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# Environmental Health, Racial/Ethnic Health Disparity, and Climate Impacts of Inter-Regional Freight Transport in the United States

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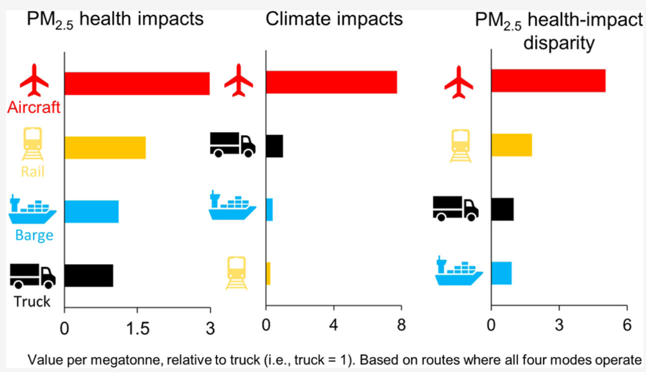
**ABSTRACT:** We quantify and compare three environmental impacts from inter-regional freight transportation in the contiguous United States: total mortality attributable to $PM_{2.5}$ air pollution, racial−ethnic disparities in $PM_{2.5}$-attributable mortality, and $CO_2$ emissions. We compare all major freight modes (truck, rail, barge, aircraft) and routes (∼30,000 routes). Our study is the first to comprehensively compare each route separately and the first to explore racial−ethnic exposure disparities by route and mode, nationally. Impacts (health, health disparity, climate) per tonne of freight are the largest for aircraft. Among nonaircraft modes, per tonne, rail has the largest health and health-disparity impacts and the lowest climate impacts, whereas truck transport has the lowest health impacts and greatest climate impacts—an important reminder that health and climate impacts are often but not always aligned. For aircraft and truck, average monetized damages per tonne are larger for climate impacts than those for $PM_{2.5}$ air pollution; for rail and barge, the reverse holds. We find that average exposures from inter-regional truck and rail are the highest for White non-Hispanic people, those from barge are the highest for Black people, and those from aircraft are the highest for people who are mixed/other race. Level of exposure and disparity among racial−ethnic groups vary in urban versus rural areas.




**KEYWORDS:** *freight transportation, fine particulate matter, health impacts, climate impacts, environmental justice*

## 1. INTRODUCTION

Freight transport plays a critical role in the United States (U.S.) economy, moving ∼46 million tonnes of goods across the U.S. each day and contributing ∼$900 billion to the U.S. GDP (year 2018).[1,2] Freight accounts for ∼40% of U.S. transport energy (∼11% of the U.S. total energy) consumption, of which >90% was consumed by four modes: freight trucks (60%), aviation (18%), marine (9%), and rail (5%).[3] Trucks carried the most weight (tonne), weight-distance (tonne-km), and value (U.S. dollars) (85, 55, 93%, respectively, of total U.S. domestic freight for the four modes in 2017), followed by rail (11, 35, 4%), water (4, 9, 3%), and air (0.02, 0.09, 1%).[1] Freight activity by these four modes is expected to grow in the future, e.g., annual tonnage rising 46% from 2017 to 2050, with the largest relative increase being air freight.[4]

In addition to delivering large economic value, freight transport consumes fossil fuels and emits pollution that impacts air quality, human health, and climate. Most (∼94%) human health impacts from air pollution are associated with fine particulate matter ($PM_{2.5}$),[5] a regulated pollutant linked to premature mortality from cardiovascular disease (ischemic heart disease and stroke), chronic obstructive pulmonary disease, and lung cancer.[6] Emissions from fossil-fuel vehicles include "primary" (i.e., directly emitted) $PM_{2.5}$, and gasses (sulfur dioxide ($SO_2$), oxides of nitrogen ($NO_x$), volatile organic compounds (VOCs), ammonia ($NH_3$)) that form "secondary" $PM_{2.5}$. Diesel heavy-duty vehicles, rail, commercial marine vessels, and aircraft combined contributed 87, 50, and 43%, respectively, of $SO_2$, $NO_x$, and primary $PM_{2.5}$ total mobile emissions in 2014.[7] Freight represents 29% of transportation greenhouse gas emissions.[1]

Environmental health impacts from transportation have been previously quantified using various air quality models, model spatial resolution, and health impact assessment methods and tools.[8−17] Existing estimates of annual $PM_{2.5}$-related mortality by transportation mode or subsector include the following: (i) using U.S. EPA's 2005 National Emissions Inventory (NEI) emissions: 52,800 from road, 8300 from marine, and 4500 from rail;[11] (ii) using 2014 NEI emissions: 9700 from passenger vehicles, 7700 from trucks, 1800 from railroad, 1400 from marine vessels, and 700 from aircraft;[18] (iii) using 2014 NEI

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emissions: 8600 from heavy duty diesel vehicles and 7500 from off-highway vehicles and equipment;[17] (iv) for the year 2002: 7000 in North America from oceangoing ships;[8] (v) for the year 2006: 458 in the U.S. from aircraft emissions;[9] and (vi) for the year 2006: 1350 in North America from aircraft emissions.[14] Dedoussi et al. reported that across three years (2005, 2011, 2018), $PM_{2.5}$-related mortality decreased for road and marine, remained constant for rail, and slightly increased for aviation.[19] Looking at the decreases in on-road transportation emissions in the U.S. from 2008 to 2017, Choma et al. estimated that vehicle-related $PM_{2.5}$-attributable deaths decrease from 27,700 in 2008 to 19,800 in 2017.[20] Some recent studies have quantified impacts specifically for freight transportation. Annual $PM_{2.5}$-related mortality reported by Tessum et al. included 4250 deaths from combination long-haul truck, 1550 from combination short-haul truck, 1480 from diesel-fueled line-haul locomotives, 431 from diesel marine vessels, and 400 from commercial aircraft.[17] Liu et al. estimated ∼3200 and ∼900 $PM_{2.5}$-related mortalities from inter-regional freight truck and rail in the U.S. for 2010.[21] Popovich et al. estimated 1000 $PM_{2.5}$-related mortalities from freight diesel trains in the year 2019 based on an estimate of 1500 deaths (monetized: \$12 billion) by Goodkind et al. for the year 2011 and a linear reduction in $PM_{2.5}$ and $NO_x$ emissions under Tier 4 requirements for locomotives by U.S. EPA.[22,23] Zhang et al. estimated 94,200 global premature deaths associated with $PM_{2.5}$ exposure due to international (83%) and domestic (17%) maritime shipping in 2015.[24] Corbett et al. showed that using low-sulfur fuels in ships can reduce $PM_{2.5}$-related premature mortality by 34% globally.[25]

