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The state of modelling for evaluating health equity impacts of freight emissions

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ABSTRACT

Evaluating health equity impacts of freight emissions is crucial for developing a sustainable and just freight system. It is a complex process that requires interdisciplinary knowledge, including transportation, environment, and public health. Full-chain simulation is an important approach for forecasting freight planning outcomes. However, a systematic framework that integrates available models in full-chain and is specifically designed for the freight sector has not been developed. We review 36 empirical studies covering this interdisciplinary topic, and summarise the commonly used models. We find that EMission FACtor (EMFAC) and Motor Vehicle Emission Simulator (MOVES) models are commonly used to estimate freight vehicle emissions, with their outputs serving as inputs for air quality models, such as Community Multiscale Air Quality Model (CMAQ) or Intervention model for air pollution (InMAP). To estimate the health effects, concentration-response (C-R) functions, combined with static or dynamic demographic and socioeconomic data, are used to quantify the relationship between changes in pollutant concentrations and health outcomes. Then, disparity analysis relies on the assumption of age-specific C-R functions and examines statistical differences between demographic groups – including racial/ethnic groups, income levels, age groups, and other vulnerable communities. This study comprehensively outlines this state-of-the-art, integrated framework identified through the synthesis of this interdisciplinary literature. This framework can support future researchers in this field and policymakers.

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Health; equity; freight; emissions; simulation; air quality

1. Introduction

Diesel heavy-duty trucks and drayage trucks emit significant amounts of nitrogen oxides (NO_x), particulate matter (PM), and black carbon (BC), posing serious risks to respiratory and circulatory health (Koolik et al., 2024; Slaughter et al., 2005; Thind et al., 2022). Despite heavy-duty vehicles representing about 10% of total traffic volume, they contribute over 50% of tailpipe NO_x emissions in the US (Badshah et al., 2019). Additionally,

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environmental justice (EJ) research underscores that the disproportionate placement of warehousing facilities in neighbourhoods with high percentages of socially disadvantaged populations forces these communities to bear a greater burden of air pollution from diesel freight vehicles (Minet et al., 2020; Yuan, 2018). This disparity is particularly evident in California, where, despite overall reductions in air pollution, exposure inequalities persist, especially in areas with high levels of heavy-duty truck traffic (Koolik et al., 2024). Given freight's contribution to traffic-related air pollution and its different operating characteristics compared to passenger transport, freight emissions deserve special attention. Therefore, it is crucial for methods that evaluate the health effects of freight emissions to also examine how these impacts compare across populations and geographies.

Empirical field studies are one approach, and essential to evaluating these impacts. However, a simulation approach is a complementary alternative, allowing for the exploration of unobserved scenarios. Simulation approaches also serve as valuable tools to forecast freight planning outcomes (Tavasszy et al., 2012; Tavasszy & de Bok, 2023). Although previous literature reviews have summarised related models involving freight demand modelling (Tavasszy et al., 2012; Tavasszy & de Bok, 2023; Zhou & Dai, 2012), vehicle emission estimation (Mądziel, 2023), air quality modelling (Gilmore et al., 2019; Khan & Hassan, 2020), and exposure and health effect estimation (HEI, 2022; Mueller et al., 2015; Ramani et al., 2019; Vallamsundar et al., 2016), few studies have reviewed simulation approaches across the full chain to assess the health equity impacts of freight emissions. Moreover, while some studies have integrated the key analytical stages for such evaluation (Bickel et al., 2006; Lefebvre et al., 2013), a systematic framework that integrates available models and is specifically designed for the freight sector has not yet been developed.

This paper outlines the analytical stages in evaluating the health equity impacts of freight emissions. By reviewing the current state of research in this field, it provides a comprehensive summary of the methods and tools commonly used at each stage and presents a framework specific to freight emissions. We will achieve the following goals:

(1) define the essential contributors to health equity impacts of freight, providing a foundation for understanding the factors involved;
(2) outline the key analytical stages to evaluate the health equity impacts of freight emissions, and overview the commonly used models in each stage;
(3) summarise specific methods and data required of each stage within a framework for effectively evaluating the health equity impacts of freight emissions.

The paper is structured as follows: Section 2 describes the analytical stages of evaluating health equity impacts of freight emissions. Section 3 outlines the methodology. Section 4 presents results of previous research, and summarises their methods. Finally, Section 5 discusses the integrated framework, and the implication and application of this research. Section 6 concludes the contributions and limitations of this study.

2. Stages of evaluating health equity impacts of freight emissions

Health equity is broadly defined as the principle that everyone has a fair opportunity to reach their full health potential, without distinction based on race, ethnicity, socioeconomic background, physical or mental abilities, gender, income, or other social factors (Rojas-Rueda et al., 2024). Transportation systems can produce harmful externalities, such as air pollution, noise pollution, and traffic injury, as well as co-benefits, such as physical activity in transportation (Cole et al., 2019). This study, however, narrows its focus to the health equity impacts of freight emissions.

Evaluating the health equity impacts of freight emissions is a complex process, involving multiple stages. Based on recent review studies related to health and health equity impacts of freight and general transport (Bickel et al., 2006; Glazener et al., 2021; Patton et al., 2024; Ramani et al., 2019; Vallamsundar et al., 2016), this evaluation process can be divided into four analytical stages (see Figure 1). However, the models and tools available at each stage are not yet unified.

The first stage is freight demand modelling, involving freight trip generation and traffic assignment. It aims at simulating the activities of freight vehicles on the road network (Tavasszy et al., 2012), which helps identify the location and intensity of freight emissions.

The second stage, emissions and air quality modelling, aims at assessing the air pollution resulting from freight emissions. It comprises two interconnected steps: emission estimation and air pollution concentration estimation. Emissions models estimate air pollutants emitted by freight vehicles based on their activity (McNeil et al., 2023; Park, 2022; Xiao et al., 2024; Zhang et al., 2019). Air quality modelling simulates the dispersion and chemical transformation of the pollutants in the atmosphere to predict concentrations considering the influence of the built environment and atmospheric conditions on pollutant behaviour (Khan & Hassan, 2020; Matthias et al., 2018).

The third stage is health effect estimation, which assesses how these air pollution concentrations translate to population exposure and subsequent health outcomes (e.g. disease cases and mortality). This stage quantifies population exposure by integrating air pollution data with population distribution data. Epidemiological effect estimates are used to estimate the health risks associated with these air pollution exposures (Brusselaers et al., 2023a; Mommens et al., 2019; Torbatian et al., 2024).

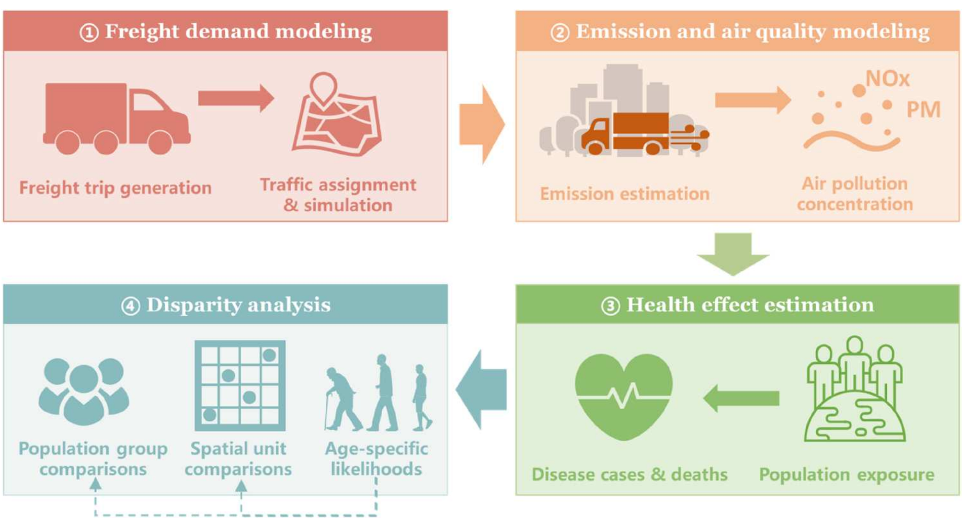

Figure 1. Analytical stages of evaluating health equity impacts of freight emissions.

