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Distributional impacts of fleet-wide change in light duty transportation: mortality risks of $PM_{2.5}$ emissions from electric vehicles and Tier 3 conventional vehicles

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Abstract

Light-duty transportation continues to be a significant source of air pollutants that cause premature mortality and greenhouse gases (GHGs) that lead to climate change. We assess $PM_{2.5}$ emissions and its health consequences under a large-scale shift to electric vehicles (EVs) or Tier-3 internal combustion vehicles (ICVs) across the United States, focusing on implications by states and for the fifty most populous metropolitan statistical areas (MSA). We find that both Tier-3 ICVs and EVs reduce premature mortality by 80%–93% compared to the current light-duty vehicle fleet. The health and climate mitigation benefits of electrification are larger in the West and Northeast. As the grid decarbonizes further, EVs will yield even higher benefits from reduced air pollution and GHG emissions than gasoline vehicles. EVs lead to lower health damages in almost all the 50 most populous MSA than Tier-3 ICVs. Distributional analysis suggests that relying on the current gasoline fleet or moving to Tier-3 ICVs would impact people of color more than White Americans across all states, levels of urbanization, and household income, suggesting that vehicle electrification is more suited to reduce health disparities. We also simulate EVs under a future cleaner electric grid by assuming that the 50 power plants across the nation that have the highest amount of annual SO_2 emissions are retired or retrofitted with carbon capture and storage, finding that in that case, vehicle electrification becomes the best strategy for reducing health damages from air pollution across all states.

1. Introduction

In the United States, emissions standards set upper limits on emissions per mile for various air pollutants for new vehicles. These standards have helped drastically reduce air pollutants from light-duty vehicles (LDVs). Between Tier 1 (1994) and Tier 3 standards (2017), the allowed NO_x (nitrous oxide) and $PM_{2.5}$ (particulate matter less than 2.5 μm) emissions per mile from gasoline vehicles decreased by more than 90% [1, 2]. However, LDVs continue to contribute to 10% of the total $PM_{2.5}$ attributable premature mortality, with disproportionate impacts on people of color and minorities [3–5]. Historical race-based housing segregation and land-use practices like building freeways through communities of color perpetuate these systemic transportation inequalities despite massive improvements in overall air quality [3, 6]. Studies have shown people of color are consistently exposed to higher concentrations of NO_2 (a marker for traffic pollution) than White people [7, 8]. Reduction in traffic congestion with the introduction of electronic tolls has reduced premature mortality by ∼8% and low birth weight among mothers by ∼10%, with larger benefits for African Americans [9]. On the climate front, the transportation sector leads in total greenhouse gas (GHG) emissions in the U.S. (1.7 billion metric tons per year), with LDVs contributing to 58% of the total transportation-related emissions [10].

Primary $PM_{2.5}$ emissions from gasoline internal combustion vehicles (ICVs) include tailpipe emissions, dust re-suspension, and tire and brake wear. Secondary $PM_{2.5}$ is also formed due to chemical reactions of precursor species such as nitrous oxides (NO_x), non-methane organic gases (NMOGs—a subclass of volatile organic oxides comprising of non-methane hydrocarbons and oxygenated hydrocarbons), and ammonia [2]. Emissions standards set a quantitative limit of pollutant emissions that new vehicles can emit per mile. The first set of standards, called Tier 1 standards, were phased in between 1994 and 1997, followed by Tier 2 standards between 2004 and 2009. Tier 3 standards were finalized in 2015 and will be phased between 2017 and 2025. The standards have been tightened considerably: per-mile gasoline NO_x + NMOG and $PM_{2.5}$ limits under regulatory test conditions have decreased by 91% and 97%, respectively, between 1994 and 2022. In SI section S.2a, we provide more details on how the standards for different pollutants, vehicles, certification bins, and test procedures have evolved.

Under Tier 3 standards, manufacturers need to adhere to emissions limits under laboratory testing conditions for their total annual sales as well as for each vehicle. Tier 3 standards introduced a limit on per mile NMOG + NO_X emissions instead of limits of NMOG and NO_x individually, as was done previously. The standard also includes per-mile limits for $PM_{2.5}$, carbon monoxide (CO), and formaldehyde [2]. Manufacturers can balance NO_x + NMOG emissions across individual vehicles sold in a year as long as the new-sale fleet-wide emissions standard is achieved. Each vehicle is required to attain the $PM_{2.5}$ emission standard. Standards also depend on the driving conditions they are tested on. Federal Test Procedure or FTP simulates city driving conditions, US06 approximates high acceleration aggressive driving, and supplemental FTP is a mixture of city driving, aggressive driving, and driving with air conditioning (SI section S.2a) [11]. For this work, we consider FTP and SFTP emissions standards as two scenarios for Tier-3 ICVs. New vehicles on the road generally emit below the emissions standards [12, 13], but in the past, some manufacturers have used defeat devices to disable emissions controls under real-world driving [14]. Also, vehicle emissions per mile increase significantly with age and cumulative mileage [15–21].

Electric vehicles (EVs) have emerged as another alternative. EVs can reduce transportation-related air pollution, associated inequities, and GHG emissions under a low-emitting electricity grid. $PM_{2.5}$ health damages from EVs depend on the emission intensity of the electricity used to charge them. Vehicle charging demand, which constituted only 11 out of 4116 TWh of electricity demand [22, 23], will significantly increase with rising EV penetration. Total electricity generation in the U.S. was associated with ∼16 400 $PM_{2.5}$ premature deaths in 2014, with Black and White people experiencing higher premature mortality. Coal power plants were responsible for ∼93% of electricity $PM_{2.5}$-related premature mortality in the U.S [24]. Hence, coal retirements will be crucial to reducing the health impacts of large-scale EV transition.

Previous work has found that EVs powered by low-emitting electricity reduce health impacts by 50% compared to conventional gasoline vehicles. In comparison, those powered by coal-based or the then 'grid-average' emissions intensity increase damages by 80% [25]. Hence, reducing upstream air emissions from electrified transportation will require reducing air emissions from the power sector. This shift will have different consequences across the country, given the different composition of electricity generation. Several studies have compared the health damages of transportation technologies in the US using a marginal damages approach, wherein an incremental vehicle mile traveled (VMT) is small enough to be treated as marginal, and damages are calculated as the product of emission factor (emissions per mile) and marginal damages of a pollutant [26]. Using a marginal damages approach, Tong and Azevedo find that in the Western US and New England, switching to an EV would reduce monetized damages when compared to gasoline vehicles, whereas gasoline hybrid vehicles would be less damaging in the Midwest [27]. Choma *et al* show that EVs have less health damages than ICVs in all U.S. metropolitan statistical areas (MSAs) [28]. Holland *et al* calculate the net environmental benefits of vehicle electrification, finding those to be positive for Asian and Latino Americans (data from 2010 to 2014) [29, 30]. Other studies have used chemical transport models to estimate air quality and distributional equity consequences of LDV electrification to find similar conclusions. $PM_{2.5}$ changes due to electrification depend on the source and location of electricity generation used to charge electric vehicles. EVs increase pollution in areas close to coal power plants [31] but reduce pollution in urban regions [32, 33] and in states with low-carbon electricity like California [34]. Peters *et al* [35] estimate health benefits and avoided mortality at 25% and 75% EV adoption with three different electricity grid scenarios, including the current grid and a future low-emissions one. The highest health benefits are achieved with a low-emitting grid, and increasing EV adoption without reducing emissions from the grid only provides small health benefits. The composition of electricity generation, the concentration of local air pollutants, and vehicle technologies have changed substantively since these previous studies were published. For example, the per-mile emissions from Tier

3 vehicles for NO_X, $PM_{2.5}$, and volatile oxides are 96%, 80%, and 95% smaller than those of the current LDV fleet (table 1). EVs and the electricity sector have also evolved. Since 2015, the range of new EVs has increased by 9%, and coal-generated electricity has been reduced by 30% [36, 37].

In this work, we estimate $PM_{2.5}$ related health impacts and change in socio-economic disparities associated with four scenarios: (i) a business-as-usual, reflecting the current LDV fleet; (ii) a replacement of the current LDV fleet with gasoline vehicles that meet the model year 2022 Tier 3 emissions standards, (iii) replacement of the current LDV fleet with a range of EV models charged with the current electricity grid, and (iv) replacement of current LDV fleet with a range of EV models charged with a future clean electricity grid where 50 power plants with the highest SO_2 emissions have been retired or retrofitted with carbon capture and storage (CCS). In post-combustion CCS, SO_2, NO_x, and $PM_{2.5}$ are removed from the flue gas before CO_2 is captured and removed [38].

We use a reduced complexity air quality model (InMAP) [39] to estimate the change in $PM_{2.5}$ concentration due to changes in emissions from point sources (power plants) and area sources (gasoline ICVs) across the U.S [40]. Reduced complexity air quality models (RCM) have become a popular tool in recent years to evaluate the air quality implications of different policies or technologies [4, 24, 25, 29, 30, 41–44]. Some widely used RCMs include InMAP, AP3, and EASIUR [39, 45–47]. Previous research has shown that the three RCMs produce marginal damages within the same order of magnitude despite structural differences. For example, for ground-level primary PM2.5, the models have very similar values across all counties, with Pearson's correlation ranging from 0.73 to 0.81. Benchmarking studies also indicate that RCMs can be used instead of chemical transport models for scenario modeling with only a modest loss of accuracy [48, 49].

We use local air pollutant emissions and emissions of GHGs from the electricity sector [40, 50, 51]. For Tier-3 ICV, we use Tier-3 emission standards for model year 2022 in FTP and SFTP test conditions [1, 2]. We use census block group data (ACS 2019–2020) [52, 53] as a source of information for demographic characteristics. We use our previous estimates of the energy needed to charge EVs in different locations, which account for ambient temperature conditions, drive cycle (city, rural, or combined), vehicle make, and model [54].