Several studies report climate impacts from freight modes.[26] Evidence suggests that to the extent that shipping and e-commerce companies consider environmental impacts in mode selection, they typically focus on climate rather than health impacts.[27−30] Rail is considered a fuel-efficient mode choice that emits less $CO_2$ emissions per unit mass and distance traveled than a truck,[31] and thus, some reports have focused on truck-to-rail conversion. For example, a 2013 report by the U.S. Department of Energy (DOE) highlighted the potential of truck-to-rail modal shift since rail serves many of the same routes as truck and uses substantially less energy.[32] Prior studies have used differing assumptions to evaluate climate, air quality, and health impacts of truck-to-rail modal shifts. Bickford et al. show significant reduction in $CO_2$ emissions and minor improvement in net air quality ($NO_2$ and primary $PM_{2.5}$ concentrations) from shifting freight from truck to rail in the upper Midwestern U.S, though added that rail freight activity degrades air quality along rail lines.[33] Projecting emissions from freight truck and rail in the U.S. through 2050, researchers reported that climate policy in the form of carbon tax causes a shift from truck to rail, resulting in reduction in long-term climate forcing,[21] pollutant emissions,[34] and air quality-related net health impacts[21,35] by 2050. Liu et al. estimated $PM_{2.5}$-related mortality from freight truck and rail in the U.S. for baseline and future policy scenarios (compact urban form, carbon tax, and truck fleet maintenance); their future scenarios (which modeled engines as being cleaner in the future than today) show greater total damages from truck than rail,[21] although that study did not report normalized damages by payload and distance traveled. Pan et al. find regional differences in health impacts from a truck-to-rail transition: locations where truck traffic decreases experience health benefits and locations where rail freight increases experience health disbenefits.[35] The existing literature generally investigates total emissions and impacts representing total freight tonnage and distance traveled, rather than impacts by mode for a given route and/or impacts per tonne-km (as is done in this study).

Strategy documents[36,37] and tools[38,39] from transportation agencies of the U.S. federal government highlight the need to consider and address environmental injustice. Highly impacted communities have identified transportation sources, including diesel trucks, trains, airports, and shipping ports as important contributors to air pollution disparities.[40−48] Peer-reviewed research on environmental justice (EJ) aspects of transportation[17,47−54] include the following: Patterson et al. investigated improvements in air quality and environmental equity from the use of diesel engine emission controls in heavy-duty diesel trucks in Oakland, California (CA).[52] In another Oakland, CA-based study, urban transportation policies such as freeway rerouting and boulevard replacement not only produced substantial air quality benefits but also resulted in environmental gentrification, with property value increases and the displacement of long-time Black residents.[53] National studies of a transportation-related pollutant ($NO_2$) report that the average exposures are, for Hispanic, Black, and Asian people, higher than the national average, and for White people are lower than the national average.[51,55,56] A study of many sectors of the economy highlighted heavy-duty and off-highway vehicles as important contributors to exposure disparities for $PM_{2.5}$.[17]

In this work, we investigate the health and EJ impacts of $PM_{2.5}$ and climate impacts of $CO_2$ from inter-regional domestic freight movement in the U.S. by four modes (road, rail, water, air) for each route separately. These results advance the literature on environmental impacts of freight by (1) comprehensively comparing the four modes on a functionally equivalent basis (i.e., 1 tonne traveling along a route between a specific origin and destination), (2) comparing across three environmental impacts (climate change, total health, and health disparity), and (3) investigating, separately, more than 30,000 individual origin–destination pairs.

## 2. METHODS

We investigate health, climate impacts, and exposure disparity from inter-regional freight movement in the contiguous U.S. Impacts are investigated separately for each selected route. This work only considers impacts of exhaust emissions from the vehicle operation and does not consider emissions from vehicle manufacture or from nonexhaust systems (e.g., brake and tire wear; road salt). We investigate four freight modes: combination long-haul heavy-duty truck (HDT; referred to herein as "truck"), freight rail, barge, and freight aircraft. Modes that are not investigated are pipeline, multiple modes and mail, and other and unknown—which, in total, account for ∼25% of annual tonne-km and <10% of freight transport energy consumption.

**2.1. Mode Emission Factors (EFs).** EFs used here (Figures S1, S2, and Table S1) represent the most current vehicle and fuel properties for each mode. We use 2019 exhaust EFs from the Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) model for primary $PM_{2.5}$, $NO_x$, $SO_2$, VOC, and $CO_2$ emissions (truck, rail, barge: diesel, 11 ppm sulfur; air: jet fuel, 700 ppm (sensitivity analysis (Table S2): 11 ppm sulfur)).[57] For $NH_3$, EFs are from the MOVES model for trucks,[58] from EPA studies for rail and barge,[59,60] and, based on the 2017 NEI,[7] are zero for aircraft. For truck, EFs are for long-haul HDTs; in a sensitivity analysis, we employ short-haul HDT EFs for all trips <322 km (Table S3). Four types of aircraft are modeled: single aisle (SA), small twin aisle (STA), large twin



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Environ. Sci. Technol. 2023, 57, 884−895

aisle (LTA), and large quad (LQ), which are categorized based on average payload and average flight distance (Table S4). Aircraft EFs differ for landing and take-off (LTO) versus for cruise; we further separated LTO emissions into five categories: (1) taxi/idle-in, (2) taxi/idle-out, (3) approach/landing, (4) take-off, and (5) climb-out (Tables S1 and S5).[61,62] Units on truck, rail, and barge EFs are kg/Mt-km, i.e., mass of pollution emitted per payload mass per geodesic (i.e., on earth's surface) distance traveled. Units on aircraft EFs are, for cruise, kg per megatonne payload per km great-circle distance traveled and, for LTO, kg per megatonne payload.

**2.2. Origin−Destination (O−D) Pairs.** The Department of Transportation's Freight Analysis Framework (FAF, version 4, for 2017)[2,4] provides tonnage, tonne-km, and value of commodity flows between 132 FAF regions (or "CFS areas"; these are the O−D pairs studied here) by mode (Figure S3). We studied inter-regional transport (but not intraregional transport), which is composed of 16,293 O−D pairs (accounting for 84% of total tonne-km) for truck, 4875 pairs (99% of total tonne-km) for rail, 732 pairs (97%) for water, and 7913 pairs (98%) for air. Most (69, 97, 93, and 98% for truck, rail, water, and air tonne-km, respectively) but not all inter-regional freight transport is interstate.

**2.3. Modal Routing.** Geospatial data for road, waterways, and airport runways are from the DOT's National Transportation Atlas Database (NTAD)[63,64] (Figure S4); the rail network is from the EPA's 2014 NEI.[65] Our analysis assumes the shortest network route (for air: great-circle path) between origin and destination, using ArcGIS network analyst. For air, we employ an average cruise height of 11 km (∼36,000 ft).[66,67] A simplified LTO cycle is used at an airport based on the ICAO's LTO cycle[62] (Figure S6). The LTO cycle is assumed to be between 0 and 0.914 km (∼3000 feet) above ground level.[9,62,68] All components of LTO are assumed along a straight line (i.e., along a physical extension of airport runways); slopes for climb-out and approach (landing) paths are from the FAA's Aeronautical Information Manual: 200 feet per nautical mile (ft/NM) or 2.1° for climb-out and 250 ft/NM or 2.6° for approach.[69] We employ actual runway orientations for each specific airport studied; since a linear runway could potentially involve climb-out and approach from either direction (e.g., a north−south runway could be approached from the north or south), at each airport, we model both directions and take the average.