Vulnerable groups, such as the elderly and children, face higher health risks due to factors like chronic lung, asthma, heart conditions in older adults, and the greater air intake per pound of body weight in children and infants compared to adults (Brusselaers et al., 2023a; Slaughter et al., 2005). Additionally, areas near freight facilities and corridors experience higher exposure to freight emissions compared to other communities (Ramirez-Ibarra & Saphores, 2023; Wen et al., 2024), making residents at higher health risk. Therefore, the fourth stage considers the age-specific mortality and morbidity likelihood, and analyses the health disparity across different population groups and spatial units (Lathwal et al., 2022; Thind et al., 2022; Torbatian et al., 2024).

3. Methodology

The literature on the health equity impacts of freight emissions uses varying terminology to describe these impacts. To ensure a thorough review, this study adopts a broad search strategy using key terms frequently utilised in the field, including “health equity”, “health disparity”, “health effect”, “air quality impact”, “environmental impact”, “exposure assessment”, and “environmental justice”. These terms are combined with “truck emissions” to guide the literature search.

To ensure all relevant studies were identified, we conducted systematic searches across leading scientific databases, including Google Scholar, Elsevier Scopus, and Web of Science. After removing literature that did not refer to at least one key term, we included 85 studies in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) workflow (see Figure 2). Following the removal of duplicate records, 84 studies proceeded to title, abstract, and full-text screening. During the title and abstract screening, we exclude studies that did not involve freight or not assessing health and equity impacts of freight emissions, eliminating 31 articles. During the full-text screening, studies were excluded if: (1) the health and equity impacts were not directly linked to freight vehicle emissions (n = 3); (2) the analysis was purely theoretical or literature-based, lacking a modelling approach (n = 5); or (3) disparity analysis used the field observed data, and does not involve simulation approaches (n = 9). Ultimately, we include 36 articles for analysis.

While some studies cover only partial stages of the full process, such as from freight demand modelling or air quality modelling to health effect estimation, they also provide the references to the full modelling process. Therefore, we categorised the selected studies according to their analytical stage (see Table 1).

4. Results

4.1. Assessing contributors to health equity impacts of freight emissions

To explore how freight contributes to health equity impacts, we focus on the following aspects: (1) specific air pollutants, (2) the health endpoints (e.g. mortality, cardiovascular and respiratory disease), and (3) disparities in population groups and spatial units.

4.1.1 Air pollutants

$PM_{2.5}$ is the most widely studied pollutant for health effects from transportation sources (n = 26) due to its severe health risks. Hennessy et al. (2024a) found that the $PM_{2.5}$ from diesel truck fleet contributed to 1,484-3,336 premature deaths annually in the United

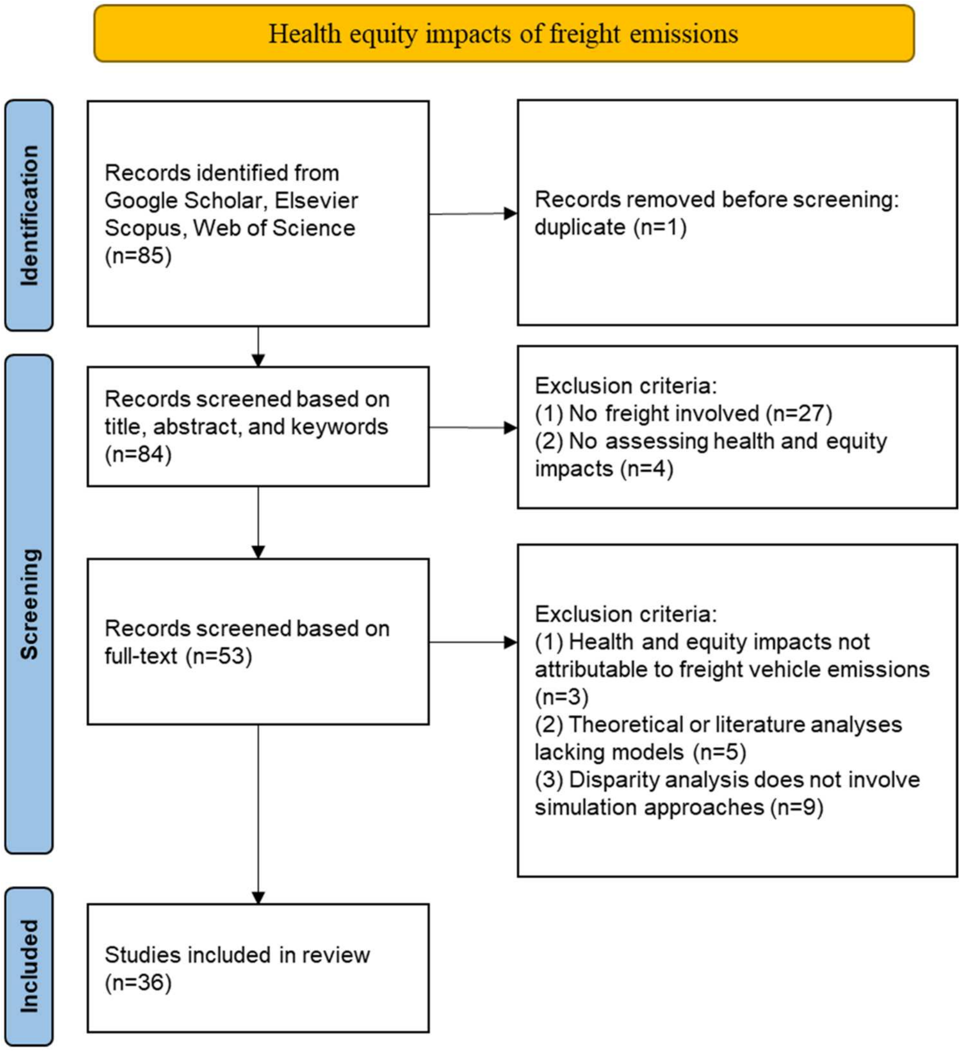

Figure 2. PRISMA workflow for reviewing freight health equity literature.

States. Ramirez-Ibarra and Saphores (2023) found that regulations and technological advancements could prevent 377 premature deaths and 13,326 asthma attacks annually from $PM_{2.5}$ of drayage trucks operating at the Ports of Los Angeles and Long Beach in Southern California.

NO_x is the second most studied air pollutant (n = 17), and other air pollutants, such as SO_x, O_3, VOCs, and NH_3 have also been studied (n = 10). Mommens et al. (2019) estimated a total of €51.692 is generated on a daily basis for PM and NOx emissions from freight transport in the Brussels Metropolitan Region. Similarly, Brusselaers et al. (2023a) found that vulnerable populations in the Brussels-Capital Region face daily health costs of €37,000 due to PM and NOx emissions from freight vehicles. Liu et al. (2019) found that in 2010, emissions from urban short-haul trucks in the United States resulted in the following mortality per kiloton: 1.9 from VOCs, 28 from NH_3, and 3.7 from SO_x. The health

Table 1. Classification of selected studies ($N = 36$).