The rest of this paper is organized as follows: we describe data and methods used for the analysis, followed by air quality and climate change impacts of the fleet-wide use of EVs and Tier-3 ICVs. We assess equity implications across different socio-economic aspects and conclude with findings and recommendations. The key contribution of this work is to assess how less polluting conventional vehicles (Tier-3 ICVs) would fare when compared to electric vehicles in terms of air pollution and distributional equity across the nation. While past studies have detailed the increasing stringency of emissions over time [21, 55] and their positive impact on air quality [56–58], our work incorporates Tier-3 vehicles and provides important regional conclusions.

2. Methods and data

We estimate impacts on climate change and $PM_{2.5}$-related health and socio-economic disparities associated with the following scenarios: (i) a business-as-usual scenario, where we compute the health damages from the current fleet of LDV across the U.S.; (ii) a replacement of the current fleet with gasoline vehicles that meet the strictest emissions standards (Tier-3 ICV), and (iii) a replacement of the current fleet of LDVs with electric vehicles that are charged with the current grid and (iv) a possible future low-carbon electricity grid where 50 plants with highest annual SO_2 emissions are retired or retrofitted with CCS. We estimate health impacts from these scenarios by race, ethnicity, geography, and income for states in the contiguous United States and for the 50 most populous MSAs. Throughout this work, health consequences refer to the attributable premature mortality associated with the increase in $PM_{2.5}$ concentration associated with primary $PM_{2.5}$ emissions and precursor pollutants, such as SO_2 and NO_x, from the different transportation technologies studied in this paper.

There are three modeling steps in our methods. Firstly, we estimate annual tailpipe emissions from ICVs (Tier-3 and current fleet) at the census tract level. These emissions are treated as ground-level area source emissions, i.e. the annual emissions of each pollutant are assumed to be uniformly distributed across the census tract (SI sections S.1 and S.2). InMAP, the reduced complexity air quality model used in this work, allocates these input emissions to model cells using area weighting (SI section S.5c) and converts pollutant emissions to changes in $PM_{2.5}$ concentration. The grid cell size in InMAP varies depending on population density (figure 1), with the largest grid cell of 48 km $\times$ 48 km in sparsely populated regions and 1 km $\times$ 1 km in densely populated urban areas. Pollution from electric vehicles is attributed as an increase in emissions proportional to the increase in electricity generation due to electric vehicle charging demand. Emissions from power plants are treated as point sources in a specific InMAP grid cell, and the change in PM2.5 concentration is estimated for all power plants. After estimating the change in $PM_{2.5}$ concentration due to each technology choice, we spatially overlay the census block group with InMAP grid cells to find the counts of the total population and population of races and

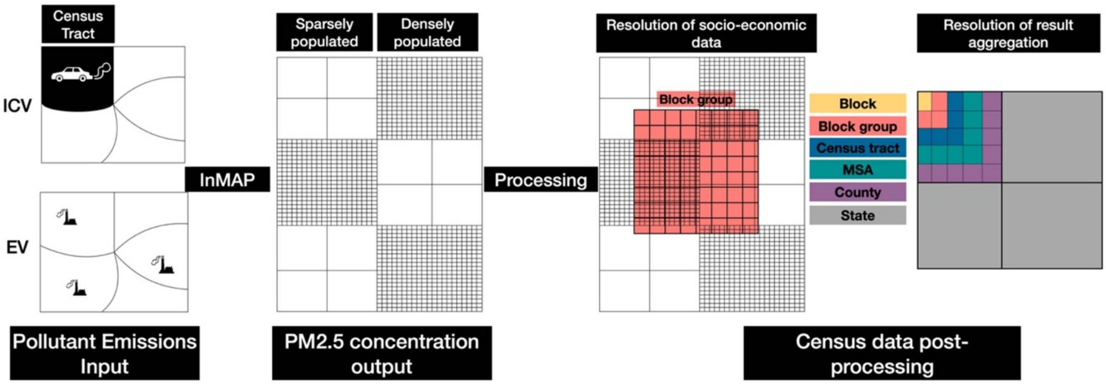

Figure 1. Modeling steps and spatial resolution of inputs, outputs, and post-processing used in this work.

ethnicities exposed to the change in $PM_{2.5}$. Using a concentration-response function, total premature deaths are calculated at the census block group level. Mortality rate (deaths per 100 000 people) is reported at two aggregation resolutions—MSA level and state level. State level captures the heterogeneity in transportation and electricity emissions and provides analysis to sub-national decision-makers regarding EV adoption policies.

2.1. Assumptions regarding driving patterns

For all scenarios, we use estimates of VMT at the census tract level using multiple data sources [40, 59, 60] and as explained in detail in SI section S.1. We assume that census tract level miles driven are the same across scenarios. In the SI section S.6c, we also run our analysis using county-level emissions as the National Emissions Inventory, one of our primary sources of emissions from the current LDV fleet, reports total emissions at the county level and discuss the differences in the results. Across all scenarios, dust suspension and tire break-and-wear emissions of ICVs and EVs are not included. However, emerging evidence shows EVs may have smaller brake wear emissions due to regenerative braking but larger tire wear emissions due to higher weight [61, 62]. Internal combustion engines equipped with selective catalytic reactors are an emerging source of ammonia due to 'ammonia slipping,' which occurs due to non-optimal temperatures in the exhaust chamber [63–65]. We do not include this effect in the main results as emissions standards currently do not regulate ammonia, but it could be an emerging source of secondary $PM_{2.5}$.

2.2. Census data

We use population, race, and ethnicity data from ACS 2016–2020, obtained via NHGIS IPUMS [53]. We use eight racial-ethnic groups. People who self-identify as Hispanic or Latino ethnicity are included here as Latino (all races). The seven racial groups in ACS (i.e. Black, White, Asian, Native American & American Indian (Native), Hawaiian & Pacific Islander (HPI), Other, and Mixed here refer to non-Hispanic individuals.

Census block group-level population data are distributed to the InMAP grid as an area-weighted average (figure 1). The total population is 324.41 million, out of which 195.5 million are White, 59.1 million are Hispanic/Latino, 39.94 million Black, 17.6 million Asian, 8.8 Mixed, 1.96 million Native American and American Indian, and 0.4 HPIs.

2.3. Baseline: characterization of the current LDV transportation fleet

National Emissions Inventory (NEI 2017) reports that total on-road non-diesel LDVs drove 2.65 trillion miles, emitting 1.9 million short tons of nitrogen oxides (NO_x), 1.5 million short tons of VOCs, and 0.05 million short tons of primary $PM_{2.5}$ [40]. We use county-level emissions of NO_x, NMOG (VOC), and primary $PM_{2.5}$ reported by NEI and redistribute them to census tracts based on VMT estimates described above to model the health consequences of emissions as our current LDV fleet. Ammonia emissions for the current LDV fleet are not included in the analyses in the main text to enable comparison with emissions standards that do not regulate ammonia. Change in pollution exposure with changes in emissions is modeled using InMAP, a reduced complexity air quality model.

2.4. Scenario 1: fleetwide adoption of gasoline Tier-3 ICV

Emissions standards set quantitative limits of pollutant emissions that new vehicles can emit per mile. Between Tier 1 (1994) and Tier 3 standards (2022), per-mile gasoline NO_x + NMOG and $PM_{2.5}$ limits under regulatory test conditions have decreased by 91% and 97%, respectively. For this work, we rely on model year 2022 Tier 3 emissions standards in the FTP drive cycle and supplemental FTP drive cycle as two possible scenarios (SI section S2a). We use fleet-wide average emissions standard values for

Table 1. Scenarios considered for Tier-3 ICVs.

Scenario	Drive cycle	NO_X + NMOG (mg/mile)	NO_X/NMOG ratio	$PM_{2.5}$ (mg/mile)
1a	FTP	51	50/50	3
1b	SFTP	70	50/50	10
1c	FTP	51	70/30	3
1c	FTP	51	30/70	3

Table 2. Electricity requirements for vehicle electrification.

NERC region	Sub-region represented in the continental United States	Electricity generated in the NERC region in 2019 (TWh)	Average energy requirement of short-range and long-range EV in sample per 1000 vehicle-miles (kWh)	Total electricity requirement from converting the fleet (TWh)
MRO	Upper Midwest and Great Plains	448	326–396	52–68
NPCC	New York + New England	231	312–406	68–93
RFC	Great Lakes	918	306–401	170–228
SERC	Southeast and Florida	1,354	296–379	233–306
TRE	Texas	414	292–365	49–65
WECC	Rocky Mountain, Southwest, and Pacific Coast	738	317–396	167–223

NO_X and NMOG. Since Tier 3 standards regulate total NO_x + NMOG emissions, we assume different ratios of NO_X and NMOG (50:50, 30:70, or 70:30) to account for uncertainty [66] (SI sections S2b and S6b). We assume that all vehicles meet the $PM_{2.5}$ mandated standard. Because the emissions of new Tier 3 vehicles will change with age and cumulative mileage, our estimates represent a lower bound of health damages for ICVs. Table 1 shows the emissions per mile for Tier 3 emissions standards (model year 2022) on FTP and SFTP drive cycles with different NO_x and NMOG ratios.

2.5. Scenario 2: fleetwide adoption of electric vehicles

We use results from previous works to estimate a range of electricity consumption if the entire existing stock of vehicles were to be substituted by electric vehicles [54]. In brief, the energy consumption of electric vehicles is significantly impacted by both temperature and type of driving. We estimate the electricity required by an electric vehicle by using publicly available laboratory-tested data on energy consumption per mile at different temperatures, drive cycles, and vehicle miles traveled, as described above. Our estimates account for the effect of hourly ambient temperature at the county level and whether the type of driving in a county is predominantly city, highway, or combined driving. We use the Nissan Leaf (economy car, 40 kWh battery) and the Tesla Model S (luxury car, 100 kWh battery) as reasonable low and high bounds of the energy requirements of EVs (SI section S.3a) [67]. We assume vehicles are charged with the fleet of electricity generators in their NERC regions (SI section S.5b). NERC regions roughly divide the contiguous United States into six regional reliability entities and differ in power systems characteristics and resources. In table 2, we report the range of average energy requirements for Nissan Leaf and Tesla Model S across counties in different NERC regions, as estimated in our previous work, and the rough geographic representation of each NERC region by sub-regions of the United States.

