EXPLORING THE HEALTH IMPACTS OF TRAFFIC-RELATED AIR POLLUTION: METHODS AND DATA SOURCES

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16. Abstract

This study comprehensively reviews and investigates approaches, methods, data, tools, and models for assessing health impacts of transportation emissions, focusing on the quantitative health impact assessment (QHIA) and burden of disease (BoD). It discusses the practicalities of conducting such research, including the exact methods, calculations, data requirements, and data sources, in the context of the health impacts of traffic-related air pollution (TRAP). Specifically, this study emphasizes compiling a comprehensive inventory of methods, functions, and sources, comparing their strengths, limitations, and data requirements, and offering an elaborate step-by-step procedure for integrating health outcomes into the modeling process of the full chain pathway from exposure assessment to health impact assessment. Additionally, it explores existing health outcome data and sources that can be overlaid to provide a more comprehensive perspective on the relationship between TRAP and health. This work serves as an exploratory effort, setting the stage for future research and modeling endeavors. The aims are to strengthen the linkage between air pollution epidemiology and the health impact of TRAP, leading to more robust QHIA or BoD studies for assessing the full chain of TRAP's impacts on health.

Currently, there is a lack of standards and best practices for assessing health impacts of TRAP and selecting input data from diverse data sources. Additionally, there is a lack of comprehensive syntheses on available datasets for these assessments. This study provides insights for future studies to choose the most suitable methods and data sources for conducting exposure to health impact assessments. Furthermore, it explores the potential integration of the extensive health data from CDC PLACE to improve model accuracy of health impact assessments conducted at the local scale.

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Executive Summary

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Background and Introduction

Communities in the Unites States are currently facing a critical health challenge characterized by an alarming increase in chronic diseases, soaring healthcare costs, and widening health disparities. Disturbingly, children are now being affected by illnesses that were traditionally seen in adults alone, and recent patterns indicate that today's youth might be the first generation in the United States to have shorter life expectancies than their parents. Simultaneously, we are confronted with pressing environmental problems such as air pollution, climate change, natural disasters, water shortages, etc., all of which will present further health-related difficulties.

Air pollution is a determinant risk factor for various adverse health effects in humans. Air pollution stands out as a crucial and extensively researched environmental exposure due to the following compelling factors [1]:

- **Ubiquitous nature**: It permeates various environments, making it a pervasive concern with wide-ranging implications.
- **Diverse health-related effects**: Air pollution influences a wide spectrum of health states and events, encompassing various respiratory and cardiovascular diseases, as well as other ailments.
- **Impact on all segments of the population**: It affects individuals of all ages and backgrounds, posing risks to both vulnerable groups and the general population.
- **Significant and modifiable health burden**: The health implications are substantial, but with appropriate interventions, the burden can be reduced and managed effectively.

Transportation sector emissions are one of the major sources of air pollutants. Traffic-related air pollution (TRAP) is a strong contributor to the global burden of disease due to air pollution. TRAP is derived during the combustion of gasoline or diesel fuel and can also include particles from the wear and tear of other mechanical components. TRAP is comprised of carbon monoxide (CO), nitrogen oxides (NO_2), particulate matter (PM), hydrocarbons, and mobile-source air toxics, and most of those pollutants can also come from other sources [2]. Quantifying exposures is challenging because concentrations decrease rapidly when individuals move away from roadways. Furthermore, it can be challenging to assess the associations between TRAP and health because there is no perfect measure of exposure. Because of these challenges, many researchers use different metrics of exposure to look at the impact of TRAP on health. In policy decision-making, it is important to understand and be able to quantify the full chain from air pollution sources, through pathways, to the ultimate health outcomes [3].

Objective

The Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH) report "Development of Full-Chain Transportation Emissions, Exposure, and Health Modeling Platform" developed a Platform to Assess Transportation, Health, and Sustainability (PATHS) to integrate models to generate "full chain" assessments of the traffic emissions to the health impacts modeling chain [4]. This report aims to further investigate how additional health impact approaches and health-related data can be integrated into CARTEEH's work in this area. The primary focus is to explore:

- Two types of health impact approaches: Health impact assessment (HIA) and burden of disease (BoD).
- Two different types of data:
    - Sources for adding health outcomes to model full chain pathways from air pollution exposure to health outcomes (e.g., concentration-response functions such as those in the Environmental Benefits Mapping and Analysis Program [BenMAP] developed by the U.S. Environmental Protection Agency [EPA]).

- Health data that can be overlaid to provide a more comprehensive perspective on the relationship between TRAP and health (e.g., Centers for Disease Control and Prevention [CDC] PLACE: Local Data for Better Health).

In addition to the two health impact approaches and two distinct types of health-related data, this report specifically discusses the practicalities of conducting such research, including the exact methods, calculations, data requirements, and data sources, in the context of the health impacts of TRAP. It comprehensively reviews and investigates health impact approaches and corresponding methods and data to enhance CARTEEH's PATHS modeling platform and informs the evolution of full chain from air pollution sources to health impacts.