Studies included	Study count	Analytical stages involved
Hartle et al. (2022)	1	Freight demand modelling Air quality modelling
Lee et al. (2012); Lee et al. (2009); Liu et al. (2019); Mommens et al. (2019)	4	Freight demand modelling Air quality modelling Health effect estimation
Sahin et al. (2023); Zalzal and Hatzopoulou (2022)	2	Freight demand modelling Air quality modelling Disparity analysis
Brusselaers et al. (2023a, 2023b); Ramirez-Ibarra and Saphores (2023); Torbatian et al. (2024)	4	Freight demand modelling Air quality modelling Health effect estimation Disparity analysis
Bickford et al. (2014); Dong et al. (2018); Hu et al. (2022); Kijewska et al. (2016); Malik et al. (2019); Oranges Cezarino et al. (2021); Seo et al. (2013)	7	Air quality modelling
Luo et al. (2022); Mac Kinnon et al. (2021); McNeil et al. (2023); Minet et al. (2020); Moretti et al. (2021); Pan et al. (2019); Ross et al. (2015); Tong et al. (2021)	8	Air quality modelling Health effect estimation
Ma et al. (2023); Wen et al. (2024); Xiao et al. (2024)	4	Air quality modelling Disparity analysis
Camilleri et al. (2023); Hennessy et al. (2024a); Hennessy et al. (2024b); Lathwal et al. (2022); Park (2022); Tessum et al. (2019); Thind et al. (2022)	7	Air quality modelling Health effect estimation Disparity analysis

impacts of these three air pollutants are primarily attributable to exposure to secondary $PM_{2.5}$ formed through atmospheric chemical reactions involving these precursors, rather than direct exposure to the gaseous pollutants themselves.

4.1.2 Health endpoints

Research on the health effect and health equity impact of freight emissions highlight the significant role of air pollutants in contributing to morbidity and mortality. Several studies ($n = 15$) identified premature deaths as a major health endpoint linked to freight-related air pollution. Ramirez-Ibarra and Saphores (2023) found that air pollution from diesel heavy-duty drayage trucks serving the Ports of Los Angeles and Long Beach in Southern California is associated with 483 premature deaths in 2012.

Four studies considered the association between freight vehicle emissions and respiratory diseases, such as asthma and chronic bronchitis (Brusselaers et al., 2023a; Lee et al., 2009; Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024). For example, Torbatian et al. (2024) pointed out that under the heavy-duty truck electrification scenario, annual cases of adult chronic bronchitis decrease by over 200, while respiratory-related emergency room visits decline by nearly 45 cases in Greater Toronto and Hamilton Area.

Moreover, four studies have considered the impact of freight vehicle emissions on cardiovascular conditions, such as heart rhythm disturbances and ischaemic heart disease (Brusselaers et al., 2023a; Mommens et al., 2019; Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024). Ramirez-Ibarra and Saphores (2023) found that heavy-duty drayage trucks in Southern California were linked to 139 cardiovascular cases in 2012. Brusselaers et al. (2023a) showed that electrifying heavy-duty trucks leads to the largest estimated reduction in cardiovascular-related cases, including emergency room visits and hospital admissions, compared to medium-duty and light-duty trucks in Brussels-Capital Region.

4.1.3 Disparities in population groups and spatial units

Previous studies related to health equity impact of freight also focused on the health disparity across racial groups (Hennessy et al., 2024a; Lathwal et al., 2022; Tessum et al., 2019; Thind et al., 2022), income level (Hennessy et al., 2024a), age groups (Brusselaers et al., 2023a; Ross et al., 2015), and communities (Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024), highlighting health disparities within different population groups and spatial units.

Seven studies focused on the disparities across racial groups (Camilleri et al., 2023; Hennessy et al., 2024a; Hennessy et al., 2024b; Lathwal et al., 2022; Ross et al., 2015; Tessum et al., 2019; Thind et al., 2022). They commonly confirmed that Black and Hispanic/Latino populations bear a disproportionate burden of air pollution from freight emissions, with evidence from case studies in Chicago, Georgia, California, and nationwide analyses across the U.S.

Health disparities also vary by income levels and age groups. Low-income populations generally face higher health risks from freight-related air pollution compared to their high-income counterparts (Hennessy et al., 2024a; Park, 2022). Brusselaers et al. (2023a) found that vulnerable population groups, including toddlers (aged 0-3), school children (aged 3-18), and elderly individuals (aged 65+) bear €34,517.47 to €40,047.13 in daily health costs, accounting for 60% of the total costs, despite representing only 25.34% of the total population of Brussels Capital Region.

Areas near freight facilities and corridors often bear a disproportionate share of the environmental harms caused by freight activities, worsening social health inequities (Torbatian et al., 2024; Wen et al., 2024). Studies on the health equity of freight also investigate health disparities at various spatial units, such as community level (Ma et al., 2023; Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024; Wen et al., 2024). In some disadvantaged communities, a higher number of annual asthma exacerbation cases and premature deaths have been linked to emissions from heavy-duty diesel trucks (Ramirez-Ibarra & Saphores, 2023; Wen et al., 2024).

4.2. Freight demand modelling

Freight vehicle traffic flow is a critical input for estimating freight vehicle emissions. Several studies have utilised the Freight Analysis Framework and California Air Resources Board's EMissions FACtor (EMFAC) fleet database to directly capture the truck traffic flows on road networks (Bickford et al., 2014; Hennessy et al., 2024a; Hennessy et al., 2024b; Lathwal et al., 2022; McNeil et al., 2023; Ross et al., 2015; Thind et al., 2022; Tong et al., 2021; Wen et al., 2024). In addition, some studies (n = 5) used observed monitoring data (e.g. GPS data, vehicle telematics, and entry point monitoring) to estimate the freight traffic flow within specific study areas (Brusselaers et al., 2023b; Dong et al., 2018; Hu et al., 2022; Oranges Cezarino et al., 2021; Pan et al., 2019). However, these studies often lack the incorporation of freight vehicle traffic simulations. Hence, we emphasise those studies employing simulation approaches to estimate the freight traffic flow (see Table 2).

4.2.1 Freight trip generation

According to Zhou and Dai (2012), freight demand models can be classified as five groups: (i) Growth-factor and Origin/Destination (O/D) synthesis, (ii) Commodity-based, (iii) Trip or vehicle-based, (iv) Tour-based, and (v) Logistics or supply-chain. In the studies of health equity impacts of freight emissions, trip-based models and commodity-based models are broadly applied to generate freight demand. Trip-based models typically use zonal economic and land use attributes to directly estimate the total freight trips. In contrast, commodity-based models concentrate on freight flows or commodity movements between traffic analysis units.

Trip-based models are commonly used to generate freight trips (n = 6). Key variables such as establishment counts, employment, and special generators were incorporated to directly predict zonal 24-hour trip generation for light, medium, and heavy trucks. For example, Hartle et al. (2022) used land use data and establishments data to estimate the number of freight trip attraction (FTA) and freight trip production (FTP) for each establishment category in polygon, and then convert business FTA and FTP to the number of different types of trucks. Alternatively, Ramirez-Ibarra and Saphores (2023), Sahin et al. (2023), Lee et al. (2012), and Lee et al. (2009) did not employ specific methods to estimate freight trip generation. Instead, they extracted freight O/D pairs from broader regional traffic trip simulations, such as the Southern California Association of Governments regional trip-based model and the Atlanta Regional Commission's Activity-Based Model.