**2.4. Air Quality Modeling.** $PM_{2.5}$ concentrations are modeled using "Intervention Model for Air Pollution" (InMAP)[70] and the InMAP source−receptor matrix (ISRM).[23] InMAP (and the ISRM) predicts the change in annual-average $PM_{2.5}$ concentration attributable to a change in annual emissions. Additional details about the model are available elsewhere.[23,71]

The maximum height of sources modeled in the ISRM is ∼1000 m above ground level. We used the ISRM for sources below 1000 m from the surface; for aircraft cruise emissions (height above ground >1000 m), we use InMAP. InMAP/ISRM output for each grid cell includes ground-level annual-average concentrations ($\mu g/m^3$) of primary $PM_{2.5}$, particulate nitrate ($pNO_3$), particulate sulfate ($pSO_4$), particulate ammonium ($pNH_4$), and secondary organic aerosols (SOAs).

The three main inputs to InMAP/ISRM are as follows:

(i) Annual emissions of VOC, $NO_x$, $NH_3$, $SO_2$, and primary $PM_{2.5}$ for shortest road, rail, waterway, and air (LTO and cruise) routes as line sources. The ground-level ISRM grid is intersected with each route, and emissions (i.e., emissions per length × route-segment length in that grid cell) are allocated to truck, rail, and barge routes.

(ii) Census data on population by block group for the year 2016 are taken from the 2018 American Community Survey (ACS) (see Table S6).[72] We use all age groups for the main results and ≥35 years for sensitivity analysis. Demographic information in the ACS is self-report in five racial groups (White, Black, Asian, Native American, and mixed/other) and two ethnic groups (Hispanic, non-Hispanic). In our summaries, White people are distinguished by ethnicity (non-Hispanic White and Hispanic White); the remaining four racial groups combine both ethnicities. Results further disaggregated by race−ethnicity are in the Supporting Information (SI) (MS Excel sheet data).

(iii) Baseline all-cause mortality data by county are for the year 2016 from the National Center for Health Statistics (NCHS) Office of Analysis and Epidemiology (OAE) at the Centers for Disease Control and Prevention (CDC).[73] Race-specific health impacts are calculated using all-cause mortality rates for the entire population of all age groups (and ≥35 years for sensitivity analysis).

**2.5. Health Impact Quantification.** We quantify health impacts attributable to long-term $PM_{2.5}$ exposure using a standard log-linear concentration−response (C-R) function for all-cause mortality from the American Cancer Society (ACS) re-analysis.[74] Here, a 10-$\mu g/m^3$ change in $PM_{2.5}$ was estimated to cause a 7.8% change in mortality rates. This value is consistent with a recent meta-analysis estimate suggesting an 8% change per 10 $\mu g/m^3$.[6]

**2.6. Calculations and Metrics.** We run InMAP/ISRM for each mode and O−D pair (>30,000 runs) nationally and disaggregated by urban/rural impact location. Impacts per O−D pair are linearly scaled to represent (real) FAF v4 tonne-km by multiplying with the ratio of actual FAF v4 tonne-km to the tonne-km estimated using the shortest route assumption. (For all modes, the total distance estimated using the shortest route assumption is approximately near to the total distance from the FAF v4 data, suggesting that the shortest-route assumption is reasonable; see Table S7.) We investigate health impacts in terms of total damages and disparities in damages (i.e., the difference in risk for the most-exposed racial−ethnic group versus for the overall population average). For comparing across modes, we use both simple arithmetic mean ("simple average") and tonnage-weighted mean ("weighted average") across O−D pairs. One advantage of using both metrics is that the amount of freight per mode or O−D pair may change over time; this shift would directly impact the weighted averages but not the simple average.

To estimate monetary damages (year 2020 dollars), we first use a social cost of $CO_2$ (SCC) of $53.53 per tonne $CO_2$ (corresponding to a 3% discount rate) from the 2017 National Academy of Sciences (NAS) report[75] and a value of statistical life (VSL) of $9.7 million derived by the U.S. EPA as the mean of a Weibull distribution from 26 studies.[76] Next, as a sensitivity analysis, we consider the impact of alternative values for SCC and VSL. Specifically, for SCC, we employ the four values ($/t$CO_2$) of 15, 54, 79, and 157 given in the NAS report, and for VSL, we separately employ results from each of the 26 studies documented in the U.S. EPA report.


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Environ. Sci. Technol. 2023, 57, 884−895