We assume the electricity generated to meet the electricity demand from charging the vehicles will be distributed across power plants proportionally to their annual 2019 generation. We ignore the potential redispatch of power plants due to the demand for EV electricity. We also do not account for potential electricity generation capacity limits for a plant that may occur at high charging levels or for marginal generator characteristics. This assumption is suitable given that we are considering scenarios where many vehicles are being replaced, and we are using annual emissions from the electricity grid. We estimate plant-level emissions of SO_2, and NO_X using NEI 2017 and primary $PM_{2.5}$ e-GRID 2019 data [40, 50, 68]. Our dataset includes 3342 fossil power plants out of a total of 3400. Our estimates of total emissions are 0.13 million short tons for $PM_{2.5}$, 1.08 million short tons for SO_2, and 1.16 million short tons of NO_x. We exclude from our analysis 30 renewable plants that have a small percentage of oil, coal, or gas. To our knowledge, this is the most exhaustive and up-to-date

Table 3. Total electricity generation (TWh) and total pollution emissions in NERC regions (2019).

NERC region	Electricity generation (TWh)	SO_2 (tons)	NO_x (tons)	$PM_{2.5}$ (tons)	CO_2 (million tons)	Percentage of renewable generation
MRO	448	175 209	160 380	12 684	232	34
NPCC	231	8,227	30 046	4,764	49.2	25
RFC	918	286 512	289 743	38 741	443	6
SERC	1,354	369 212	321 104	46 632	618	7
TRE	414	118 936	106 874	9,525	180	20
WECC	738	98 667	216 045	16 548	284	39

characterization of the current electricity system for evaluating air pollution-related health impacts.

For our analysis of the future clean grid where 50 most SO_2 polluting power plants were retired or retrofitted with CCS, we assume that they are either replaced by renewable energy or did not have a reduction in their generation due to CCS. All retired or retrofitted plants in the continental US, except one, are coal power plants (SI section S.3d). These 50 power plants constituted 78 GW in nameplate capacity, 335 TWh of generation, and emitted 253 kilotons NO_x, 663 kilotons SO_2, 20 kilotons $PM_{2.5}$, and 364 447 kilotons CO_2 emissions. For context, cumulative wind and solar capacity in the US are nearly 136 GW and 73.5 GW [69, 70] and 300 GW of wind and 947 GW of solar are currently in transmission interconnection queues [71]. A complete list of power plants, state-wise capacity, generation removed or retrofitted, and emissions avoided are given in SI section S.3d.

Table 3 shows the total electricity generation in each NERC region, the percentage of renewable generation, and the total emissions of SO_2, NO_x and, $PM_{2.5}$, and CO_2 for 2019 (more details in SI sections S.3b and c).

2.6. Modeling the change in $PM_{2.5}$ concentration

We use InMAP, a reduced complexity air quality model [39, 45] to estimate the change in concentration of $PM_{2.5}$ across our different scenarios. InMAP uses an Eulerian grid model to estimate the annual average $PM_{2.5}$ concentration change attributed to a change in annual emissions based on steady-state solutions to equations representing pollution emission, transport, transformation, and removal. InMAP's representation of chemistry and meteorology uses spatially varying parameters obtained from a detailed chemical transport model simulation (the WRF-Chem model coupled with the National Emission Inventory). The InMAP source-receptor matrix (ISRM) provides a relationship between source damages (i.e. damages across the country that are attributable to emissions in a specific grid cell) and receptor damages (i.e. the damages suffered by people in a particular grid cell, regardless of where the emissions occurred). This ISRM was built by running more than 150 000 runs of InMAP, each time inputting a 1-t emission change from a single grid (out of ~50 000 grid cells) at three different heights (ground, medium, and high height). ISRM as a dataset contains estimates of a linear relationship between marginal changes in emissions at every source location and marginal changes in annual-average $PM_{2.5}$ concentration at a receptor location [44, 72]. The grid-cell size in InMAP varies from 1 km × 1 km (typically in urban areas) to 48 km × 48 km (typically in rural areas), depending on the gradient in the population density and pollutant concentrations. Fine grid in populated areas is critical to accurately estimate air pollution-related health disparities [43, 73]. Our study explicitly looks at receptor damages (where the damages occur) along with a granular characterization of where damages originate (sources).

2.7. Estimating health damages due to $PM_{2.5}$

Premature mortality due to $PM_{2.5}$ concentration changes is calculated using the county-wide hypothetical 'underlying incidence,' the mortality hazard ratio derived from the concentration-response function, and the population in the grid cell. We use the approach of Apte *et al* [74] to calculate the hypothetical underlying incidence rate if there were no $PM_{2.5}$ emissions, $I_{o,c}$ as:

$$I_{o,c} = \frac{I_c}{\overline{\mathrm{HR}_c}}$$

where I_c is the reported county-level all-cause mortality, $\overline{\mathrm{HR}_c}$, is the average mortality hazard ratio caused by $PM_{2.5}$ in county c. $\overline{\mathrm{HR}_c}$, in turn, is calculated as:

$$\overline{\mathrm{HR}_c} = \frac{\sum_{i=1}^{n} P_i \times \mathrm{HR}(C_i)\, f_{i,c}}{\sum_{i=1}^{n} P_i}$$

where P_i is the population in grid cell i; n is the number of grid cells in county c; $\mathrm{HR}(C_i)$ is mortality hazard ratio (GEMM in this study) resulting from ambient $PM_{2.5}$ concentration C_i i, and $f_{i,c}$ is the area fraction of grid cell i that overlaps with county c. We use ambient $PM_{2.5}$ concentration from Meng *et al* for 2019 [75]. The authors estimate ambient $PM_{2.5}$ concentration using chemical transport modeling, satellite remote sensing, and ground-based measurements. We use baseline population-wide all-cause mortality rates at the county level from the

US Center for Disease Control (CDC) [76] for 2019. Our unit of analysis is limited to the county level as this is the smallest geographic unit with publicly available health data from the CDC. While this CDC data has been used extensively in studies to examine health outcomes and environmental disparities in disadvantaged communities [77–79], health data at finer spatial resolutions would increase the certainty and accuracy in exposure and health disparity estimates. Unfortunately, there is no such data in a publicly available form. The average mortality rate I_c is 833.71 deaths per 100 000 people per year, and our $I_{o,c}$ estimate is 790 deaths per 100 000 people per year (SI section S5d).

Throughout this work, we use the mortality hazard ratio $\mathrm{HR}(C_i)$ function from the Global Exposure Mortality for non-accidental mortality (GEMM) to calculate both the underlying incidence rate mentioned above and change in premature mortality due to change in $PM_{2.5}$ concentration from our scenarios. Non-accidental mortality in GEMM corresponds to non-communicable diseases and Lower Respiratory Infections and uses data from 41 cohort studies from 16 countries to estimate the shape of the association of ambient $PM_{2.5}$ exposure and non-accidental mortality. GEMM function is supralinear at lower concentrations, near linear at high concentrations, and applies a counterfactual threshold of 2.4 μg m^{-3}, the lowest concentration observed in any of the cohort studies. GEMM function assumes that $PM_{2.5}$ exposure does not affect health below this level. Some versions of the GEMM function are parameterized differently depending on whether the function is segmented by age and whether a cohort of Chinese men with a wider $PM_{2.5}$ exposure range than the other studies is included. Our version applies a single function to estimates of non-accidental mortality for all ages above 25 and includes the Chinese male cohort [80]. We use GEMM's equation that uses non-accidental mortality for all ages, which is as follows:

$$\mathrm{HR}\,(C_i) = e^{0.143\times\left(\frac{\ln\left(\frac{\max(0,\,C_i-2.4)}{1.6}+1\right)}{1+e^{\frac{-(\max(0,\,C_i-2.4)-15.5)}{36.8}}}\right)}$$

where $\mathrm{HR}(C_i)$ is the hazard ratio of mortality incidence at $PM_{2.5}$ concentration C_i in units of micrograms per cubic meter—compared with a hypothetical underlying incidence rate, I_o in the absence of ambient $PM_{2.5}$. Comparison of GEMM with other dose-response functions is given in SI section S.4.

Mortality associated with the concentration of $PM_{2.5}$ in a grid cell is computed as:

$$M(C_i) = P_i \sum_{c}^{n} I_{o,\,c} f_{i,c} \mathrm{HR}(C_i)$$

where $M(C_i)$ are premature deaths caused by the concentration of $PM_{2.5}$ at location i, P_i is the population in grid cell i, $I_{o,\,c}$ underlying incidence rate for one n counties overlapping grid i and $f_{i,c}$ is the fraction of grid cell i that overlaps county c.

The transportation-attributable mortality rate is aggregated at the state and MSA levels as follows:

$$\text{Transportation attributable mortality rate}_{\text{pop or race}} = \frac{M(C)_{\text{state or MSA}}}{\left(\text{Population}_{\text{pop or race}}\right)_{\text{state or MSA}}} \times 100{,}00$$

3. Results

3.1. Switching the U.S. LDV fleet to EVs or Tier-3 ICVs reduces premature mortality from air pollution in all states and metropolitan statistical areas (MSA)

For results across different scenarios, the concentration-response function, all-cause mortality, the underlying incidence rate, and the population counts remain the same. The changes in premature mortality are only due to changes in air emissions from different transportation choices. Tier-3 ICVs and EVs reduce total mortality by 80%–92% compared to the current fleet (SI section S6b). While the underlying assumptions and risk function differ, our estimates of premature mortality due to electric vehicles are in agreement with the most recent study by Peters *et al* [35]. We also present changes in $PM_{2.5}$ exposure from different transportation choices in SI section S6a.

The health benefits are particularly large for states and MSAs with large populations. Figure 2(a) shows the state-wide mortality rate of the current LDV fleet compared to two alternative scenarios: a fleet-wide transition to Tier-3 ICVs and EVs charged on the current electricity grid. Estimates for Tier-3 ICVs may, in practice, be higher in real-world conditions and will increase with age and cumulative mileage. In the future, electric vehicle emissions will be lower than our estimates suggest since the grid is expected to continue decarbonizing.