Three studies used commodity-based models to estimate the freight demand for various commodity types, which were then combined with vehicle fleet data to estimate the corresponding freight trips (Brusselaers et al., 2023a, 2023b; Liu et al., 2019; Mommens et al., 2019). For example, Liu et al. (2019) estimated the commodity shipment demand and combined it with the vehicle fleet composition to estimate the freight trips in long-haul and short-haul scenarios. Mommens et al. (2019) employed socio-economic data, including employment, ground surface, and population density, to generate shipments of specific commodity and cargo type. Freight demand was then used as input data for the Transport Agent-Based Model (TABM) to simulate individual vehicle activity.

4.2.2 Traffic assignment and simulation

Traffic assignment methods are used to estimate traffic flow based on O-D trip data. They include static and dynamic traffic assignment methods, which differ in loading traffic flows on road networks, either with or without considering time variations (Saw et al., 2015). In contrast, route-based models calculate possible routes within the network and directly distribute traffic flows along possible routes (Han, 2007). Agent-based models estimate commercial vehicle traffic flow by simulating individual vehicle activities. These models offer higher spatial and temporal resolution than traditional assignment and route-based models, enabling more detailed information of vehicles. Using these categories, we summarise the methods widely used to estimate freight vehicle traffic flows in empirical studies.

Traditional traffic assignment methods rely on freight trip generation and trip distribution to allocate freight traffic flow across road networks, either statically or dynamically (Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024). Torbatian et al. (2024) employed linear regression for freight trip generation, a standard doubly constrained gravity model for trip distribution, and a static multiclass user equilibrium assignment approach to allocate freight traffic flow at the hourly link level. In contrast, Ramirez-Ibarra and Saphores (2023) used dynamic traffic assignment (DTA) for traffic allocation at the link level.

Table 2. Examples of studies estimating freight traffic flow.

Source	Freight segment	Freight trip generation	Traffic assignment and simulation	Output spatial-temporal resolution
Torbatian et al. (2024)	Light-, medium-, and heavy-duty trucks	Trip-based model	• Static Traffic Assignment Method • Multiclass user equilibrium assignment	• Spatial: link level • Temporal: hourly
Ramirez-Ibarra and Saphores (2023)	Heavy-duty drayage trucks	Trip-based model	• Dynamic Traffic Assignment Method • Use TransModeler to simulate network traffic flow	• Spatial: vehicle-specific level • Temporal: second-by second
Sahin et al. (2023)	Light-duty, medium-duty, heavy-duty vehicles	Trip-based model	• Transport Agent-Based Model • Use Polaris to simulate vehicle trajectories	• Spatial: vehicle-specific level • Temporal: 6 s
Hartle et al. (2022)	Last mile delivery	Trip-based model	• Route-based approach • Use QGIS to calculate travel distance based on shortest path	• Spatial: link level • Temporal: daily
Brusselaers et al. (2023a, 2023b)	Light-duty vehicles, rigid trucks, and truck-trailer combinations	Commodity-based model	• Transport Agent-Based Model • Use MATSim to simulate vehicle activity	• Spatial: vehicle-specific level • Temporal: 15 min
Mommens et al. (2019)	Vans, light-duty, and heavy-duty vehicles	Commodity-based model	• Transport Agent-Based Model • Use MATSim to simulate vehicles activity	• Spatial: vehicle-specific level • Temporal: 30 min
Liu et al. (2019)	Long-haul and short-haul trucks	Commodity-based model	• Route-based approach • Asymptotic vehicle routing model	• Spatial: link level • Temporal: yearly
Lee et al. (2012, 2009)	Medium-duty trucks and heavy-duty trucks	Trip-based model	• Dynamic Traffic Assignment Method • Use TransModeler to simulate network traffic flow	• Spatial: vehicle-specific level • Temporal: second-by-second
Zalzal and Hatzopoulou (2022)	Light-duty vehicle and trucks	/	• Use Gradient Boost Models (XGBoost models) to predict the truck counts and traffic conditions	• Spatial: link level • Temporal: yearly

The route-based methods use routing algorithms (e.g. shortest-path algorithms and asymptotic vehicle routing models) to allocate traffic flow to possible routes. Hartle et al. (2022) assumed that truck drivers follow the shortest path and allocate truck flow across the road network. Liu et al. (2019) applied an asymptotic vehicle routing model to distribute shipment flows, and then subsequently incorporate vehicle fleet composition to estimate freight traffic flows at the link level.

Compared to traditional traffic assignment methods and route-based methods, agent-based traffic models offer higher spatial and temporal output resolution. These models focus on individual vehicles, simulating their trajectories at minute or even second-level intervals (Brusselaers et al., 2023a; Mommens et al., 2019). Brusselaers et al. (2023a) used the MATSim tool to simulate the individual freight vehicles entering or leaving network links, and aggregated to 15-minute time intervals for computational purposes. Mommens et al. (2019) similarly simulated the freight vehicle movements between 4,933 TAZs in the Belgian territory, and then counted the traffic flow at 30-minute intervals. In addition, TransModeler simulation tool can perform the DTA and generate the vehicle trajectories second-by-second, providing an integrated approach for traffic assignment and simulation (Lee et al., 2009; Lee et al., 2012; Ramirez-Ibarra & Saphores, 2023).

4.3. Emission and air quality modelling

Based on the output from freight demand modelling, including traffic condition and traffic volumes, emission models are used to estimate freight vehicle emissions. Air dispersion processes determine how pollutants spread, dilute, and transform in the atmosphere, influencing their spatial and temporal distribution. These air dispersion processes are important to capture to estimate how vehicle emissions translate to air pollution concentrations. In this section, we illustrate the parameters of the models and tools commonly used to estimate emissions and air pollution concentrations.

4.3.1 Emissions estimation

Given the input size of emission models, emission models are commonly classified into two categories: macroscopic models and microscopic models (Zhang et al., 2022). The summary of emission models used in previous studies is presented in Table 3. Macroscopic models, such as HBEFA, GREET, MOBILE, and COPERT are typically designed to estimate the amount of emissions over a broader spatial and temporal scale, such as an entire city, region, or road network for a given year. They usually rely on average travel speed to estimate the emission factors (in the unit of grams per mile), overlooking different driving behaviours in the same average travel speed (Mądziel, 2023). In contrast, microscopic models, such as CMEM, focus on specific driving conditions. These models incorporate parameters like instantaneous speed and acceleration to estimate real-time pollutant emission rates (grams per second), which are then converted to emission factors in grams per mile (Mądziel, 2023) (Camilleri et al., 2023; Pan et al., 2019; Zalzal & Hatzopoulou, 2022). In addition, some emission models, such as EMFAC and MOVES, integrate multiple spatial scales, allowing applications from vehicle level to regional level. They can be applied under macroscopic settings by using average travel speeds, or under microscopic settings when detailed traffic conditions and data are available.

Among these emission models, EMFAC and MOVES are widely used in studies related to health equity impact of freight. EMFAC is the recommended model for use in California, while MOVES is designated for a broader range of locations across the United States, including District of Columbia, Puerto Rico, and the U.S. Virgin Islands. Seven studies utilise the EMFAC model to estimate the emission factors of heavy-duty vehicles. In these studies, link-based traffic activities (e.g. average traffic speed), vehicle characteristics (e.g. vehicle type and model year), and fuel type are the important inputs to determine exhaust emissions factors.

