dudhia, J.; Gill, D. O.; Barker, D. M.; Duda, M. G.; Huang, X.-Y.; Wang, W.; Powers, J. G. *A Description of the Advanced Research WRF*; Version 3, NCAR/TN−475+STR, 2008.
(41) Montgomery, A.; Schnell, J. L.; Adelman, Z.; Janssen, M.; Horton, D. E. Simulation of Neighborhood-Scale Air Quality With Two-Way Coupled WRF-CMAQ Over Southern Lake Michigan-Chicago Region. *J. Geophys. Res.:Atmos.* **2023**, *128* (6), No. e2022JD037942.
(42) McDonald, B. C.; Dallmann, T. R.; Martin, E. W.; Harley, R. A. Long-Term Trends in Nitrogen Oxide Emissions from Motor Vehicles at National, State, and Air Basin Scales. *J. Geophys. Res.* **2012**, *117* (D21), D00V18.
(43) Hassler, B.; McDonald, B. C.; Frost, G. J.; Borbon, A.; Carslaw, D. C.; Civerolo, K.; Granier, C.; Monks, P. S.; Monks, S.; Parrish, D. D.; Pollack, I. B.; Rosenlof, K. H.; Ryerson, T. B.; Von Schneidemesser, E.; Trainer, M. Analysis of Long-term Observations of NO_x and CO in Megacities and Application to Constraining Emissions Inventories. *Geophys. Res. Lett.* **2016**, *43* (18), 9920−9930.
(44) Harkins, C.; McDonald, B. C.; Henze, D. K.; Wiedinmyer, C. A Fuel-Based Method for Updating Mobile Source Emissions during the COVID-19 Pandemic. *Environ. Res. Lett.* **2021**, *16* (6), 065018.
(45) Jones, P. W. First- and Second-Order Conservative Remapping Schemes for Grids in Spherical Coordinates. *Mon. Wea. Rev.* **1999**, *127* (9), 2204−2210.
(46) Jiawei, Z.; Dussin, R.; Huard, D.; Bourgault, P.; Banihirwe, A.; Stephane, R.; Brewster, M.; Schupfner, M.; Filipe; Levang, S.; Gauthier, C.; Jüling, A.; Almansi, M.; RichardScottOZ; RondeauG; Rasp, S.; Smith, T. J.; Stachelek, J.; Plough, M.; Pierre Bell, R.; Caneill, R.; Li, X.. *Pangeo-Data/xESMF*: V0.8.2, 2023.
(47) Goldberg, D. L.; Tao, M.; Kerr, G. H.; Ma, S.; Tong, D. Q.; Fiore, A. M.; Dickens, A. F.; Adelman, Z. E.; Anenberg, S. C. Evaluating the Spatial Patterns of U.S. Urban NOx Emissions Using TROPOMI NO2. *Remote Sens. Environ.* **2024**, *300*, 113917.
(48) Nunez, Y.; Benavides, J.; Shearston, J. A.; Krieger, E. M.; Daouda, M.; Henneman, L. R. F.; McDuffie, E. E.; Goldsmith, J.; Casey, J. A.; Kioumourtzoglou, M.-A. An Environmental Justice Analysis of Air Pollution Emissions in the United States from 1970 to 2010. *Nat. Commun.* **2024**, *15* (1), 268.
(49) Zalzal, J.; Hatzopoulou, M. Fifteen Years of Community Exposure to Heavy-Duty Emissions: Capturing Disparities over Space and Time. *Environ. Sci. Technol.* **2022**, *56* (23), 16621−16632.
(50) Bistline, J.; Onda, C.; Browning, M.; Emmerling, J.; Iyer, G.; Mahajan, M.; McFarland, J.; McJeon, H.; Orvis, R.; Fonseca, F. R.; Roney, C.; Sandoval, N.; Sarmiento, L.; Weyant, J.; Woollacott, J.; Yuan, M. Equity Implications of Net-Zero Emissions: A Multi-Model Analysis of Energy Expenditures across Income Classes under Economy-Wide Deep Decarbonization Policies. *Energy Clim. Change* **2024**, *5*, 100118.
(51) Camilleri, S.; Montgomery, A.; Visa, M.; Schnell, J.; Adelman, Z.; Janssen, M.; Grubert, E.; Anenberg, S.; Horton, D. Air Quality, Health and Equity Implications of Electrifying Heavy-Duty Vehicles. *Nat. Sustain.* **2023**, *6*, 1643.
(52) Li, M.; McDonald, B. C.; McKeen, S. A.; Eskes, H.; Levelt, P.; Francoeur, C.; Harkins, C.; He, J.; Barth, M.; Henze, D. K.; Bela, M. M.; Trainer, M.; de Gouw, J. A.; Frost, G. J. Assessment of Updated Fuel-Based Emissions Inventories Over the Contiguous United States Using TROPOMI NO_2 Retrievals. *J. Geophys. Res.:Atmos.* **2021**, *126* (24), No. e2021JD035484.
(53) Yu, K. A.; McDonald, B. C.; Harley, R. A. Evaluation of Nitrogen Oxide Emission Inventories and Trends for On-Road Gasoline and Diesel Vehicles. *Environ. Sci. Technol.* **2021**, *55* (10), 6655−6664.
(54) Jiang, Y.; Tan, Y.; Yang, J.; Karavalakis, G.; Johnson, K. C.; Yoon, S.; Herner, J.; Durbin, T. D. Understanding Elevated Real-World NOx Emissions: Heavy-Duty Diesel Engine Certification Testing versus in-Use Vehicle Testing. *Fuel* **2022**, *307*, 121771.
(55) U.S. Environmental Protection Agency. *Overview of Progress and Findings from the Cross-EPA Coordination Effort for Understanding and Evaluating NOx Emissions Discrepancies*; EPA-454/R-21−008, 2021. https://www.epa.gov/system/files/documents/2021-12/epa-454_r-21-008_final.pdf.
(56) Environmental Defense Fund. *Warehouse Boom Places Unequal Health Burden on New York Communities*, 2024. https://globalcleanair.org/wp-content/blogs.dir/95/files//EDF-NY-Warehouse-Boom-Report-1-18-23.pdf.
(57) Environmental Defense Fund. *Illinois Warehouse Boom: Tracing the Growth of Mega-Warehouses and Their Health Impacts*, 2024. https://news.wttw.com/sites/default/files/article/file-attachments/IL_Warehouse_Boom_Report_EDF_4-24-24.pdf.
(58) Yu, K. A.; Li, M.; Harkins, C.; He, J.; Zhu, Q.; Verreyken, B.; Schwantes, R. H.; Cohen, R. C.; McDonald, B. C.; Harley, R. A.

Improved Spatial Resolution in Modeling of Nitrogen Oxide Concentrations in the Los Angeles Basin. *Environ. Sci. Technol.* **2023**, *57* (49), 20689−20698.

(59) Bradley, A. C.; Croes, B. E.; Harkins, C.; McDonald, B. C.; De Gouw, J. A. Air Pollution Inequality in the Denver Metroplex and Its Relationship to Historical Redlining. *Environ. Sci. Technol.* **2024**, *58*, 4226−4236.



https://doi.org/10.1021/acs.est.4c09777
Environ. Sci. Technol. 2025, 59, 4560−4570