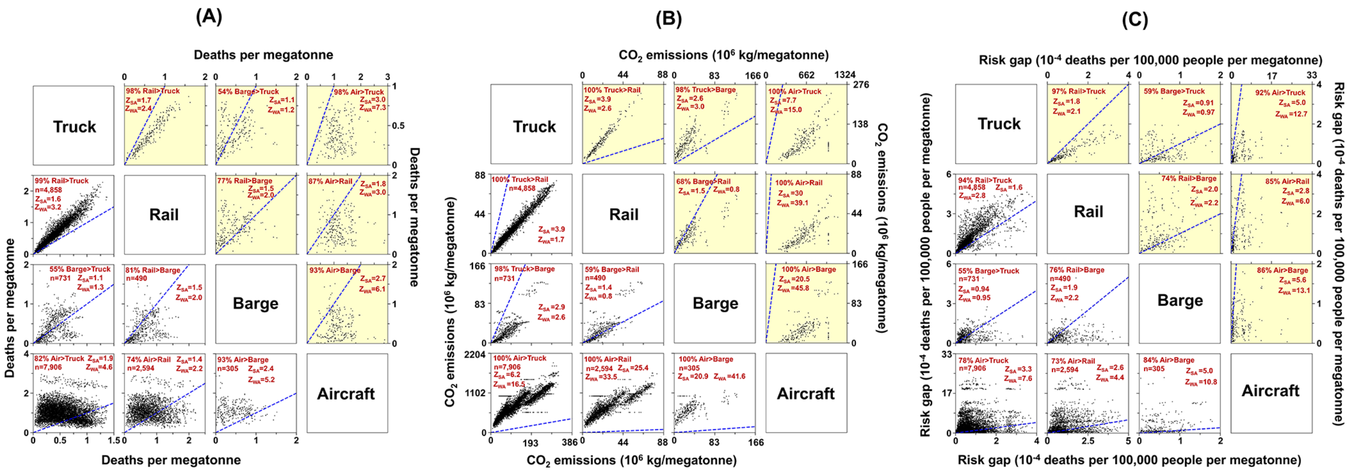


**Figure 1.** Pairwise health, climate, and exposure disparity impacts from each origin−destination (O−D) pair by mode. Each dot in the scatterplots represents one O−D pair. (A) Deaths per megatonne payload from $PM_{2.5}$, (B) carbon dioxide ($CO_2$) emissions in kg per megatonne payload, (C) health risk gap between most-exposed racial−ethnic group and population average (deaths per 100,000 people per megatonne payload). In panels (A)−(C), the lower six plots (background color: white) show all O−D pairs in common between the two modes; the upper six plots (background color: yellow) show the $n = 214$ O−D pairs that are common across all four modes. The blue dashed line signifies $y = x$. Percentages in each plot show percent of data points above $y = x$ line for a mode. For example, 99% of the $n = 4858$ truck−rail O−D pairs have greater health impacts from rail than truck. $Z_{SA}$ ($Z_{WA}$) represents the ratio of simple average (2017 tonnage-weighted average) of the mode with a greater percentage to the mode with a lower percentage. For example, for truck−rail O−D pairs, $Z_{SA} = 1.6$ means average deaths per megatonne for rail are 1.6 times of truck and $Z_{WA} = 3.2$ means tonnage-weighted average deaths per megatonne for rail is 3.2 times of truck.

## 3. RESULTS

**3.1. Health, Climate, and Health Risk Gap from Each O−D Pair by Mode.** Premature deaths, $CO_2$ emissions, and health risk gap per megatonne are estimated for each of 16,293 (truck), 4875 (rail), 732 (barge), and 7913 (aircraft) O−D pairs (Figure S8). The median (interquartile range [IQR]) value for deaths per megatonne is 0.5 (0.3−0.8) for truck, 0.7 (0.5−1.1) for rail, 0.4 (0.2−0.7) for barge, and 1.1 (0.8−1.4) for aircraft. Median (IQR) of $CO_2$ emissions per tonne is 107 (65−166) for truck, 23 (14−36) for rail, 21 (10−35) for barge, and 772 (581−1009) for aircraft. Median (IQR) of the health risk gap ($\times 10^{-5}$) per megatonne is 6 (4−9) for truck, 9 (5−14) rail, 5 (3−8) barge, and 12 (7−31) aircraft. Examples of O−D pairs with the largest deaths per megatonne include Los Angeles (CA) to Boston (MA), San Diego (CA) to Boston, and Los Angeles to Hartford (CT) for truck; Los Angeles to New York City (NY); New York to San Francisco (CA); and Philadelphia (PA) to Los Angeles for rail; Pittsburgh to Remainder of Ohio, Pittsburg to New York (NY), and Kansas City (MO) to Philadelphia for barge; and Los Angeles to Maine, Houston (TX) to San Diego (CA) for aircraft. Examples of O−D pairs with the largest health disparity include Arkansas to Remainder of CA, Memphis (TN) to Remainder of CA, and Arkansas to Las Vegas (NV); Kansas City to Remainder of Louisiana, Arkansas to Sacramento, CA, and Mobile, Alabama (AL) to Hartford, CT for rail; Tulsa, Oklahoma (OK) to Arkansas, Mississippi, and Savannah (GA) for barge; and Los Angeles to Maine, San Francisco, and Fresno (CA) for aircraft. Results for all O−D pairs by mode are provided in the SI (as MS Excel sheet data).

Impact per megatonne increases for a longer travel distance (Figure S9), with two exceptions: barge for large distances (>3001 km) and aircraft. The former result reflects open-ocean routes crossing the Panama Canal, outside the InMAP (and, U.S. Census) domain. The latter result reflects, for aircraft, (1) more efficient, lower-emission engines used for larger distances and (2) most modeled impacts for aircraft are near-airport rather than during cruising. Specifically, we estimate that total average aircraft damages are composed of 63% runway emissions (taxi-in, taxi-out, and take-off), climb-out 23%, approach 14%, and cruising ∼0% (reflecting that cruising emissions occur relatively far from population centers).

**3.2. Pairwise Comparison between Modes for Each O−D Pair and Averages.** There are 4858 common O−D pairs that carry freight by both truck and rail (truck−rail), representing 66 and 99.6% of total truck and rail tonne-km, respectively; 731 truck-barge O−D pairs (12 and 99.9%, respectively, of total truck and barge tonne-km); 490 rail−barge O−D pairs (6 and 68% of total rail and barge tonne-km); 7906 air−truck O−D pairs (91 and 61% of total air and truck tonne-km); 2594 air−rail O−D pairs (29 and 44% of total air and rail tonne-km); and 305 air−barge O−D pairs (2 and 41% of total air and barge tonne-km). There are 214 O−D pairs common between all four modes, carrying 6, 3, 28, and 1%, respectively, of total truck, rail, barge, and aircraft tonne-km. Intercomparisons by mode (Figure 1) reflect only the O−D pairs, where these two modes operate.

Considering the separate pairwise mode intercomparisons (Figure 1A, lower-left, e.g., 4858 O−D pairs for the rail−truck plot), $PM_{2.5}$-related health impacts are greater for rail than truck for almost all (99%) of the routes and are larger for barge than truck for a little over half (55%) of the routes. Rail has greater impacts than barge for 81% of the routes; aircraft has greater impacts than truck, rail, and barge for 82, 74, and 93% of the routes, respectively. In pairwise comparison for aircraft, certain data points can be seen as a separate patch with higher-than-average health impacts (>∼2.4 deaths per megatonne); those are routes that start or end with Los Angeles International Airport. Average unweighted (tonnage-weighted) aircraft health impacts are 1.9 (4.6), 1.4 (2.2), and 2.4 (5.2) times larger than truck, rail, and barge, respectively. Average unweighted (tonnage-weighted) rail health impacts are 1.6 (3.2) and 1.5 (2.0) times greater than truck and barge, respectively. Average (tonnage-weighted) health impacts from barge are slightly greater than truck (1.1 (1.3)). We observe that if routes are