The MOVES model is also widely used (n = 7). This model is effective to provide detailed emission estimates when integrated with second-by-second vehicle speed and acceleration data from microscopic traffic simulations. Lee et al. (2012) and Ramirez-Ibarra and Saphores (2023) employed the TransModeler tool to generate these parameters as

Table 3. Summary of emission models used in previous research.

Model scale	Emission model	Main input parameters	Sources
Macroscopic	Handbook of Emission Factors for Road Transport (HBEFA)	• Vehicle type, fuel type, model year	Brusselaers et al. (2023a, 2023b); Kijewska et al. (2016); Mommens et al. (2019)
	Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET)	• Vehicle type, engine type; Technology level, fuel economy • Temperature, humidity	Lathwal et al. (2022); McNeil et al. (2023); Sahin et al. (2023); Thind et al. (2022); Tong et al. (2021)
	Mobile Source Emission Factor Model (MOBILE)	• Vehicle type, fuel type, model year • Average speed, driving cycle, months and times of day • Temperature, humidity	Bickford et al. (2014)
	Computer Programme to Calculate Emissions from Road Transport (COPERT)	• Vehicle type, fuel type, load, emission standard • Average speed, road type, peak or off-peak travel	Dong et al. (2018); Hu et al. (2022)
	US National Emissions Inventory (NEI)	• Vehicle type, furl type, model year, spatial scale (national/state, county or tribe)	Ross et al. (2015); Tessum et al. (2019)
Microscopic	Comprehensive Modal Emissions Model (CMEM)	• Vehicle type and age, load, fuel type, engine technology, model year • Average speed, driving cycle • Temperature, humidity, ambient pressure, wind velocity and direction	Lee et al. (2009)
Multi-scale (macroscopic and microscopic)	EMission FACtor (EMFAC)	• Vehicle type and age, load, fuel type, model year • Operating mode, average speed, road type • Season or month, temperature, humidity	Hartle et al. (2022); Hennessy et al. (2024a); Hennessy et al. (2024b); Lee et al. (2009); Luo et al. (2022); Moretti et al. (2021); Wen et al. (2024)
	Motor Vehicle Emission Simulator (MOVES)	• Vehicle type and age, fuel type, model year • Average speed, road type, driving cycle, month and times of day • Temperature, humidity	Camilleri et al. (2023); Lee et al. (2012); Pan et al. (2019); Park (2022); Ramirez-Ibarra and Saphores (2023); Torbatian et al. (2024); Zalzal and Hatzopoulou (2022)

input into the MOVES model, enabling a detailed estimation of truck emissions at the microscopic level. In contrast, Camilleri et al. (2023), Torbatian et al. (2024) and Zalzal and Hatzopoulou (2022) utilised the model's default driving cycles to estimate average emission factors for average speeds in specific road types. Additionally, the MOVES model can estimate idling emission factors in grams per hour (g/hr). Park (2022) used MOVES to assess idling emissions from port drayage trucks at the Port of New York and New Jersey, reporting NO_x and $PM_{2.5}$ emission factors of 52.9 and 4.281 g/hr, respectively.

4.3.2 Air pollution concentration estimation

A wide variety of approaches and models are used to estimate the air pollution concentrations. Among them, land use regression (LUR) models rely on statistical relationships between observed concentrations and spatial characteristics to estimate the concentrations (Beelen et al., 2013). However, they require large amounts of data to develop robust results and cannot capture the underlying physical and chemical processes. As a result, most studies still prefer dispersion models for estimating air pollution concentrations. Table 4 shows the air dispersion models commonly used in previous research. They fall into three categories: Gaussian models (e.g. R-LINE, C-LINE, CALPUFF, and the Gaussian Plume Model), chemical transport models (e.g. CMAQ, CAMx, and Polair3D), and reduced-complexity models (e.g. InMAP, EASIUR, and APEEP).

Gaussian models simulate physical dispersion processes and are broadly classified into steady-state and puff models. Steady-state models (e.g. R-LINE, C-LINE, and Gaussian Plume) assume continuous emissions and fixed meteorological conditions, making them computationally efficient and suitable for long-term average concentration estimates. Among them, Gaussian Plume models and R-LINE are mostly used. Gaussian Plume models are based on classic Gaussian theory, which assumes that pollution dispersion follows a Gaussian distribution. These models require relatively simple meteorological inputs, such as wind speed and direction. R-LINE focuses on road-based line source emissions modelling, and requires detailed meteorological conditions (e.g. temperature, wind speed, wind direction, surface friction velocity) and road geometry. It provides pollutant concentration estimates at specific sensitive receptor locations. The C-LINE model is

Table 4. Summary of dispersion models used in previous research.

Type of model	Emission model	Input parameters	Sources
Gaussian models	R-LINE	Traffic emissions, meteorology, road geometry	Luo et al. (2022); Ma et al. (2023); Moretti et al. (2021); Wen et al. (2024)
	C-LINE	Traffic composition and volume, meteorology	Ross et al. (2015)
	California Puff Model (CALPUFF)	Traffic emissions, terrain coastal interactions, building downwash, and land use	Lee et al. (2012); Lee et al. (2009)
	Gaussian Plume Model	Traffic emissions, wind speed, wind direction, stability class	Brusselaers et al. (2023a, 2023b); Kijewska et al. (2016); Mommens et al. (2019); Xiao et al. (2024)
Chemical Transportation models	Community Multiscale Air Quality Model (CMAQ)	Traffic emissions, Emissions inventory, meteorology, land use, initial and boundary condition	Bickford et al. (2014); Camilleri et al. (2023); Mac Kinnon et al. (2021); Pan et al. (2019)
	Polair3D	Traffic emissions, Emissions inventory, meteorology, land use, initial and boundary condition, other emission source	Minet et al. (2020); Torbatian et al. (2024)
Reduced-complexity models	Intervention model for air pollution (InMAP)	Primary pollutants (SO_2, NO_x, NH_3, VOC, $PM_{2.5}$), emission source location, emission rate, meteorology, emission source height	Hennessy et al. (2024a, 2024b); Liu et al. (2019); McNeil et al. (2023); Ramirez-Ibarra and Saphores (2023); Tessum et al. (2019); Thind et al. (2022)
	Estimating Air pollution Social Impact Using Regression (EASIUR)	Primary pollutants (SO_2, NO_x, NH_3, $PM_{2.5}$), emission source location, emission rate, meteorology, emission source height	Lathwal et al. (2022); Tong et al. (2021)

similar to the R-LINE model in terms of input variables but is intended for broader geographic areas, such as grids. In contrast, puff models (e.g. CALPUFF) represent pollutants as discrete puffs, enabling simulation of dynamic meteorology and complex terrains, though they require more detailed inputs and computational resources. However, they are more suitable for short-term or episodic assessments across diverse spatial and temporal scales.

Chemical transport models (CTM) account for the spatial and temporal distribution of pollutants and incorporate processes such as diffusion, chemical transformation, sedimentation, and secondary pollutant formation (Matthias et al., 2018; Tessum et al., 2017). The CMAQ and Polair3D are the most commonly used models (n = 6). CMAQ supports simulations from local (city-level) to national and even continental scales, whereas Polair3D focuses on smaller domains, making it more suitable for city – and regional-scale air quality assessments.