Black circles and squares indicate Tier 3 emissions standards for FTP and SFTP driving schedules, respectively, with a ratio of 50:50 between NO_x and NMOG. Red and maroon circles indicate the mortality attributable to low-range and high-range EVs, respectively. The energy efficiency of EVs is calculated using temperature and urbanization level characteristics at the county level, as described in our previous work [54]. The carbon intensity of electricity for each state is obtained from the Power Sector Carbon Index [81, 82]. In figure 2(b), we show estimates of CO_2 emissions from the current LDV fleet, of Tier-3 ICVs (gray bars), and of the EVs considered in this study, using fuel economy of the latest Corporate Average Fuel Economy (CAFE) standards for passenger cars and trucks for 2021 (46.1, 32.6 MPG) and 2022 (48.2, 34.2 MPG) [83] and

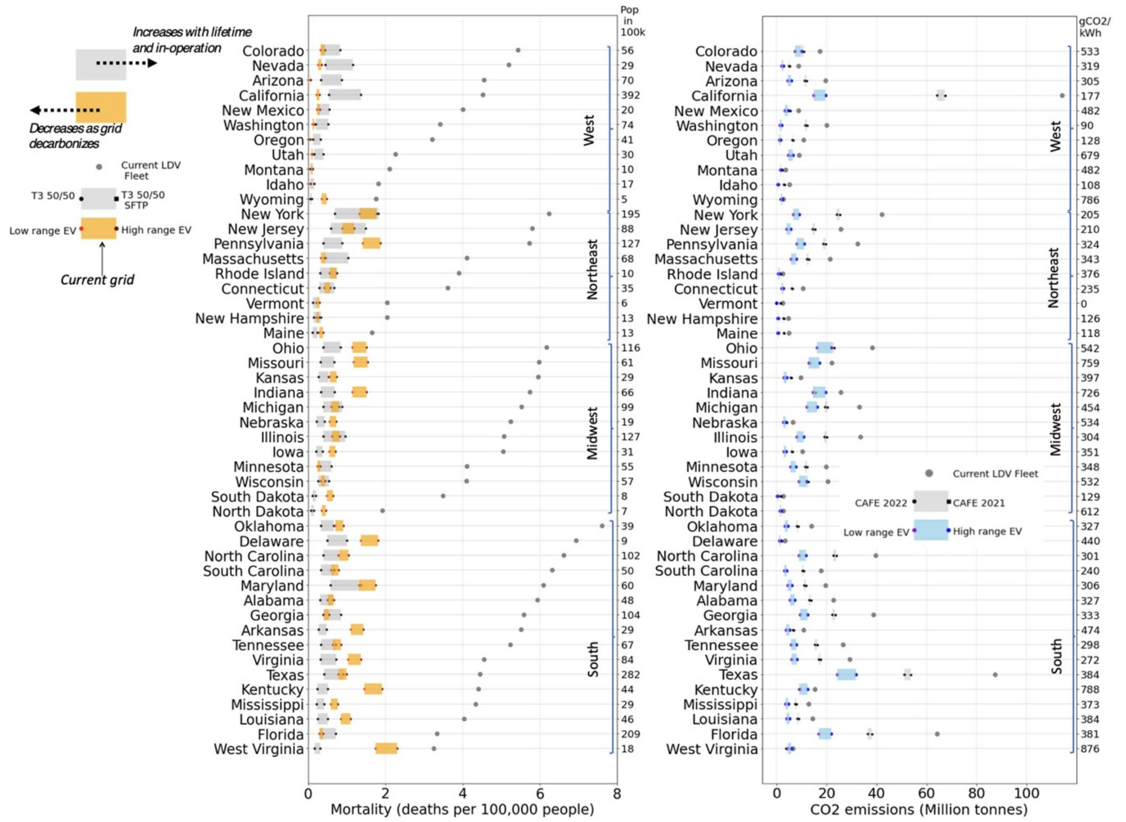

Figure 2. Comparison of mortality (deaths per 100 000 people) (a) and total CO_2 emissions (million tonnes) (b) due to Tier-3 ICVs and EVs charged on the current grid compared to the current LDV fleet by state. States are arranged in decreasing order of current LDV mortality by census region. Mortality ranges for Tier-3 ICVs are given by FTP and SFTP drive cycle with an assumed ratio between NO_X and NMOG of 1:1. In contrast, mortality ranges for EVs are given by whether the fleet-wide electrification is done through a low-range Nissan Leaf or a high-range luxury Tesla Model S. CO_2 emissions from ICVs are estimated using the CAFE standards for the year 2021 and 2022 and EV CO_2 emissions are calculated using the state Power Sector Index of 2021 as outlined by [75, 76] along with data on miles driven and energy consumption details given in methods and data. The two columns on the secondary Y axis show the state population (100 000 people) and state power sector carbon intensity [75].

the fuel economy of current LDV fleet (23 MPG) [84].

We assume that the vehicle miles traveled are constant for both technologies and are derived from NEI 2017, as explained in the methods and SI section S.1. The secondary Y-axis in subfigures indicates the size of the population of each state (2019) [52] and state's power sector carbon intensity (2021) [82]. The states are ordered based on the decreasing mortality attributable to the current LDV fleet for each census region, i.e. South, Midwest, West, and Northeast (SI section S.5a). In the Western US, EVs have a lower mortality rate than Tier-3 ICVs, except for Wyoming, which still relies on a significant coal fleet. In the Northeast, EVs have similar health damages to Tier-3 ICVs in all states except Pennsylvania. In the Midwest, EVs have higher mortality than Tier-3 ICVs in most states, particularly in the Ohio Valley. In the Southern US, EVs have higher mortality rates than Tier-3 ICVs in most states but perform better in populous states like Florida, Texas, and Georgia. Altering NOX/NMOG ratios to 70:30 from 50:50 did not significantly change the results, with a 3% increase in total deaths (41 deaths). On the other hand, EVs have lower CO_2 emissions in all states except West Virginia (state carbon intensity of 876 gCO_2/kWh) (figure 2(b)). Removing or retrofitting 50 most SO_2 plants achieves health damages parity between EVs and Tier-3 ICVs for almost all states except West Virginia and Kentucky (figure 3).

Figure 4 compares damages from changing the US LDV fleet to EVs and Tier 3 ICVs for the 50 most populous MSAs in the U.S. 55% of health damages (∼9 k out of 16 k deaths) from the current LDV fleet occur in the 50 most populous MSAs. Fleet-wide change to Tier-3 ICVs and EVs reduces mortality in all. EVs provide more health benefits than Tier 3 standards in all MSAs except for a few MSAs in the Ohio River Valley (figure 4(a)), where power plants are the predominant source of $PM_{2.5}$ [85, 86]. A future decarbonized grid can reduce electrification mortality in the region (figure 4(b)).

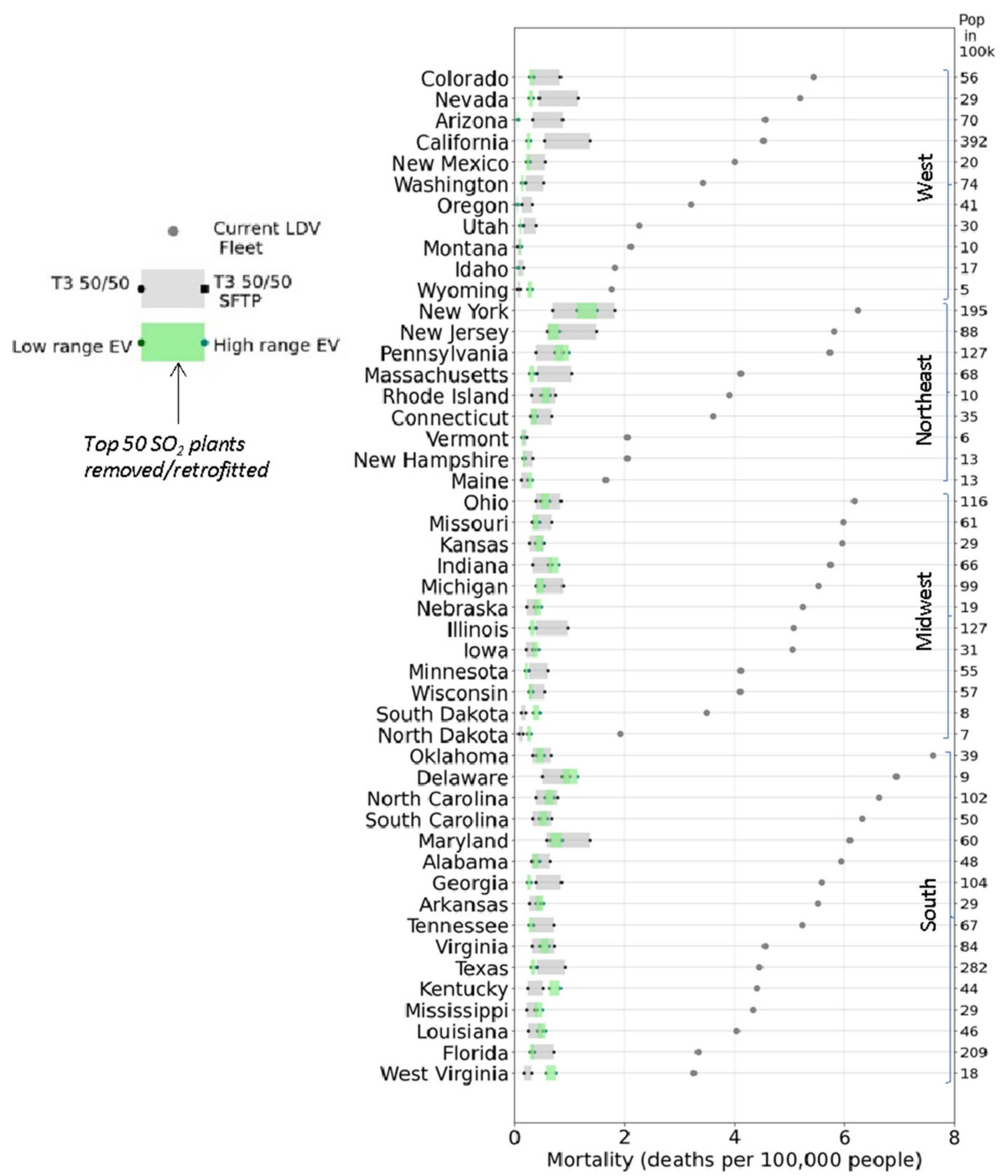

Figure 3. Comparison of mortality (deaths per 100 000 people) for Tier-3 ICVs and EVs charged on a future decarbonized grid where 50 power plants with the highest SO_2 emissions are retired or retrofitted with carbon capture and storage (CCS). Post-combustion CCS necessitates the removal of pollutants in flue gas, which include SO_2, NO_x, and $PM_{2.5}$.