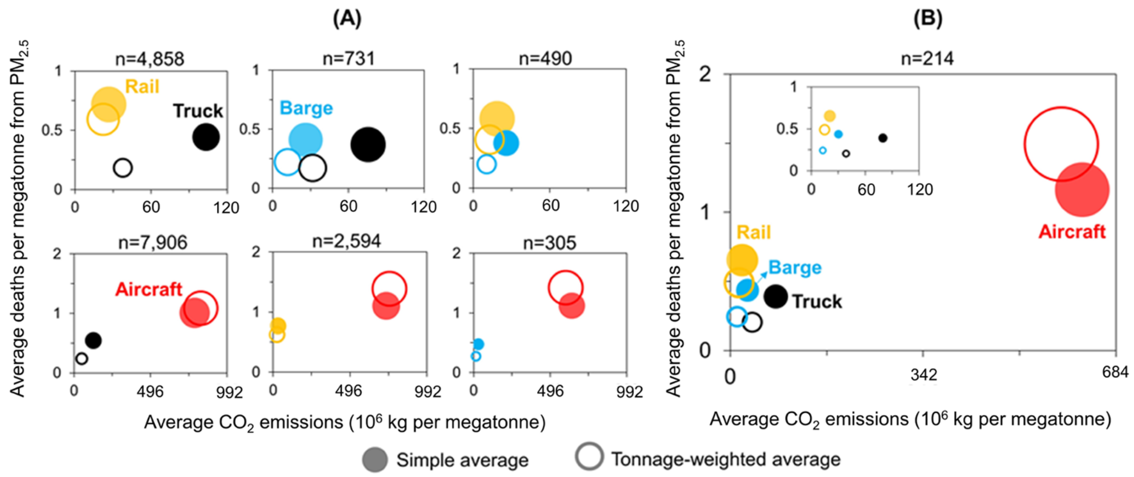


**Figure 2.** Pairwise health, climate, and exposure disparity impacts, averaged across origin−destination (O−D) pairs by mode. Simple average (shaded icons) and tonnage-weighted average (unshaded icons) for (A) all O−D pairs in common between the two modes and (B) the 214 O−D pairs that are common across all four modes. Icon size (area) is proportional to health risk gap (deaths per 100,000 people per megatonne); "*n*" is the number of O−D pairs.

weighted by 2017 tonnage (i.e., reflecting the state of freight in a recent year), average (in Figure 1: "$Z_{WA}$") impacts are larger for all modes than if routes carry equal weightage ("$Z_{SA}$"). This result reflects that more freight weight travels on higher-impact routes than on lower-impact routes.

The simultaneous intercomparisons across all modes (i.e., Figure 1A upper-right six plots; 214 O−D pairs for all six plots) yield broadly similar order of pairwise comparison as for the separate pairwise comparisons (i.e., Figure 1A lower-left six plots). Analogous pairwise comparisons for each $PM_{2.5}$ chemical species (Figures S10−S14) reveal, for example, that primary $PM_{2.5}$ impacts from aircraft are lower than those from truck, rail, and barge for most (>50%) of the O−D pairs, and $pSO_4$ and SOA impacts from truck are greater than those from rail and barge for >90% of the O−D pairs.

Considering $CO_2$ emissions (Figure 1B), truck has greater impacts than rail and barge for 100 and 98% of the routes, respectively; barge has greater impacts than rail for 59% of the routes; aircraft has greater impacts than truck, rail, and barge for 100% of the routes. Average unweighted (tonnage-weighted) $CO_2$ emissions for aircraft are 6 (17), 25 (34), and 21 (42) times those for truck, rail, and barge, respectively. Average unweighted (tonnage-weighted) $CO_2$ emissions per megatonne for truck are 3.9 (1.7) and 2.9 (2.6) times that for rail and barge, respectively. Average unweighted $CO_2$ emissions from barge are 40% greater than rail but 20% lower than rail when weighted by tonnage. Figure 1 presents "*Z*" values: the ratio of unweighted ($Z_{sa}$) or weighted ($Z_{wa}$) average impact from one mode to another mode. (The mode with impacts greater than the other mode for >50% of the routes comes first in the ratio. *Z* is usually but not always >1; see Figure 1.) *Z* values are generally larger for the aircraft pairs than for the other pairs, reflecting aircraft's comparatively greater impacts. In many cases (e.g., deaths per megatonne for air−truck), Z values are larger when weighted than when unweighted, indicating that more freight travels on routes where the difference in impacts is greater (e.g., here, greater for air than for truck) than on routes where the difference in impacts is lesser. For reverse cases with *Z* (e.g., $CO_2$ impacts for truck−rail), the reverse holds (i.e., more freight is shipped on routes where the difference is lower than where the difference is higher). The large-emission outliers in Figure 1B for barge (>75 kg $CO_2$ emissions per ton) reflect long routes that travel through the Panama Canal. In the scatter plot (Figure 1B), aircraft impacts appear "lumped" because the $CO_2$ emission factor is a function of aircraft type. Modal comparison for 214 O−D pairs (Figure 1B upper-right panels) show similar conclusions for weighted and for unweighted comparisons.

For exposure disparity (Figure 1C lower-left), we find that rail has a greater disparity than truck for 94% of the routes, barge has a greater disparity than truck for 55% of the routes, rail has a greater disparity than barge for 76% of the routes, and aircraft has a greater disparity than truck, rail, and barge for 78, 73, and 84% of the respective common routes. Average unweighted (tonnage-weighted) aircraft exposure disparity is 3.3 (7.6), 2.6 (4.4), and 5.0 (10.8) times larger than truck, rail, and barge, respectively. Average unweighted (tonnage-weighted) rail exposure disparity is 1.6 (2.8) and 1.9 (2.2) times larger than truck and barge, respectively. Barge and truck have the lowest exposure disparity among nonaircraft modes with truck slightly higher, 1.06 (1.05) times greater than barge.

To further explore mode intercomparisons, we calculated average impacts across O−D pairs (see Figure 2; these data correspond to the lower-left portions of Figure 1A−C), using unweighted average (Figure 2, shaded circles) and tonnage-weighted average (open circles). Each plot in Figure 2 presents all three impacts ($CO_2$ [*x*-axis], total population mortality [y-axis], and disparity in mortality [icon-size]). For the separate pairwise comparisons (Figure 2A), aircraft has the largest average and tonnage-weighted health, climate, and exposure disparity impacts per megatonne. Among nonaircraft modes, rail has the largest average and tonnage-weighted health impacts, and exposure disparity, and lowest $CO_2$ emissions; among nonaircraft modes, truck has the largest average and tonnage-weighted $CO_2$ emissions and the lowest average and tonnage-weighted health impacts. When restricting to the 214 routes with all four modes (Figure 2B), conclusions are similar, with the exception that, if weighted by tonnage, rail has larger $CO_2$ emissions impact than barge. An investigation of the same comparisons, segregated by travel distance (Figure S15), reveals the same rank-order of health impacts between modes at all distance bands. Health impacts per tonne-km (Figure S16) reveals the same rank-order as Figure 2 except for truck and



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barge (truck > barge; though the difference is modest, $Z_{SA}$ = 1.3). Disaggregating the unweighted impacts by chemical species (Figures S17 and S18), particulate nitrate accounts for most (>75%) of damages for all modes. Particulate sulfate contributes 13% for aircraft and <2% for the other modes.

*3.2.1. National Estimates.* Using U.S. DOT's FAF data to scale from per-tonne-km to total impacts (Table S8), we estimate total premature deaths and $CO_2$ emissions from each mode in the year 2017 at 660 premature deaths and 124 billion kg of $CO_2$ from truck, 663 premature deaths and 23 billion kg of $CO_2$ from rail, 65 premature deaths and 3 billion kg of $CO_2$ from barge, and 2 premature deaths and 1 billion kg of $CO_2$ from aircraft. A sensitivity analysis based only on people aged ≥35 years yields similar results (<8% difference). Total deaths by mode differ by the distance between origin and destination. Deaths from truck are the largest for shorter distances (<898 km) and deaths from rail are the largest for longer distances (1648−3001 km) (Figure S19).