Given the complexity of CTM, reduced-complexity models (RCMs), such as InMAP, EASIUR, and APEEP, are used to reduce computational demands and user effort while maintaining predictive accuracy (Tessum et al., 2017). InMAP is the most commonly used RCM in this sample (n = 7). It allows estimating average annual air pollutants concentrations at resolutions varying from 1 km x 1 km to 48 km x 48 km. EASIUR is limited to a coarser spatial resolution of 36 km x 36 km. Similarly, APEEP also operates at a county or state level, limiting its ability to capture fine-scale spatial variability.

Dispersion models require inputs such as traffic emissions, land use (e.g. land cover, surface roughness, heat exchange parameters), meteorological conditions (e.g. temperature, wind speed, wind direction, surface friction velocity), and other pollution sources. Land use data are often obtained from global databases, such as USGS Land Cover, GLC2000, and MODIS. Meteorological data come from observational networks (e.g. SCAQMD, National Oceanic and Atmospheric Administration) or numerical models such as WRF, and estimates of other pollution sources typically rely on emission inventories processed with tools like SMOKE.

4.4. Health effect estimation

Exposure to $PM_{2.5}$, NO_x, and O_3 are associated with increased mortality and morbidity from cardiovascular diseases, such as ischaemic heart disease, stroke, chronic obstructive pulmonary disease, and lung cancer (HEI, 2022; Patton et al., 2024). To estimate the health effects of freight emissions, previous studies (n = 16) commonly employed concentration–response (C-R) functions to quantify the relationship between changes in pollutant concentrations and corresponding health endpoints.

Three studies assume the relationships between air pollution and mortality and morbidity are standard linear (Mommens et al., 2019; Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024). For example, Mommens et al. (2019) showed that, in the Brussels Capital Region, the rates of hospital emergency visits for conditions such as pneumonia, chronic obstructive pulmonary disease, ischaemic heart disease, and heart rhythm disturbances increase within a range of 0.4% to 1.2%.

Thirteen studies assumed a nonlinear (i.e. log-linear) relationship between mortality incidence and air pollutant concentrations (Brusselaers et al., 2023a; Camilleri et al., 2023; Hennessy et al., 2024a; Hennessy et al., 2024b; Lee et al., 2012; Liu et al., 2019;

Mac Kinnon et al., 2021; McNeil et al., 2023; Minet et al., 2020; Pan et al., 2019; Tessum et al., 2019; Thind et al., 2022; Tong et al., 2021). The common log-linear C-R function used to estimate the relationship between changes in air quality and health endpoints is presented in Equation (1).

$$\Delta y = (1 - exp(-\beta \Delta x)) \cdot y_0 \cdot Pop \tag{1}$$

In this equation, Δy is the change in health outcome, y_0 is the baseline rate of the health outcome (i.e. the rate in the absence of increased air pollutant concentrations), β is the epidemiological hazard ratio associated with exposure to air pollution, Δx is the change in air pollutant concentrations (e.g. $PM_{2.5}$ concentrations), and *Pop* is the size of the total affected population. Camilleri et al. (2023) assumed hazard ratios of 1.04 per 10 µg/m^3 for annual mean NO_2, 1.03 per 5 µg/m^3 for annual mean $PM_{2.5}$.

Alternatively, Ross et al. (2015) used odds ratios to estimate the relative risks of diseases from freight exposures. Five studies employed approaches to indirectly assess the health effects of freight emissions without estimating mortality or morbidity. Four of these studies analyzed population spatial distribution to estimate exposure (Lee et al., 2009; Luo et al., 2022; Moretti et al., 2021; Park, 2022) while Lathwal et al. (2022) monetised health outcomes using marginal social cost assessments.

The spatial and temporal distribution of populations plays a critical role in health effect estimation. This involves static and dynamic approaches to estimate the exposure (Beckx et al., 2009; Bickel et al., 2006; Dons et al., 2011). Most studies (n = 33) rely on static approaches, which assume a fixed population distribution over time and space based on census or residential data. In contrast, dynamic approaches incorporate spatiotemporally varying population data, enabling a more accurate estimation of exposure peaks in specific time and areas. Mommens et al. (2019) considered population movements during four time intervals – 3:00–3:30 am, 10:00–10:30 am, 15:00–15:30, and 21:00–21:30 – to estimate health effects for these periods. Brusselaers et al. (2023a, b) incorporated dynamic exposure by linking freight transport emissions with the spatiotemporal presence of vulnerable populations – toddlers (8:00–18:00 at childcare centres), school children (8:30–16:00 at schools), and elderly individuals (>65 years).

4.5. Disparity analysis

4.5.1 Population group comparisons

Health disparities caused by freight emissions among various racial/ethnic groups have been analysed in previous studies (n = 7) (Camilleri et al., 2023; Hennessy et al., 2024a; Hennessy et al., 2024b; Lathwal et al., 2022; Ross et al., 2015; Tessum et al., 2019; Thind et al., 2022). These studies estimated the total number of deaths for each racial group within the study area and analysed health disparity by comparing total deaths across these groups or comparing to average mortality rates. For instance, Tessum et al. (2019) aggregated the total number of deaths for Black, Hispanic, and White/Other groups across all grids and compared the total deaths among these racial and ethnic groups in the United States. These studies often assume a uniform distribution of populations and mortality within each grid cell. A similar approach has been used to examine the health disparities across income levels groups (Hennessy et al., 2024a; Hennessy et al., 2024b).

Additionally, three studies indirectly highlighted health inequities among racial/ethnic groups by comparing the average levels of air pollution experienced by these populations (Lathwal et al., 2022; Ross et al., 2015; Wen et al., 2024). For instance, Wen et al. (2024) quantified racial and ethnic disparities in near-roadway $PM_{2.5}$ exposure in Los Angeles County using population-weighted average concentration values, as seen in Equation (2).

$$PWAC_i = \sum_j (P_{i,j}C_j) / \sum_j (P_{i,j}) \tag{2}$$

where $PWAC_i$ is the population-weighted average $PM_{2.5}$ concentration of racial/ethnic group i; $P_{i,j}$ is the population of racial/ethnic group i in census block j; C_j is $PM_{2.5}$ concentration in census block j.

The above-mentioned studies assume that air pollutant exposure poses the same health risks to everyone within the same grid cell. However, vulnerable populations, such as older adults, children, and infants, face higher health risks from PM exposure compared to the general adult population, contributing to health disparities across age groups (Slaughter et al., 2005). To address this, researchers use age-specific functions to link health risks with air pollution levels, allowing for the estimation and comparison of health outcomes across different age groups. For example, (2023a) reported that children (0–15 years) and older adults (76–90 years) had the highest risk of emergency hospitalisations for pneumonia, with a 1 μg/m^3 increase in NO_x concentration associated with log-linear exposure–response coefficients of 7.68×10^{-6} and 5.51×10^{-7}, respectively. In contrast, younger adults (16–45 years) experienced smaller log-linear exposure–response coefficients of 5.91×10^{-8} and 9.84×10^{-8}.

4.5.2 Spatial unit comparisons

Communities, typically represented by geographic units such as census tracts, are commonly used as spatial units for assessing health disparities across geographic regions. Three studies integrated air pollution burdens with population characteristics to identify communities who are comparatively disproportionately disadvantaged (Ramirez-Ibarra & Saphores, 2023; Torbatian et al., 2024; Wen et al., 2024). By comparing the health outcomes in disadvantaged communities to those in the broader study area, these studies analysed the health disparity in communities.