3.2. Demographic differences and risk gap

Figures 5 and 6 present data on passenger vehicles' state-level mortality rates by race and ethnicity across scenarios. Bar height represents the US-wide population average mortality rate for each racial and ethnic group, while black lines indicate the population-level mortality rates by state. Previous research has shown that the current LDV fleet has a greater impact on people of color than on White Americans, with Blacks, Latinos, and Asians experiencing higher mortality rates than the population average [5, 29, 42, 87]. Our estimates are consistent with these earlier findings. Mixed-race also have higher mortality rates than the population average, while Hawaiian and Pacific Island groups have lower. Tier 3 vehicles reduce mortality rates across all groups, but differences between racial and ethnic groups persist. EVs have lower relative disparities than ICVs (figures 6 and 7). White Americans, on average, face higher health consequences than the population average for electric vehicles charged on the current grid, particularly in states in and near the Midwest (Pennsylvania, Indiana, Illinois, Virginia, Maryland) (figure 6, SI section S.6d). Black and Mixed-race Americans also face higher mortality than the population average with EVs charged on the current grid. With a

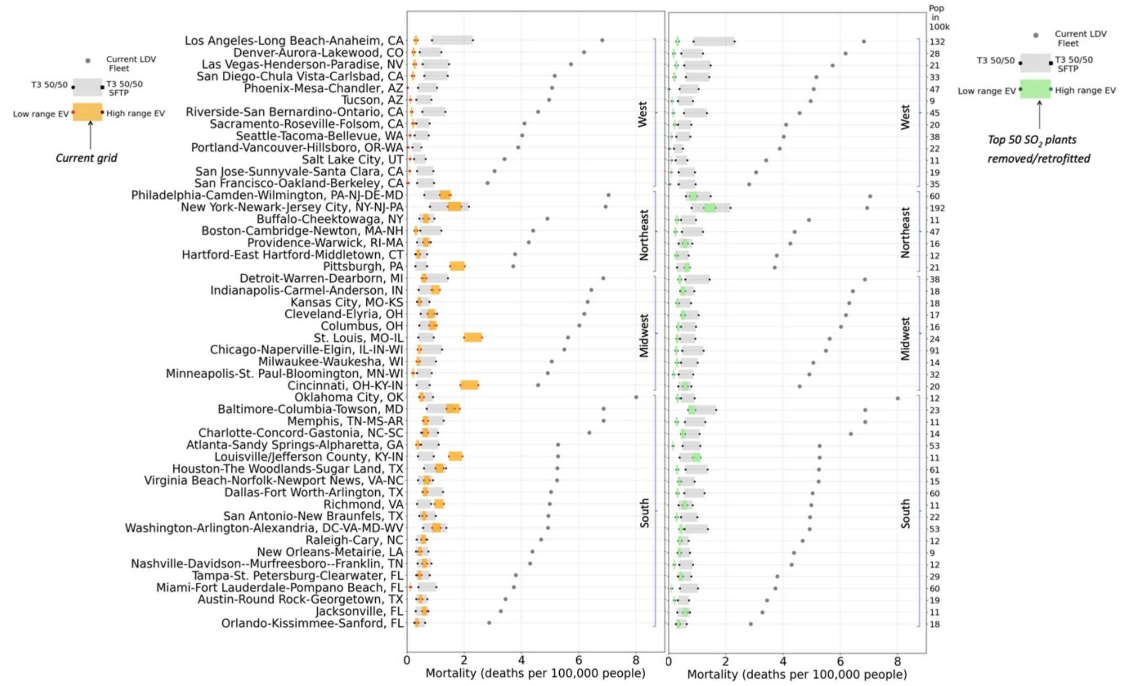

Figure 4. Mortality (deaths per 100 000 people) associated with passenger transportation for the 50 most populous U.S. MSAs under different scenarios: (i) the current LDV fleet, (ii) a Tier 3 ICE fleet, and (iii) EVs charged on the current grid (orange, figure 4(a)) and (iv) EVs charged on a future grid where the top 50 SO_2 polluting power plants are replaced or retrofit with CCS (green, figure 4(b)). We assume a Tier 3 FTP and SFTP drive cycle with a 1:1 ratio between NO_X and NMOG. The range of values for EVs corresponds to Nissan Leaf and Tesla Model S. The column on the secondary Y axis shows the state population (in 100 000 people).

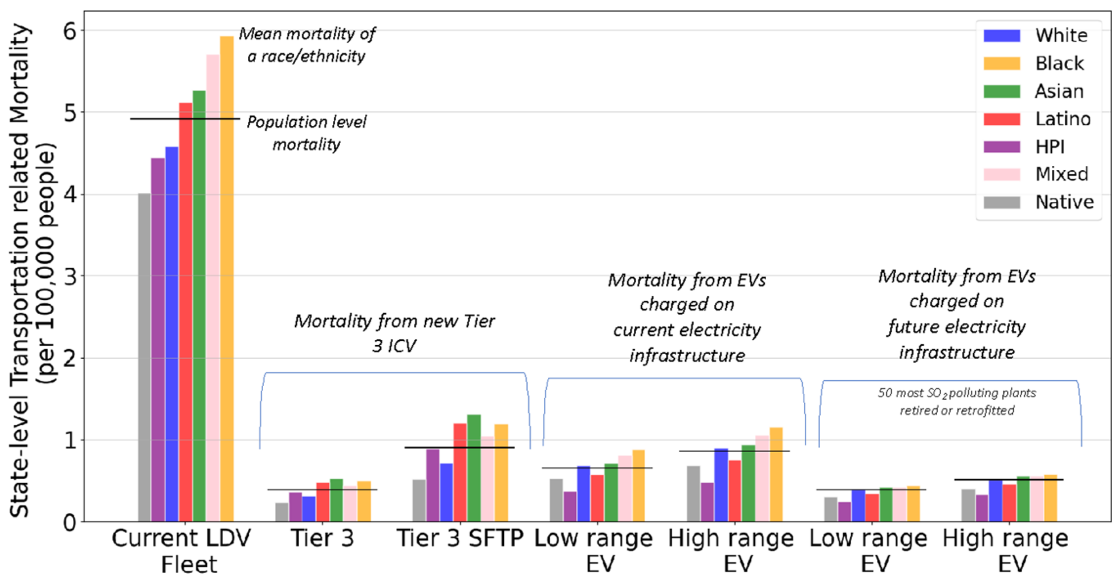

Figure 5. State-level transportation-related mortality rate for current LDV fleet, Tier 3 ICV, EVs charged on current and future electricity grid where 50 power plants with highest SO_2 emissions are retired or retrofitted with CCS. The height of the individual bars denotes the population average mortality of each race and ethnicity across all states in the U.S. In contrast, the black lines denote the population's average total mortality rate. The mortality rate is defined as the deaths of a particular race or ethnicity or overall population in the state divided by the population of a race or ethnicity or the total population in the state multiplied by 100 000.

future grid, Black and Mixed-race Americans continue to face higher mortality compared to the population average, but the relative disparity for White Americans declines. Latinos, the second largest ethnic group in the US, face lower transport-attributable mortality compared to the population average with electrification, both with current and future electricity grids (figure 6).

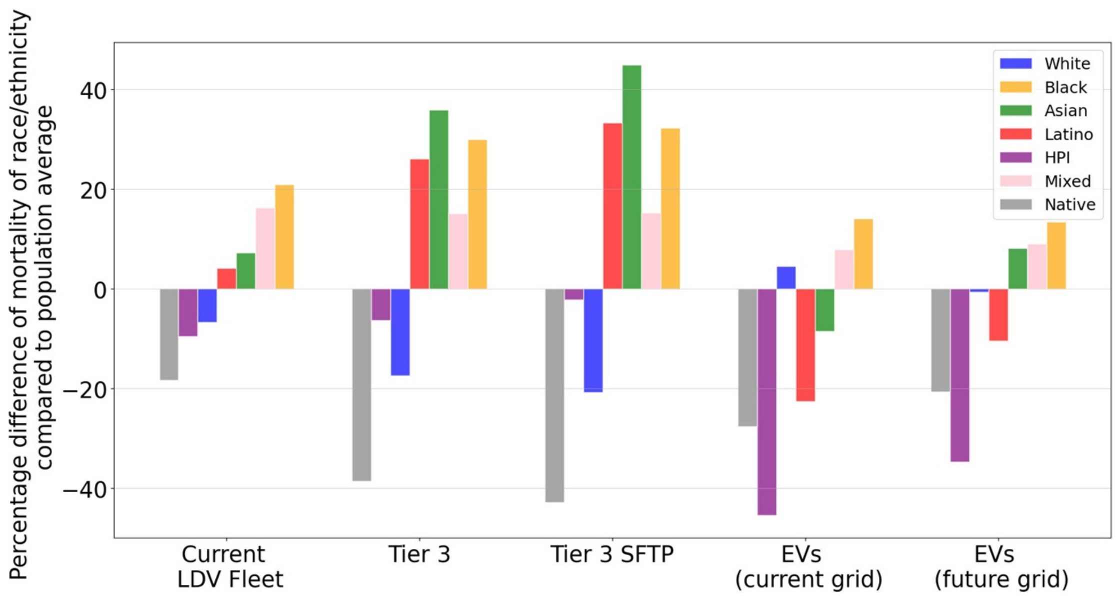

Figure 6. Percentage difference between the mortality of a race/ethnicity compared to the population average mortality for current LDV fleet, Tier 3 ICVs, EVs charged on the current grid, and a future grid where 50 power plants with the highest SO_2 emissions are retired or retrofitted with CCS.