**3.3. Health Impacts in Urban and Rural Areas and Impacts by Race−Ethnicity.** We find that truck, rail, and barge have modestly larger total health impacts to rural populations than to urban populations (see Table 1), reflecting the major portion of highways, railway lines, and navigable waterways for inter-regional freight transportation travel through rural areas (partially counterbalanced by the larger number of people in urban than in rural areas). Aircraft impacts are greater for urban than for rural populations, in part reflecting that most impacts are near-airport and most airports are near urban centers. Based on the portion of urban-impact routes (right-most column, Table 1), overall average findings given here apply to most but not all O−D pairs.

**Table 1. Health Impacts for Urban versus Rural Populations**

| | | deaths per megatonne[a] | | | [b] |
|---|---|---|---|---|---|
| mode | *n* (number of O−D pairs) | urban | rural | combined | percentage urban-impact routes (%)[b] |
| truck | 16,293 | 0.27 | 0.30 | 0.57 | 32 |
| rail | 4875 | 0.37 | 0.42 | 0.79 | 32 |
| barge | 732 | 0.19 | 0.26 | 0.45 | 19 |
| aircraft | 7913 | 0.72 | 0.40 | 1.11 | 85 |

[a]Overall average for that mode ("combined"), subdivided into impacts to urban and rural populations. Values reflect, where the impacts occur (urban versus rural), attributable to total emissions. Numbers given here might not sum because of rounding. [b]Percent of O−D pairs for which health impacts are greater in urban than in rural areas.

Among racial−ethnic groups considered here, the most-impacted group (risk per 100,000 people) is White non-Hispanic from all freight movement (Figure 3A). This finding reflects, in part, rural truck travel as a major source of emissions, and these rural areas are predominantly White; the most-impacted group to rural populations by truck and rail is non-Hispanic White (Figure 3B). If considering only impacts to urban populations, the most-impacted group (overall (Figure 3A), and separately for truck, rail, and barge (Figure 3B)) is Black people. The most-impacted group for barges is Black people (for overall, urban, and rural populations) and for aircraft is the mixed/other groups (overall and urban populations). This paper considers inter-regional freight, rather than within-region or within-urban freight; differences between the "urban" and "rural" results in Figure 3 suggest that findings for those other conditions (e.g., within-urban freight) would likely differ from results presented here.

**3.4. Monetized Damages.** Climate and health are fundamentally different impacts. To combine or compare them directly, they first must be put onto a single scale. A common way to do so is by converting to monetized damages. This conversion is necessarily imperfect and can be controversial, reflecting the many assumptions required and what is lost by converting impacts into monetary terms. Here, we do that conversion and comparison, recognizing the imperfections, in hopes that the outputs lend insight into the relative impacts to health versus climate.

As an obvious omission, we have not monetized the health disparities, i.e., we have not attempted to place a monetary value on the disparities themselves. (Monetizing disparities is different from disparities in monetization. The former refers to placing a value on the disparities; the latter refers to differences among groups in their monetized impacts.) Methods for monetizing impacts are common for climate and health damages but currently are not for health disparities.

Total average monetized damages are the largest from aircraft followed by truck and rail and lowest from barge (Figure 4A). Damages from aircraft are 4, 5, and 7 times those from truck, rail, and barge, respectively; those from truck are slightly (13%) greater than rail and ∼39% greater than barge; and those from rail are ∼33% greater than barge. Considering damages from all routes for a mode (Figure 4B) rather than only common routes between modes (Figure 4A), rail and barge have greater health-related monetized damages (8 and 4 million USD per megatonne, respectively) than climate-related damages (1 and 1 million USD per megatonne, respectively). For aircraft, monetized damages for climate are 4 times those for health (42 versus 11 million USD per megatonne). For truck, climate-related damages are slightly greater than health-related monetized damages (6.4 versus 5.6 million USD per megatonne).

Sensitivity analyses (Figure 4C) reveal that, while total damages depend on SCC and VSL, pairwise comparisons between modes (i.e., determination of which mode has higher impact) are relatively robust to variations in SCC and VSL. The one exception is truck−rail: impacts are slightly higher for truck than for rail in the base case (see Figure 4A,C), however, in the case of comparatively small SCC and large VSL (Figure 4C), the reverse holds. The reason for this sensitivity is that estimated damages are larger for trucks than for rail for climate impacts, and the reverse for $PM_{2.5}$ air pollution. In sensitivity analyses considering each mode separately (Figure S20), for trucks (but not for the other modes), impacts from climate versus from health are nearly equal; therefore, the relative impacts from climate versus from health are more sensitive to the choice of SCC and VSL for truck than for the other modes.

## 4. DISCUSSION

This work quantifies and compares health and climate impacts and exposure disparity from inter-regional transport of a unit mass of freight payload from origin to destination by four different modes: truck, rail, barge, and aircraft.

We find that aircraft poses the greatest health and climate damages among all four modes. Among the nonaircraft modes, rail has the greatest health impacts and lowest climate impacts per megatonne payload. Truck has the lowest health impacts among all modes and greatest climate impacts among the