The CalEnviroScreen 4.0 screening tool for California is commonly used to identify disadvantaged communities (Ramirez-Ibarra & Saphores, 2023; Wen et al., 2024). This tool calculates a score by multiplying two indexes: one measures pollution burden from multiple sources, and the other reflects population sensitivity to pollution (Faust et al., 2021). The pollution index includes exposure (e.g. diesel PM, traffic) and environmental effects (e.g. toxic sites). The population index combines indicators of sensitive populations (e.g. elderly) and socioeconomic factors (e.g. poverty levels, housing burdened), capturing social vulnerability. Communities are classified as disadvantaged if their CalEnviroScreen score ranks in the top quartile. Ramirez-Ibarra and Saphores (2023) identified the census tract as a disadvantaged community if CalEnviroScreen score is in the upper quartile. Wen et al. (2024) provided a more detailed classification that includes moderately disadvantaged communities (50–100% disadvantaged) and most disadvantaged communities (75–100% disadvantaged).

5. Discussion

5.1. Key takeaways of integrated framework

Figure 3 summarises the widely used models and required data in an integrated framework. This framework illustrates how outputs from one stage are prepared and passed to the next, highlighting critical considerations for resolution alignment. The key takeaways, including strengths and limitations for each analytical phase are:

Freight demand modelling: In freight trip generation, trip-based models and commodity-based models are commonly used. Trip-based models directly estimate freight trips and easily integrate with traffic simulations. However, they often neglect variations in goods type, weight, and value, which reduce the estimation accuracy. In contrast, commodity-based models incorporate detailed characteristics of goods but typically require extensive and complex goods-related data.

Based on the freight trip generation models outcomes, traffic assignment and simulation are performed, using static and dynamic traffic assignment, route-based, or agent-based approaches to simulate traffic volumes or vehicle miles travelled (VMT) at the link level. Agent-based methods capture detailed individual vehicle data, including speed and location. But they require extensive computational resources and are complex for large-scale networks. In contrast, static and dynamic traffic assignment and route-based approaches require fewer computational resources but provide less detail and accuracy in representing individual travel behaviours.

The number of trip-generating establishments (e.g. warehouses, distribution centres, retail stores, and residences in the case of e-commerce) and their characteristics (e.g. employment and vehicle fleets) are key variables for estimating freight trips. Static and dynamic traffic assignment methods typically produce outputs such as traffic volumes, vehicle type distributions, and average travel speed at hourly or daily resolutions, which are generally compatible with the input requirements of macroscopic emission models. In contrast, agent-based methods generate high-resolution outputs, including individual vehicle trajectories with location, speed, and acceleration information by the second, which are inputs for microscopic emission models.

Emission and air quality modelling: In emission estimation, macroscopic models (e.g. HBEFA, GREET, MOBILE, COPERT), microscopic models (e.g. CMEM), and multi-scale models (e.g., EMFAC and MOVES) are frequently used to estimate freight emissions. Microscopic models consider detailed vehicle operating conditions (e.g. instantaneous speed, acceleration, idling) and have high estimation accuracy by capturing the operating patterns and emission rate of individual vehicles. As such, they are useful to evaluate specific traffic management measures like traffic restrictions or signal optimlisation, but they require detailed vehicle trajectory data. In contrast, macroscopic models use average traffic conditions on the road network without specific individual vehicle information, making them efficient for estimating freight emissions across regions (e.g. cities, counties, states) and evaluating policies with minimal impacts on traffic conditions, such as changes in fuel type.

To prepare emissions data for air pollution estimation, macroscopic or microscopic emission models are used to derive stratified emission factors for various vehicle types and speeds. These factors, together with VMT, traffic volumes, and link-level speed

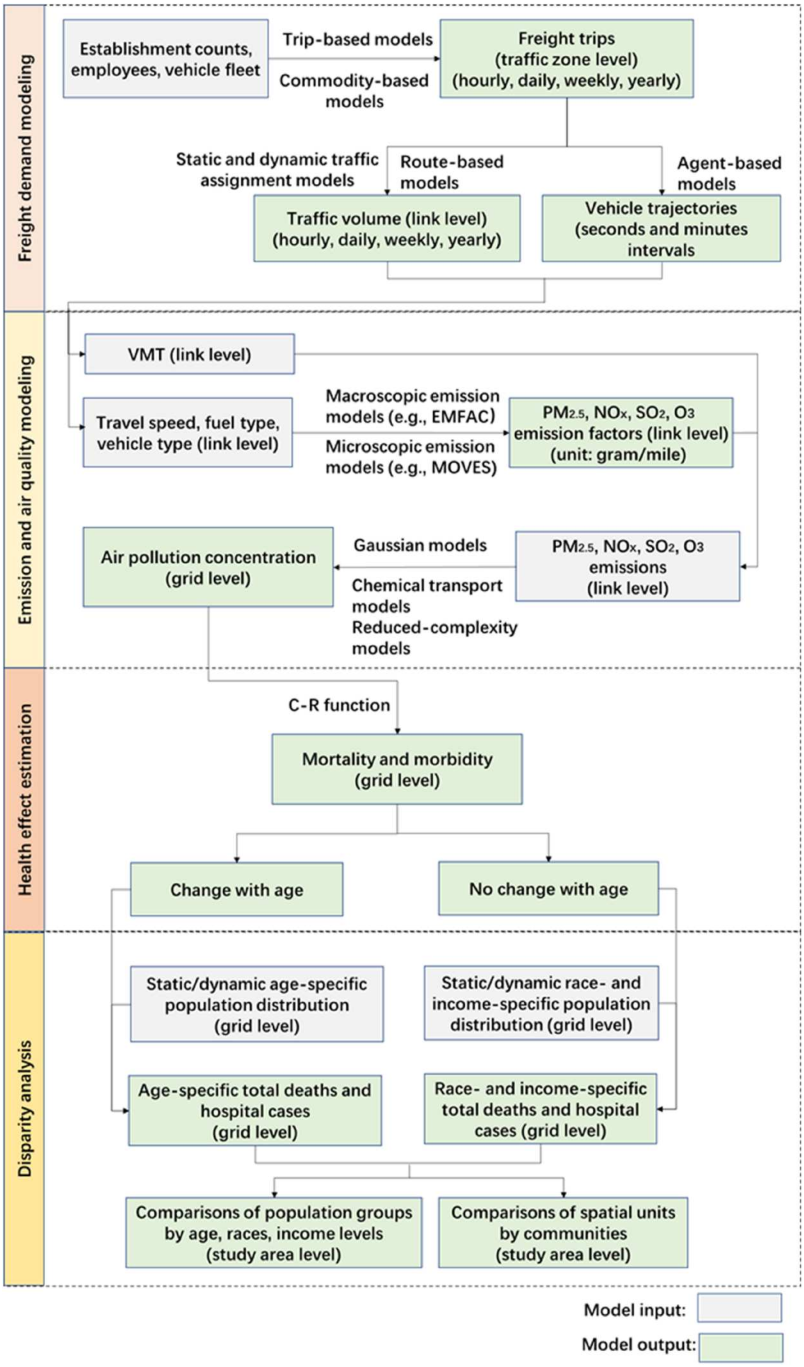

Figure 3. Integrated framework for evaluating health equity impacts of freight emissions.

data, are used to estimate total freight emissions for each road segment. The temporal resolution of these emissions depends on the resolution of the VMT and traffic volume data, which may be hourly, daily, monthly, or yearly. For example, air dispersion models require hourly inputs (e.g. Gaussian models and CMAQ) so total hourly emissions are aggregated. In contrast, for models operating at an annual scale (e.g. InMAP), total yearly emissions used. Then, air pollutant concentration can be estimated at the grid level with hourly or yearly resolution.