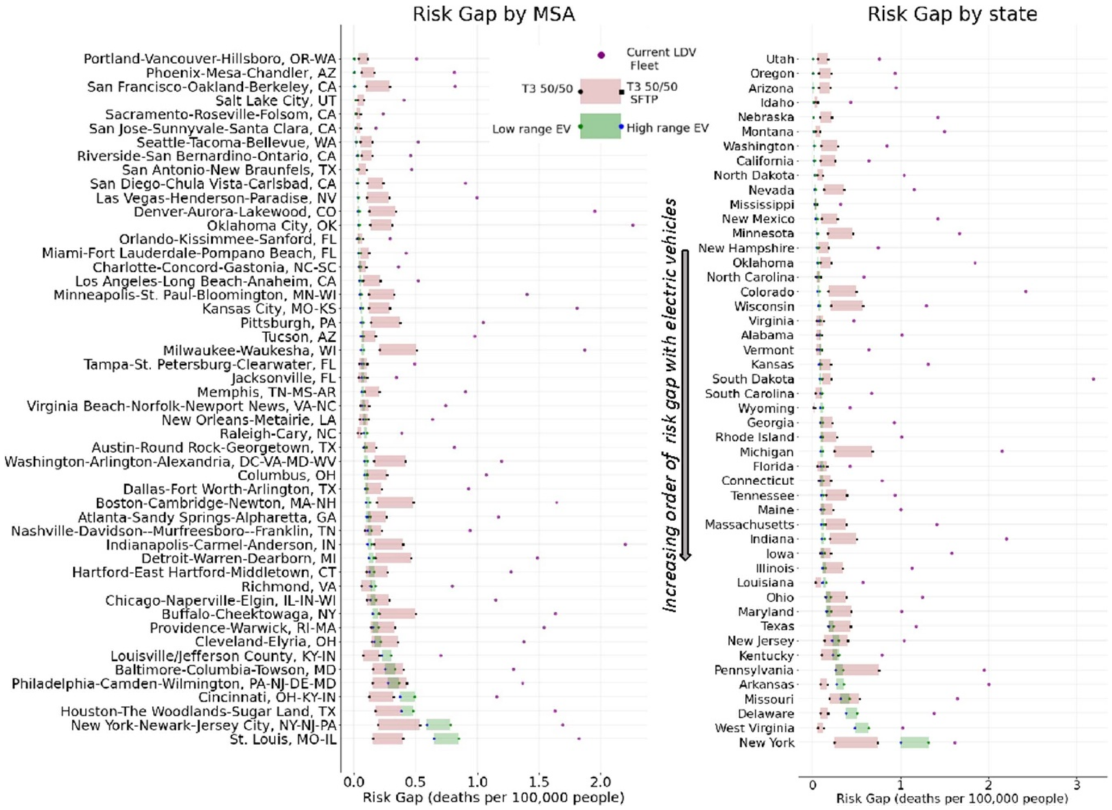

Figure 7. Risk gap of the current LDV fleet compared to Tier-3 ICVs and EVs charged on the current grid. The 50 most populous MSA (figure 7(a)) and states (figure 7(b)) are arranged in increasing order of risk gap for EVs. The risk gap is the difference between the highest mortality of a race or ethnicity and the population mortality for the states or MSA.

To further explore the potential of each technology to reduce pollution disparities, we show the risk gap for states and MSAs in figure 7. The risk gap is the difference between the mortality rate of the most burdened race or ethnicity and that of the overall population of a state or MSA. It is a race-agnostic term used only to capture the differences in pollution disparities between transportation choices. The states and top 50 most populous MSAs are arranged in increasing order of risk gap for EVs. The risk gap decreases with fleet-wide shifts from the current fleet to either Tier 3 ICVs or EVs. An overall switch to EVs (current grid) leads to a lower or almost comparable risk gap with a few exceptions (St. Louis, New York, Houston, and Cincinnati MSAs, and Wyoming, Arkansas, Delaware, West Virginia, and New York states).

3.3. The benefits from electrification or moving to Tier-3 ICV by urbanization and income

Electrifying transportation moves the air pollution from the tailpipe in urban areas to smokestacks of power plants, usually located in areas far from cities [24]. Our results show that while EVs and Tier 3 ICVs both reduce transportation-attributable mortality, they affect rural and urban populations, races and ethnicities, and income groups differently. Figure 8 displays the dependence between income and transport-related mortality categorized by various races and ethnicities for urban and rural populations. The mortality rates are compared across the median household income data for census tracts from ACS 2016–2020 for the current LDV fleet (top row), full electrification using a high-range EV charged on the current grid, and Tier 3 vehicles (FTP drive cycle, 50/50 ratio assumed). The colored lines and marker size correspond to race/ethnicity and their population in the income brackets, and the black line represents the population's average mortality rate. Tracts with a population density above 500 per square mile are defined as urban, while those less are rural as per the 2020 Census urban areas criteria [88].

Both technologies reduced mortality rates for all income groups, races, and ethnicities compared to the current fleet. White Americans have lower mortality compared to the population average in all scenarios except in low-income census tracts. Transport-attributable mortality decreases with increasing income for Asians in urban areas. However, similar trends do not hold for Black and Latino Americans, who see an increase in mortality with income, with a striking increase in urban areas. Our results suggest that within richer urban census tracts, Black and Latino residents have significantly higher transportation-attributable pollution mortality than the population average. Latinos in rural low-income census tracts, though not in high numbers, have disproportionately high mortality with conventional vehicle technologies. Similar figures for tier 3 ICVs on SFTP drive cycle and high-range EVs charged on the future grid where the top 50 SO_2 polluting plants are retired are available in SI section S6e.

4. Discussion

This study examines whether using electric vehicles and Tier 3 gasoline vehicles can reduce fleet-wise mortality and disparities associated with transportation-related health impacts and GHG emissions. The current light-duty fleet is an important source of premature mortality due to $PM_{2.5}$ emissions, especially in urban areas. 55% of health damages (∼9000 deaths out of 16 000) due to the current LDV fleet occur in the 50 most populous MSAs. A transition to EVs and the most efficient Tier 3 ICVs can substantially reduce the health damages from air pollution associated with the transportation sector. Under the current electricity grid, a fleet-wide shift to EVs improves health outcomes in many states and most MSAs compared to Tier-3 ICVs, suggesting that rapid electrification in those locations will be the best health and environmental benefits strategy. Retiring or retrofitting the 50 most polluting coal power plants closes the current gap of health consequences between EVs and Tier-3 ICVs. Lastly, EVs reduce pollution exposure disparities in most states and MSAs.

EVs have lower or comparable mortality to Tier-3 ICVs in the four most populous states—California, Texas, New York, and Florida, although in New York, EVs have a higher risk gap than Tier-3 ICVs. Electrification benefits on current electricity would be delayed for the Ohio Valley region and neighboring states, which includes Kentucky, West Virginia, Pennsylvania, Ohio, and Indiana, owing to the high number of operational coal power plants that currently contribute significantly to ambient $PM_{2.5}$. Retirement or CCS retrofit in 50 power plants with the highest SO_2 emissions can achieve the required air quality parity between EVs and Tier 3 ICVs in this region, except in West Virginia and Kentucky, which will require further pollution reduction.

If the country continues to rely on gasoline vehicles, a move towards Tier 3 vehicles would provide large benefits regarding air pollution damages from passenger vehicles. We note, however, that this ignores another damage associated with gasoline vehicles: the emissions of GHGs that lead to climate change. Furthermore, real-world emissions from these Tier 3 vehicles may deviate from laboratory-tested conditions, and vehicle emissions increase with age and mileage.

Our work has a few limitations. Firstly, while InMAP improves spatial granularity of reduced complexity chemical transport modeling, it cannot capture hyperlocal impacts of transportation-related air pollution, such as near-source proximity to freeways, and emissions can drastically vary

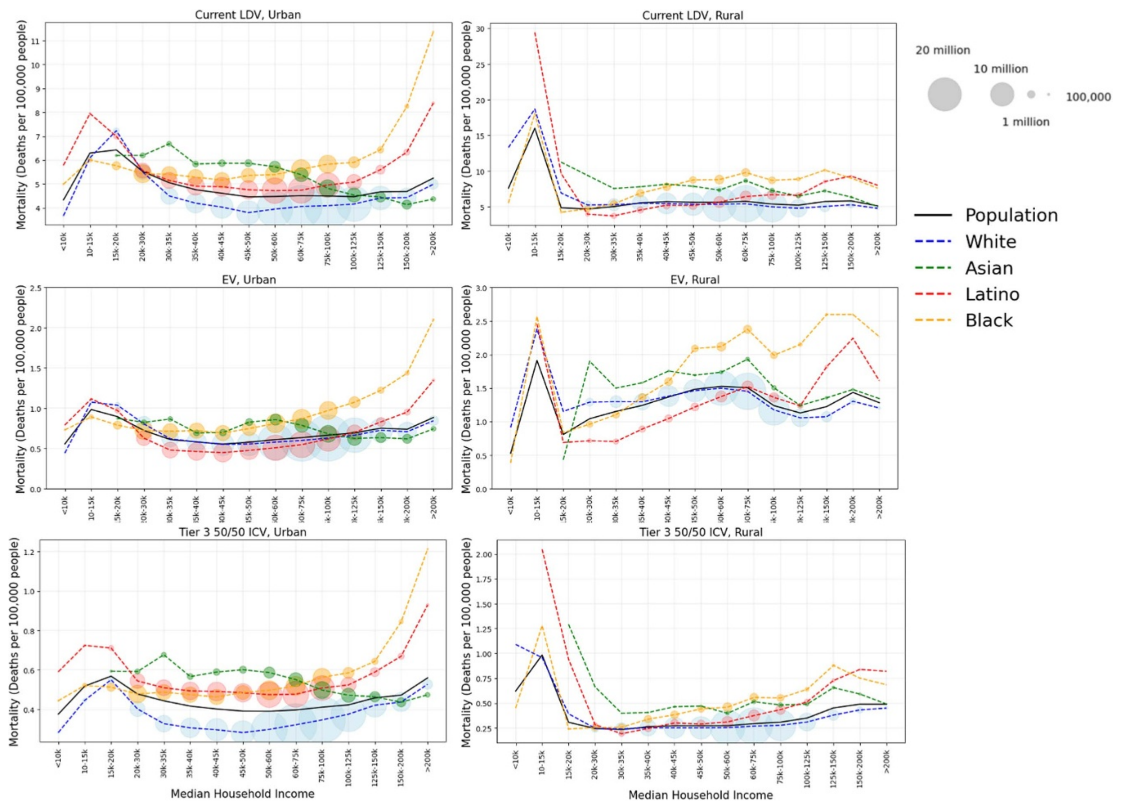

Figure 8. Transport attributable premature mortality for current LDV fleet, high-range EVs charged on the current grid, and tier 3 ICV dependence on median household income in rural and urban census tracts. Census tracts with a population density of more than 500 per square mile are characterized as urban. Note different Y-axis limits.

within a small geographic region [89]. Secondly, our concentration-response function and the underlying mortality rate are assumed to be the same across races and ethnicities. New studies show there could be differences [90]. Thirdly, this work does not take into account ammonia emissions (contributing to secondary $PM_{2.5}$ formation) from conventional vehicles equipped with selective catalytic reactors [63–65].