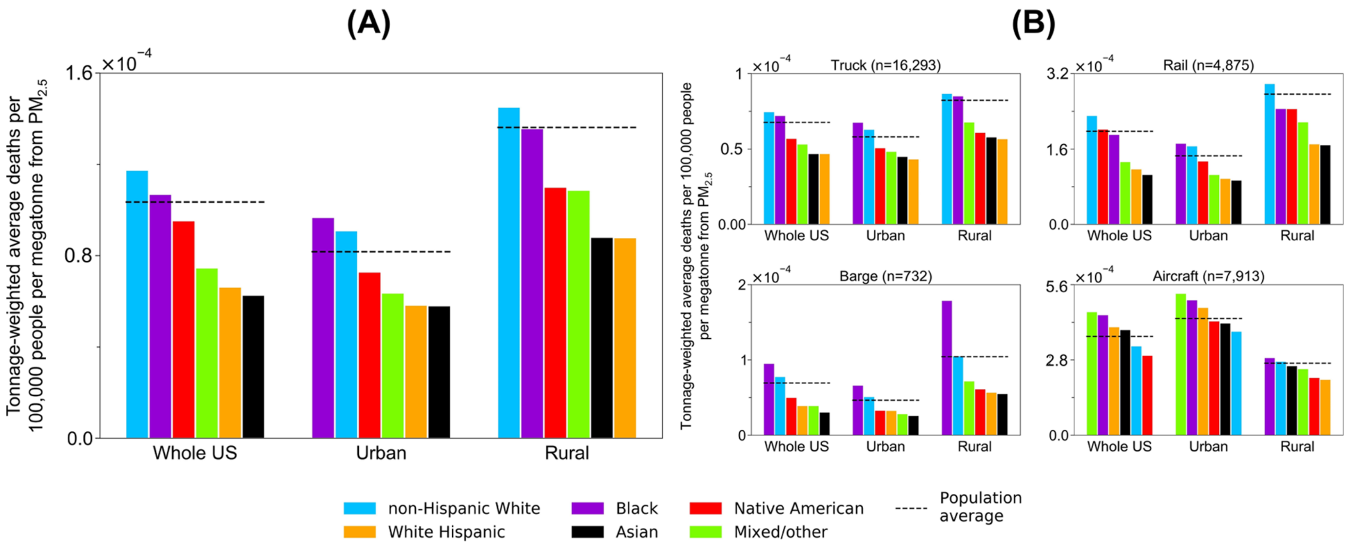


**Figure 3.** $PM_{2.5}$ health impacts by the racial−ethnic group in the whole U.S., urban, and rural areas (A) from all freight movement and (B) by mode. Dashed line indicates the population average.

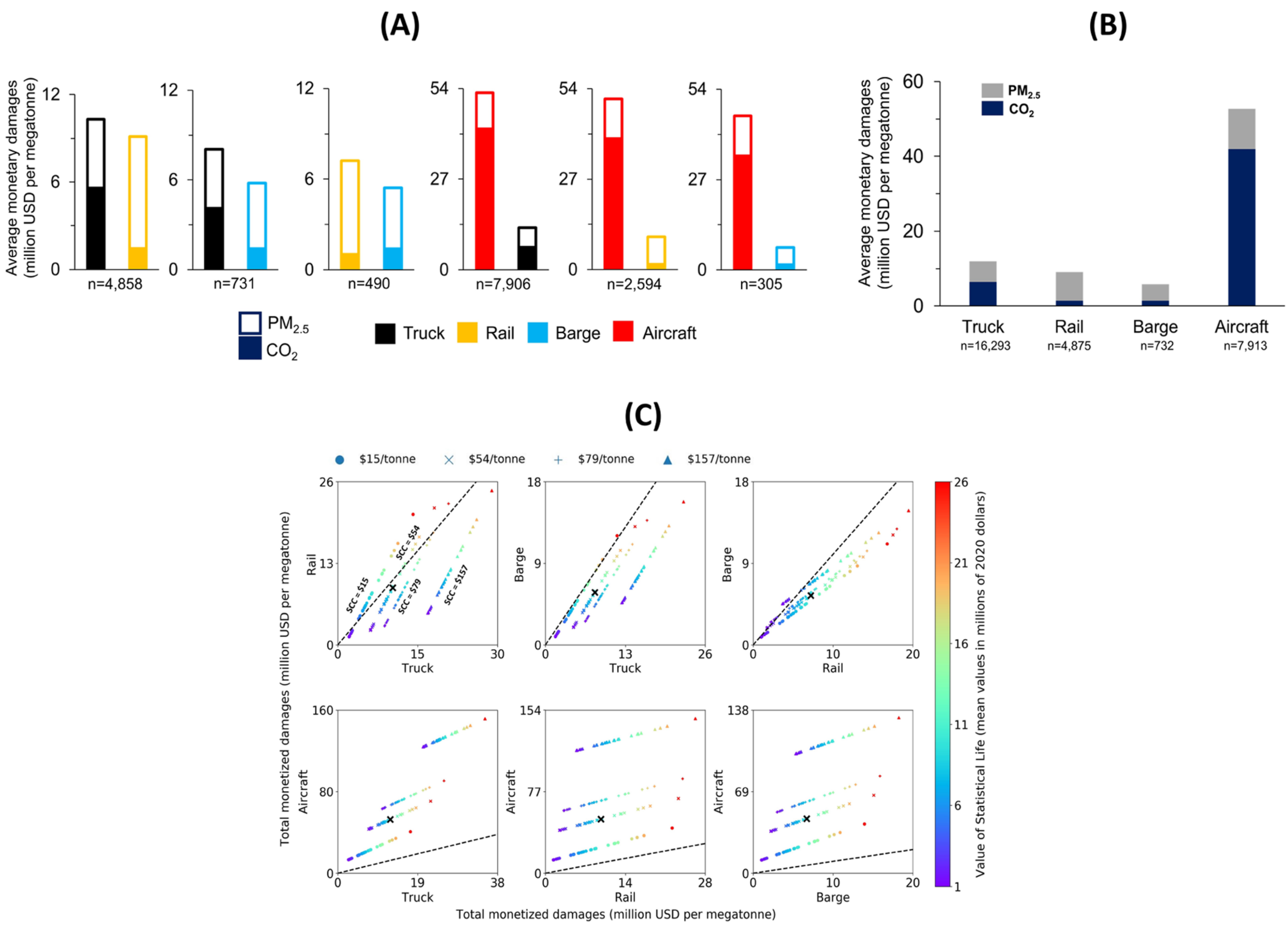


**Figure 4.** (A) Pairwise comparison of average monetized damages from $PM_{2.5}$ and $CO_2$ emissions in million USD per megatonne payload by employing central-tendency values (year 2020 dollars) for value of a statistical life (VSL; \$9.7 million) and social cost of carbon (SCC; \$54/tC); (B) average monetized health and climate damages in million USD per megatonne from all routes for a mode; (C) sensitivity of results in panel (A) to VSL (\$1.1−25.8 million) and SCC (\$15, \$54, \$79, \$157/tC), with 1:1 line (black-dashed) and base case value (black multiplication sign).

nonaircraft modes. Barge has slightly greater health impacts than truck and greater climate damages than rail.

One policy implication is that efforts from shipping companies and policymakers to incentivize rail due to its greater efficiency and lower carbon emissions per ton-mile should also consider health impacts from rail. Truck has the largest tonnage and tonne-km among all modes; hence, policymakers tend to consider truck as worst for human health, whereas we find that rail has the largest health impacts per unit tonnage, only ~30% lower than health impacts from aircraft. A second policy implication is the important benefits from electrification of inter-regional (and other) freight transportation, combined with low-emission or renewable electricity generation.[22,77] We estimate that annual damages from freight movement (combined, across the four modes) are ~1400 premature deaths (monetized: $13 billion), 150 billion kg $CO_2$ (monetized: $8 billion), and health disparity of 0.06 deaths per 100,000 people (risks are ~13% greater for the most-exposed race−ethnicity than the population-average). (These values may be underestimates; as noted in the O−D pairs Section 2, we modeled 84−98% of tonne-km by mode.) For truck and rail tradeoffs between climate and health impacts as well as lowering the exposure disparity, vehicle electrification is the key solution. A third implication is that the damages and disparities (and, potentially, the solutions) differ between inter-regional versus within-regional transportation. Figure 3 (above) reflects damages to urban and rural populations attributable to inter-region freight; our inputs and results do not investigate within-regional or within-urban freight.