Emissions data are then processed using an air quality model to estimate air pollution concentrations. Gaussian models (e.g. R-LINE) focus on physical dispersion while CTMs (e.g. CMAQ) account for chemical transformations, sedimentation, and secondary pollutant formation, which enhance simulation accuracy but require higher computational costs. RCMs (e.g. InMAP) leverage CTM data and processes, and use simplifying modelling and data collection techniques to reduce computational demand. However, this simplification limits their ability to simulate complex atmospheric processes, making RCMs more appropriate for screening-level assessments or large-scale analyses than for detailed local studies.

Health effect estimation: C-R functions are typically used to estimate mortality and morbidity based on air pollutant concentrations at the grid level. These functions can adopt linear or log-linear models, providing a straightforward quantification of the relationship between changes in pollution levels and associated health outcomes (e.g. mortality and morbidity). Their relatively low data requirements make them well-suited to efficiently evaluate health impacts over large geographic areas. However, the uniform parameters of C-R functions used in many studies often overlook regional variations, and variations in population responses and sensitivities to pollutant levels, which may reduce estimation accuracy.

Another consideration in health effect estimation is the population distributions over time and space. The literature is largely separated into static or dynamic approaches. The static approach approximates long-term average effects but may miss short-term variations from commuting and other movements or exposure environments. In contrast, the dynamic approach captures spatiotemporal changes in exposure for more accurate micro-scale and short-term analyses (Brook et al., 2010; Cesaroni et al., 2013; Brusselaers et al., 2023b), though it requires high-resolution data (e.g. mobile phone or GPS) and faces challenges of data availability and privacy.

The outcome of health effect estimation is typically a quantification of the estimated population-level morbidity and/or mortality outcomes by geographic unit, such as at the grid-level.

Disparity analysis: Grid-level mortality and morbidity are integrated with demographic and socioeconomic data (e.g. age, race, income) to examine health disparities. Since demographic data are often aggregated at administrative units such as census tracts or blocks, spatial alignment is required to match these datasets. Mortality and morbidity estimated from grid cells can be aggregated to census boundaries using area-weighted or population-weighted methods, resulting in health outcomes at the administrative unit level. These aggregated health outcomes are then combined with static or dynamic demographic and socioeconomic data to calculate total cases (e.g. deaths, hospitallisations) within each administrative unit which enables subsequent disparity analyses.

Disparity analysis can be organised into two main approaches: comparisons across population groups and across spatial units. For population group comparisons, disparity among subgroups are assessed. For example, several studies examine health effects across age groups because exposure-related mortality and morbidity are often assumed to vary by age. However, some studies also explore health disparities across other population groups according to racial, income, or other characteristics, due to differences in their spatial distributions.

In spatial unit comparisons, total deaths and hospitallisations are compared across different areas (e.g. census tracts or TAZs). These analyses often assume uniform mortality and morbidity across populations within each spatial unit. Although this assumption simplifies implementation, it can reduce estimation accuracy.

Several modelling assumptions may reduce the robustness of disparity analyses. First, most approaches overlook intersectionality and compounded effects, underestimating inequities among populations facing overlapping disadvantages (e.g. low-income racial minorities). Second, C-R functions are often derived from specific populations and may not capture susceptibility variations across more demographically diverse groups. Finally, aggregating health outcomes to administrative units can mask localised disparities within census tracts or neighbourhoods. This aggregation can also suffer from the modifiable areal unit problem (MAUP), where the results may be biased by the selection of the specific areal unit (e.g. aggregation at the county level might show different results than the tract level).

5.2. Implications and application

This study offers important implications for future research. Several studies have identified health equity issues related to freight emissions, highlighting the need for planners and policymakers to integrate equity considerations into decision-making. The proposed framework with available models supports pre-planning assessments, enabling more balanced decisions that consider economic, environmental, and social dimensions. For research, this study underscores key assumptions in existing models that may limit accuracy, such as static population data or assuming uniform exposures in a spatial unit. Future research in this field should carefully consider these barriers, assumptions, and tradeoffs in developing their analyses and to address their potential limitations.

The integrated framework can be applied to evaluate the health equity impacts of freight policies and emerging trends across both place-based and fleet-based scenarios. Place-based scenarios, such as low-emission zones for commercial vehicles and land-use reforms for e-commerce-related warehousing, reshape the spatial distribution of freight activity and may alter link-level travel behaviours. These changes require freight demand modelling to capture their potential health equity effects. Notably, this study emphasised exhaust emissions, as these are often the primary focus of $PM_{2.5}$ emissions from transportation source. However, fleet-based scenarios, such as truck electrification, adoption of cleaner alternative fuels, and stricter emission standards, directly reduce tailpipe emissions. By updating vehicle emission factor libraries and modifying fleet composition and vehicle attributes, the framework can simulate how these cleaner technologies lower pollutant concentrations along existing routes and alter disparate health outcomes across communities. Particularly in the context of truck electrification, $PM_{2.5}$ emission from non-exhaust sources, such as brake and tire wear, road surface abrasion, and resuspension of road dust, should be prioritised to develop and assess the environmental and health impacts of related policies.

Moreover, this framework supports sensitivity analyses on geographic and population segmentation within EJ assessments, helping to inform policy decisions (Baden et al., 2007; Fried et al., 2024a). The choice of spatial scale is critical: broader scales may mask local disparities, while finer resolutions can uncover micro-level inequalities. Likewise, using a single indicator (e.g. race or income) may mask intersecting vulnerabilities, whereas cross-classifying and comparing multiple groups and spatial units can reduce bias in EJ evaluations (Fried et al., 2024a). However, these technical decisions often stand-in for more community-based participatory approaches to research, which can inform freight policies that better reflect local knowledge and priorities (e.g. Garcia et al., 2013). Intersectional approaches to health equity require transdisciplinary, multi-scalar, and recognitional strategies, such as addressing environmental health disparities within broader political-economic frameworks that also consider housing affordability, displacement, and labour issues (Williams et al., 2023). These theory- and community-based elements represent a major gap in freight-related equity research (Fried et al., 2024b).

6. Conclusion

This paper, through reviewing 36 empirical studies related to health equity impacts of freight emissions, identifies the key contributors to health equity impacts, including specific air pollutants, health endpoints, and disparities across population groups and spatial units, laying the foundation for evaluating the health equity impacts of freight emissions. It then provides the first state-of-the-art synthesis of widely used models in freight demand modelling, air quality modelling, health effect estimation and disparity analysis. Finally, it summarises available models and required data for each analytical stage in a framework, providing an integrated methodology framework for this interdisciplinary issue.

This study has several limitations. First, the integrated framework is derived from existing literature and may not fully reflect regional variations in model and data availability. Second, its application to specific freight scenarios may require further refinement, particularly in data-limited settings or diverse socio-economic conditions. Future research should explore empirical validation and adaptation of the framework to real-world case studies to enhance its applicability and robustness.

Even so, the contributions of this research are two-fold. This study first reviews the methods and tools commonly used to evaluate health equity impacts of freight emissions, providing a comprehensive overview of current methodologies. Second, given the lack of a systematic framework that integrates available models for this evaluation, we develop an integrated framework tailored to the freight sector and analyse the strengths and limitations of available models at each analytical stage. This framework addresses gaps identified in previous studies, offers multiple options for implementing evaluations, and enhances flexibility to apply the suited models for research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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