Electric vehicles have enormous potential to reduce GHGs and air pollution. At the same time, vehicle exhaust emissions standards have been an essential and effective tool in reducing pollution from conventional vehicles [21]. Several policy recommendations arise from our work. The first takeaway from our work is to hasten the current fleet turnover and, if possible, remove older, more polluting vehicles from the fleet. Despite the poor cost-effectiveness of the Cash for Clunkers program in the late 2000s, strategic removal of older, more polluting conventional vehicles may be worth a revisit. The second policy choice that policymakers face is which types of vehicles to promote to replace older vehicles with. This strategy can be geographically heterogeneous. Electrification on the current grid has better health outcomes than the strictest emissions standards in many parts of the United States and in almost most MSAs. However, the targeted retirement of coal power plants will be needed in parts of the US for EVs to break even to Tier 3 vehicles, especially in Ohio Valley and neighboring states.

Data availability statement

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

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References

[1] Emission Standards USA: cars and light-duty trucks—Tier 1 (available at: https://dieselnet.com/standards/us/ld_t1.php) (Accessed 17 November 2022)
[2] US EPA Final rule for control of air pollution from motor vehicles: tier 3 motor vehicle emission and fuel standards (available at: www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-control-air-pollution-motor-vehicles-tier-3) (Accessed 13 February 2022)
[3] Park Y M and Kwan M-P 2020 Understanding racial disparities in exposure to traffic- related air pollution: considering the spatiotemporal dynamics of population distribution *Int. J. Environ. Res. Public Health* **17** 908
[4] Thakrar S K *et al* 2020 Reducing mortality from air pollution in the United States by targeting specific emission sources *Environ. Sci. Technol. Lett.* **7** 639–45

[5] Tessum C W, Paolella D A, Chambliss S E, Apte J S, Hill J D and Marshall J D 2021 $PM_{2.5}$ polluters disproportionately and systemically affect people of color in the United States *Sci. Adv.* **7** eabf4491
[6] Rothstein R 2017 *The Color of Law: A Forgotten History of How Our Government Segregated America* (Liveright Publishing)
[7] Kerr G H, Goldberg D L and Anenberg S C 2021 COVID-19 pandemic reveals persistent disparities in nitrogen dioxide pollution *Proc. Natl Acad. Sci.* **118** e2022409118
[8] Clark L P, Millet D B and Marshall J D 2014 National patterns in environmental injustice and inequality: outdoor NO_2 air pollution in the United States *PLoS One* **9** e94431
[9] Currie J and Walker R 2011 Traffic congestion and infant health: evidence from E-ZPass *Am. Econ. J. Appl. Econ.* **3** 65–90
[10] Congressional Budget Office Emissions of carbon dioxide in the transportation sector (available at: www.cbo.gov/publication/58861) (Accessed 7 March 2023)
[11] US EPA Dynamometer drive schedules (available at: www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules) (Accessed 9 June 2022)
[12] Khan T and Frey H C 2018 Comparison of real-world and certification emission rates for light duty gasoline vehicles *Sci. Total Environ.* **622–623** 790–800
[13] McCaffery C, Zhu H, Li C, Durbin T D, Johnson K C, Jung H, Brezny R, Geller M and Karavalakis G 2020 On-road gaseous and particulate emissions from GDI vehicles with and without gasoline particulate filters (GPFs) using portable emissions measurement systems (PEMS) *Sci. Total Environ.* **710** 136366
[14] Ewing J 2017 *Faster, Higher, Farther: How One of the World's Largest Automakers Committed a Massive and Stunning Fraud* (W. W. Norton & Company)
[15] Borken-Kleefeld J and Chen Y 2015 New emission deterioration rates for gasoline cars—Results from long-term measurements *Atmos. Environ.* **101** 58–64
[16] Tu R, Xue L, Meng C, Xu L, Li T and Chen H 2022 Identifying specifications of in-use vehicles failing the inspection/maintenance emission test *Transp. Res.* D **108** 103327
[17] Sjödin Å and Andréasson K 2000 Multi-year remote-sensing measurements of gasoline light-duty vehicle emissions on a freeway ramp *Atmos. Environ.* **34** 4657–65
[18] Chiang H-L, Tsai J-H, Yao Y-C and Ho W-Y 2008 Deterioration of gasoline vehicle emissions and effectiveness of tune-up for high-polluted vehicles *Transp. Res.* D **13** 47–53
[19] Kozina A, Radica G and Nižetić S 2020 Analysis of methods towards reduction of harmful pollutants from diesel engines *J. Clean. Prod.* **262** 121105
[20] Zhang Q, Fan J, Yang W, Ying F, Bao Z, Sheng Y, Lin C and Chen X 2018 Influences of accumulated mileage and technological changes on emissions of regulated pollutants from gasoline passenger vehicles *J. Environ. Sci.* **71** 197–206
[21] Jacobsen M R, Sallee J M, Shapiro J S and van Benthem A A 2023 Regulating untaxable externalities: Are vehicle air pollution standards effective and efficient? *Q. J. Econ.* **138** 1907–76
[22] McKinsey America's electric-vehicle charging infrastructure (available at: www.mckinsey.com/industries/public-and-social-needs) (Accessed 17 November 2022)
[23] U.S. Energy Information Administration (EIA) Electricity generation, capacity, and sales in the United States (available at: www.eia.gov/energyexplained/electricity/electricity-in-the-us-generation-capacity-and-sales.php) (Accessed 17 November 2022)
[24] Thind M P S, Tessum C W, Azevedo I L and Marshall J D 2019 Fine particulate air pollution from electricity generation in the US: health impacts by race, income, and geography *Environ. Sci. Technol.* **53** 14010–9
[25] Tessum C W, Hill J D and Marshall J D 2014 Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States *Proc. Natl Acad. Sci. USA* **111** 18490–5
[26] National Research Council 2010 *Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use* (National Academies Press)
[27] Tong F and Azevedo I M L 2020 What are the best combinations of fuel-vehicle technologies to mitigate climate change and air pollution effects across the United States? *Environ. Res. Lett.* **15** 074046
[28] Choma E F, Evans J S, Hammitt J K, Gómez-Ibáñez J A and Spengler J D 2020 Assessing the health impacts of electric vehicles through air pollution in the United States *Environ. Int.* **144** 106015
[29] Holland S P, Mansur E T, Muller N Z and Yates A J 2019 Distributional effects of air pollution from electric vehicle adoption *J. Assoc. Environ. Resour. Econ.* **6** S65–94
[30] Holland S P, Mansur E T, Muller N Z and Yates A J 2016 Are there environmental benefits from driving electric vehicles? The importance of local factors *Am. Econ. Rev.* **106** 3700–29
[31] Schnell J L, Naik V, Horowitz L W, Paulot F, Ginoux P, Zhao M and Horton D E 2019 Air quality impacts from the electrification of light-duty passenger vehicles in the United States *Atmos. Environ.* **208** 95–102
[32] Nopmongcol U, Grant J, Knipping E, Alexander M, Schurhoff R, Young D, Jung J, Shah T and Yarwood G 2017 Air quality impacts of electrifying vehicles and equipment across the United States *Environ. Sci. Technol.* **51** 2830–7
[33] Pan S, Roy A, Choi Y, Eslami E, Thomas S, Jiang X and Gao H O 2019 Potential impacts of electric vehicles on air quality and health endpoints in the Greater Houston Area in 2040 *Atmos. Environ.* **207** 38–51
[34] Skipper T N, Lawal A S, Hu Y and Russell A G 2023 Air quality impacts of electric vehicle adoption in California *Atmos. Environ.* **294** 119492
[35] Peters D R, Schnell J L, Kinney P L, Naik V and Horton D E 2020 Public health and climate benefits and trade-offs of U.S. vehicle electrification *Geohealth* **4** e2020GH000275
[36] IEA Trends in electric light-duty vehicles—Global EV outlook 2022—analysis (available at: www.iea.org/reports/global-ev-outlook-2022/trends-in-electric-light-duty-vehicles) (Accessed 31 January 2023)
[37] U.S. Energy Information Administration (EIA) Electricity data (available at: www.eia.gov/electricity/data.php) (Accessed 17 June 2023)
[38] IPCC Special report on carbon dioxide capture and storage (available at: www.ipcc.ch/site/assets/uploads/2018/03/srccs_chapter3-1.pdf) (Accessed 28 June 2023)
[39] Tessum C W, Hill J D and Marshall J D 2017 InMAP: a model for air pollution interventions *PLoS One* **12** e0176131
[40] US EPA 2017 *National Emissions Inventory (NEI) Technical Support Document* (available at: https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-technical-support-document-tsd) (Accessed 20 Feb 2024)
[41] Fann N, Fulcher C M and Baker K 2013 The recent and future health burden of air pollution apportioned across U.S. sectors *Environ. Sci. Technol.* **47** 3580–9
[42] Tessum C W *et al* 2019 Inequity in consumption of goods and services adds to racial—ethnic disparities in air pollution exposure *Proc. Natl Acad. Sci.* **116** 201818859
[43] Paolella D A, Tessum C W, Adams P J, Apte J S, Chambliss S, Hill J, Muller N Z and Marshall J D 2018 Effect of model spatial resolution on estimates of fine particulate matter exposure and exposure disparities in the United States *Environ. Sci. Technol. Lett.* **5** 436–41
[44] Goodkind A L, Tessum C W, Coggins J S, Hill J D and Marshall J D 2019 Fine-scale damage estimates of particulate matter air pollution reveal opportunities for location specific mitigation of emissions *Proc. Natl Acad. Sci. USA* **116** 8775–80
[45] InMAP Intervention model for air pollution (available at: https://inmap.run/) (Accessed 6 April 2023)