The health and exposure disparities by race−ethnicity in part reflect racism in urban planning, leading to the (on average) greater proximity of freight transportation-related infrastructure to communities where people of color live. Thus, as a fourth policy implication, policymakers and infrastructure planners should, at a minimum, structure future freight infrastructure such that it does not privilege nor disproportionately affect one demographic group over the other. In addition to not worsening the problem, it is also important to address existing disparities—to actively work to eliminate the observed exposure disparities.

Health impacts from $PM_{2.5}$ are dominated by $NO_x$ emissions for all modes. This finding complements previous findings[23] and emphasizes the benefits of lowering $NO_x$ emissions from all freight modes, especially aircraft. The rail−truck intercomparison reflects in part the higher $NO_x$ and $PM_{2.5}$ emission factors (mg per tonne-km) for rail than for truck ($NO_x$: 184 versus 124; $PM_{2.5}$: 5.2 versus 1.4).

This work is the first to explore exposure disparity between different racial−ethnic groups from inter-regional freight transportation. We find that impacts from truck and rail are greatest for non-Hispanic White people, impacts from barge are greatest for Black people, and impacts from aircraft are greatest for the mixed/other groups. Health impacts and disparity among groups differ in urban versus rural areas. These findings add to ongoing efforts of understanding and addressing environmental inequality and injustice from transportation[51−53,78−80] by reflecting on disparities from existing inter-regional freight flows and infrastructure. Results here do not explicitly investigate local impacts, e.g., from warehouses or intermodal facilities.[81]

Health damages from aircraft only include the LTO phase because we find that contribution of cruise emissions is negligible to ground-level $PM_{2.5}$ impacts, a conclusion from a sample of 20 routes that are representative of the U.S. geography. In contrast, findings from Barrett et al.[9] show that globally 80% of the total $PM_{2.5}$-related premature mortalities per year from aircraft are attributable to cruise emissions and only 20% to LTO emissions (for U.S., 84% from cruise and 16% from LTO). They likely underestimate near-source LTO emissions owing to the low resolution of the global atmospheric model used. Other model parameters too (e.g., rates of vertical mixing) may also play a role in explaining differences among these estimates. Yim et al.[14] estimated 57% of aircraft impacts in North America are from cruise and 43% from LTO emissions. That paper used increased regional model resolution relative to Barrett et al.[9] and found a greater share of LTO impacts. Those aircraft studies investigated all travel types and routes (including passenger travel); our estimates are only for freight movement along the routes investigated.

Our primary results use conventional jet fuel (700 ppm S) for aircraft, reflecting current practice. In sensitivity analyses, we find that shifting to ultra-low-sulfur (ULS) fuel (11 ppm S)[82] yields only modest (~9%) decreases in aircraft $PM_{2.5}$ health impacts (Figure S21). While particulate sulfate is reduced dramatically by the shift to ULS fuel (to ~2% of the conventional fuel emissions), direct $PM_{2.5}$ emissions increase (approximately double), and particle nitrate, which dominates aircraft $PM_{2.5}$ health impacts, remains unchanged. The net result is that with ULS fuel, aircraft still has higher impacts than rail, barge, and truck, though the difference between the two is lowered by 18−31% for ULS fuel compared to conventional fuel (Table S9).

Aircraft impacts presented here are for minimum slopes of approach and climb-out. In sensitivity analyses, total $PM_{2.5}$ health impacts from aircraft are not strongly sensitive to approach and climb-out slope (Figure S22). Truck emission factors employed here are for long-haul heavy-duty trucks. In sensitivity analyses (reflecting assumptions in the MOVES model),[83] health impacts for routes shorter than 322 km decrease by 58% on average (range: 51−61%) if we assume short-haul rather than long-haul trucks. Routes <322 km carry 19% of total truck tonne-km. For ship routes through the Panama Canal, the focus here on impacts in the U.S. (e.g., use of U.S. Census data and the U.S.-based ISRM grid) results in non-U.S. impacts being excluded (Figure S23). Sensitivity analyses suggest that the non-U.S. portion (i.e., the 5642 km that Panama-bound ships spend outside the ISRM domain; see Figure S23) may account for 42−78% of the total impacts for those Panama journeys depending on the route (Table S10).

Future research could usefully explore the impact on results of (1) alternative models and modeling approaches, (2) grid cell size,[84,85] (3) alternative concentration−response functions (e.g., a supralinear C−R) or allowing the C−R to vary by source, geography, or chemical components,[86−89] (4) health impacts of tropospheric (i.e., ground level) ozone formation from $NO_x$ and VOC emissions from transportation modes,[19,90] (5) improved modeling of routes between origin and destination using additional parameters such as travel time, congestion, and road conditions, and (6) emission factors that are characterized by route conditions and include non-tailpipe emissions, e.g., tire emissions from wear and tear on road.[91] Health impacts of ozone from transportation emissions have been previously modeled for the years 2005, 2011, and 2018 and are estimated to be much smaller than $PM_{2.5}$-related impacts.[19] However, recent evidence also suggest that ozone and $NO_2$-related mortalities might be seriously underestimated.[90] This study employs the mortality hazard ratio of 1.078 for all-cause mortality from the American Cancer Society (ACS) re-analysis study[74] to estimate premature deaths using a linear C−R function with no threshold. Alternative mortality hazard ratios exist, such as Lepeule et al. (i.e., reanalysis of the Harvard Six Cities (H6C) study) [1.14, 95% CI = 1.07−1.22],[92] Vodonos et al. [1.129, 95% CI = 1.109−1.150],[93] and Pope et al. [1.12, 95% CI = 1.08−1.15],[94] indicating that mortality impacts estimated in this work may be underestimated. Changing the C−R could modify the calculated health impacts (the absolute results) without changing the comparisons across modes (relative results). Evaluation of InMAP compared to other models such as EASIUR, AP3, COBRA, and WRF-Chem is presented elsewhere.[18,70,95]

Available projections from the U.S. Department of Transportation[1] and the U.S. Energy Information Agency[31] predict freight-shipment increases in coming decades, especially for aircraft. Emission reductions would be needed if total emissions from freight transport are to stay constant or not increase. With regulatory efforts, railroad emissions may come down in the future.[96] As shown here, increases in aircraft-based transport will have especially large environmental impacts, relative to the three other modes. Future work on this topic could usefully explore impacts from within-region freight transport; impacts from vehicle electrification (especially for trains and trucks, particularly the urban portion); and approaches for accounting for environmental disparities in risk, in decision-making.

## ■ ASSOCIATED CONTENT

### Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c03646.

Tables, figures, and maps cited in the manuscript and additional details on methods and results (PDF)

Full InMAP source−receptor matrix (ISRM) summary results for each mode by population age group, race−ethnicity, and $PM_{2.5}$ precursor type (XLSX)

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### Notes

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