[46] EASIUR Marginal Social Costs of Emissions in the United States (available at: https://barney.ce.cmu.edu/~jinhyok/easiur/) (Accessed 17 June 2022)
[47] Nick Muller AP4 (AP3, AP2, APEEP) Model (available at: https://public.tepper.cmu.edu/nmuller/APModel.aspx) (Accessed 17 June 2022)
[48] Baker K R, Amend M, Penn S, Bankert J, Simon H, Chan E, Fann N, Zawacki M, Davidson K and Roman H 2020 A database for evaluating the InMAP, APEEP, and EASIUR reduced complexity air-quality modeling tools *Data Brief* **28** 104886
[49] Gilmore E A 2019 An inter-comparison of the social costs of air quality from reduced- complexity models *Environ. Res. Lett.* **14** 074016
[50] US EPA Emissions & generation resource integrated database (eGRID) (available at: www.epa.gov/egrid) (Accessed 24 January 2022)
[51] U.S EPA: eGRID Related Materials (available at: https://www.epa.gov/egrid/egrid-related-materials) (Accessed 20 Feb 2024)
[52] U. C. Bureau American community survey (ACS) (Census.gov.) (available at: www.census.gov/programs-surveys/acs) (Accessed 12 December 2021)
[53] Manson S, Schroeder J, Van Riper D and Ruggles S 2017 *IPUMS National Historical Geographic Information System* (University of Minnesota) vol 12
[54] Singh M, Yuksel T, Michalek J J and Azevedo I M L 2024 Ensuring greenhouse gas reductions from electric vehicles compared to hybrid gasoline vehicles requires a cleaner U.S. electricity grid *Sci. Rep.* **14** 1
[55] Winkler S L, Anderson J E, Garza L, Ruona W C, Vogt R and Wallington T J 2018 Vehicle criteria pollutant (PM, NOx, CO, HCs) emissions: how low should we go? *npj Clim. Atmos. Sci.* **1** 26
[56] Wallington T J, Anderson J E, Dolan R H and Winkler S L 2022 Vehicle emissions and urban air quality: 60 years of progress *Atmosphere* **13** 5
[57] Koolik L, Alvarado Á, Budahn A, Plummer L, Marshall J and Apte J 2023 PM2.5 exposure disparities persist despite strict vehicle emissions controls in California *ChemRxiv* (https://doi.org/10.26434/chemrxiv-2023-669ws)
[58] Ribeiro C B, Rodella F H C and Hoinaski L 2022 Regulating light-duty vehicle emissions: an overview of US, EU, China and Brazil programs and its effect on air quality *Clean Technol. Environ. Policy* **24** 851–62
[59] U. C. Bureau Vehicles available (Census.gov) (available at: www.census.gov/programs-surveys/acs/) (Accessed 1 June 2022)
[60] Bureau of Transportation Statistics Average weekday household person-miles traveled by U.S. Census Tract (per day) (available at: www.bts.gov/browse-statistical-products-and-data/surveys/average-weekday-household-person-miles-traveled-us) (Accessed 17 June 2022)
[61] Timmers V R J H and Achten P A J 2016 Non-exhaust PM emissions from electric vehicles *Atmos. Environ.* **134** 10–17
[62] Harrison R M, Allan J, Carruthers D, Heal M R, Lewis A C, Marner B, Murrells T and Williams A 2021 Non-exhaust vehicle emissions of particulate matter and VOC from road traffic: a review *Atmos. Environ.* **262** 118592
[63] Sun K *et al* 2017 Vehicle emissions as an important urban ammonia source in the United States and China *Environ. Sci. Technol.* **51** 2472–81
[64] Farren N J, Davison J, Rose R A, Wagner R L and Carslaw D C 2020 Underestimated ammonia emissions from road vehicles *Environ. Sci. Technol.* **54** 15689–97
[65] Huang C *et al* 2018 Ammonia emission measurements for light-duty gasoline vehicles in China and implications for emission modeling *Environ. Sci. Technol.* **52** 11223–31
[66] U.S EPA Annual certification data for vehicles, engines, and equipment (available at: www.epa.gov/compliance-and-fuel-economy-data/annual-certification-data-vehicles-engines-and-equipment) (Accessed 9 June 2022)
[67] American Automobile Association Electric Vehicle Range Testing Report (available at: www.aaa.com/AAA/common/AAR/files/AAA-Electric-Vehicle-Range-Testing-Report.pdf) (Accessed 18 July 2022)
[68] US EPA Power plants and neighboring communities (available at: www.epa.gov/airmarkets/power-plants-and-neighboring-communities) (Accessed 12 June 2022)
[69] Office of Energy Efficiency and Renewable Energy: Land-Based Wind Market Report 2022 Edition (available at: https://www.energy.gov/eere/wind/articles/land-based-wind-market-report-2022-edition) (Accessed 20 Feb 2024)
[70] U.S. Energy Information Administration (EIA) Wind, solar, and batteries increasingly account for more new U.S. power capacity additions (available at: www.eia.gov/todayinenergy/detail.php?id=55719) (Accessed 28 June 2023)
[71] Electricity Markets and Policy Group Queued Up: characteristics of power plants seeking transmission interconnection (available at: https://emp.lbl.gov/queues) (Accessed 28 June 2023)
[72] Zenodo InMAP source-receptor matrix (ISRM) dataset (available at: https://zenodo.org/record/2589760) (Accessed 17 June 2022)
[73] Clark L P, Harris M H, Apte J S and Marshall J D 2022 National and intraurban air pollution exposure disparity estimates in the United States: impact of data- aggregation spatial scale *Environ. Sci. Technol. Lett.* **9** 786–91
[74] Apte J S, Marshall J D, Cohen A J and Brauer M 2015 Addressing global mortality from ambient $PM_{2.5}$ *Environ. Sci. Technol.* **49** 8057–66
[75] Meng J, Li C, Martin R V, van Donkelaar A, Hystad P and Brauer M 2019 Estimated long-term (1981–2016) concentrations of ambient fine particulate matter across North America from chemical transport modeling, satellite remote sensing, and ground-based measurements *Environ. Sci. Technol.* **53** 5071–9
[76] CDC WONDER (available at: https://wonder.cdc.gov/) (Accessed 6 April 2023)
[77] Khan S S, Krefman A E, McCabe M E, Petito L C, Yang X, Kershaw K N, Pool L R and Allen N B 2022 Association between county-level risk groups and COVID-19 outcomes in the United States: a socioecological study *BMC Public Health* **22** 81
[78] Formanack A, Doshi A, Valdez R, Williams I, Moorman J R and Chernyavskiy P 2023 Race, class, and place modify mortality rates for the leading causes of death in the United States, 1999–2021 *J. Gen. Intern. Med.* **38** 2686–94
[79] Dukhovnov D and Barbieri M 2021 County-level socio-economic disparities in COVID-19 mortality in the USA *Int. J. Epidemiol.* **51** 418–28
[80] Burnett R *et al* 2018 Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter *Proc. Natl Acad. Sci. USA* **115** 9592–7
[81] Schivley G, Azevedo I and Samaras C 2018 Assessing the evolution of power sector carbon intensity in the United States *Environ. Res. Lett.* **13** 064018
[82] C. P. S. C. Index US power sector emissions (CMU Power Sector Carbon Index) (available at: https://emissionsindex.org) (Accessed 25 November 2022)
[83] Federal Register: 2017 and later model year light-duty vehicle greenhouse gas emissions and corporate average fuel economy standards (available at: www.federalregister.gov/documents/2011/12/01/2011-30358/2017-and-later-model-year-light-duty-vehicle-greenhouse-gas-emissions-and-corporate-average-fuel) (Accessed 18 July 2022)
[84] U.S. Department of Transportation 2019 Bureau of transportation statistics (National Transportation Statistics (NTS)) (https://doi.org/10.21949/1503663)
[85] Jolley G J, Khalaf C, Michaud G and Sandler A M 2019 The economic, fiscal, and workforce impacts of coal-fired power plant closures in Appalachian Ohio *Reg. Sci. Policy Pract.* **11** 403–22
[86] Anderson R R, Martello D V, White C M, Crist K C, John K, Modey W K and Eatough D J 2004 The regional nature of

$PM_{2.5}$ episodes in the upper Ohio river valley *J. Air Waste Manage. Assoc.* **54** 971–84

[87] Holland S P, Hughes J E, Knittel C R and Parker N C 2015 Some inconvenient truths about climate change policy: the distributional impacts of transportation policies *Rev. Econ. Stat.* **97** 1052–69

[88] U.S Census Bureau: 2020 Census Urban Areas FAQs (available at: https://www2.census.gov/geo/pdfs/reference/ua/Census_UA_2020FAQs.pdf) (Accessed 20 Feb 2024)

[89] Chambliss S E, Pinon C P R, Messier K P, LaFranchi B, Upperman C R, Lunden M M, Robinson A L, Marshall J D and Apte J S 2021 Local- and regional-scale racial and ethnic disparities in air pollution determined by long-term mobile monitoring *Proc. Natl Acad. Sci.* **118** e2109249118

[90] Spiller E, Proville J, Roy A and Muller N Z 2021 Mortality risk from PM2.5: a comparison of modeling approaches to identify disparities across racial/ethnic groups in policy outcomes *Environ. Health Perspect.* **129** 127004