Research Gap and Significance

TRAP and health have historically remained two separate disciplines with limited integration. The evidence of TRAP's impacts on various health outcomes is not being fully recognized, and there is a lack of adequate studies that compare various methods to evaluate health impacts associated with TRAP. Data associated with TRAP and health are quite different. TRAP data are usually generated from spatially refined estimates and can be projected in small areas/grids. Conversely, health data are commonly gathered within broader, population-based geographic regions using survey or sampling methods, resulting in reduced precision and difficulty in projection. Few studies have comprehensively reviewed and summarized health indicators related to TRAP. Most studies examined health impacts of TRAP based on an accumulated indicator, such as premature or all-cause mortality (i.e., the deaths of individuals that occur before an expected or standard age, often before reaching the average life expectancy for a specific population); one specific disease, such as high blood pressure or stroke; or one category of disease, such as respiratory disease.

This report is exploratory in nature, identifying and inventorying approaches, methods, tools, and data in the TRAP-health context with the purpose of furthering research and modeling efforts to:

- Strengthen the linkage between air pollution epidemiology and the health impact of TRAPs.
- Lead more robust quantitative health impact assessment (QHIA) and BoD studies for assessing the full chain of TRAP's impacts on health.

Approach

Full Chain TRAP to Health Impacts

CARTEEH has developed a comprehensive framework that traces the path from air pollution sources to their resulting health impacts, visualized in Figure 1.

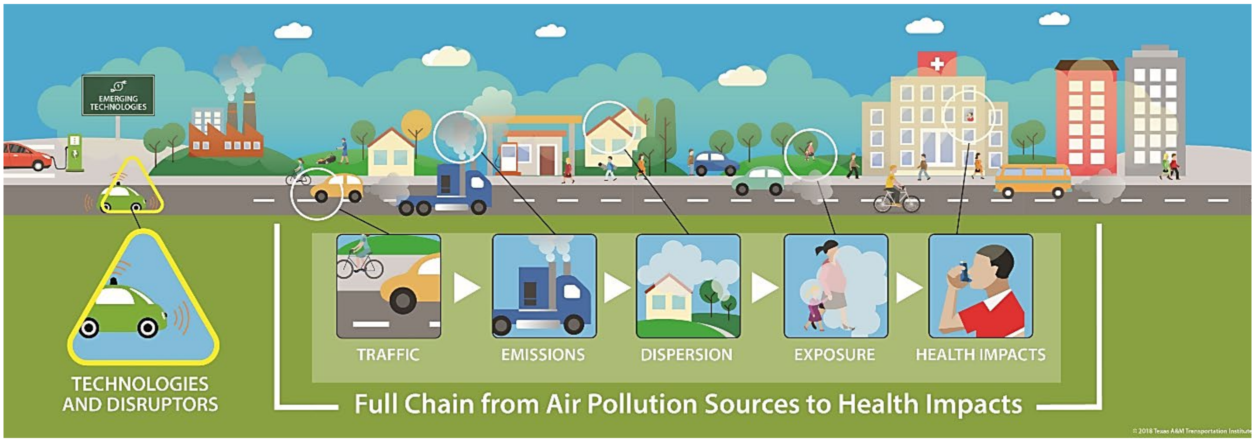

Figure 1. Full chain from air pollution sources to health impacts.

The full chain from air pollution sources to health impacts is comprised of the following components:

- Traffic and Emissions: Traffic activities result in both tailpipe and non-tailpipe emissions. Non-tailpipe emissions constitute the pollutants produced from brake wear, tire and road surface abrasion, and the suspension of road dust.
- Dispersion: The dispersion of these emissions into the ambient air hinges on a myriad of highly variable factors, including wind speed and direction, atmospheric stability, local and regional terrains, and the backdrop of air pollution from other sources like industries, agriculture, and the burning of coal and wood. Pollutant dispersion leads to heightened levels of air pollutants, either through primary emissions or via the creation of secondary pollutants like ozone.
- Exposure: Humans are exposed to these air pollutants either in the ambient air or indoors, since outdoor air pollutants infiltrate indoor spaces. The level of human exposure and the inhaled doses reaching the target organs or tissues are determined by various dynamic factors. These include mobility patterns, distance from the source, elevation, physical activity, and choice of transportation mode.
- Health Impacts: Exposure to TRAP can trigger a broad spectrum of negative health effects and impacts on population health.

In Figure 1, there is an icon representing technologies and disruptors, which include upcoming transportation technologies like automated and electric vehicles. Such advancements can affect the levels of traffic activity and vehicle emissions, both tailpipe and non-tailpipe. These influences, in turn, alter the dispersion, human exposure, and subsequent health impacts [5].

Health Impact Assessment

HIAs are well-developed and structured processes that use scientific data, professional expertise, and stakeholder input to identify and evaluate the public health consequences of proposals and suggests pragmatic actions that can be taken to minimize adverse impacts and optimize beneficial health impacts [6]. HIAs view health from a broad perspective. They look systematically across the entire spectrum of factors that drive community health and consider a wide range of environmental factors, such as housing conditions, roadway safety, employment, environmental conditions, and social factors that lead to health outcomes. A general HIA process includes screening, scoping, assessing, recommending, reporting, monitoring, and evaluating [7]. There is no specific methodology for implementing HIA; the selection of methods depends on the scope of projects being evaluated, as well as the most relevant methods for the assessment step and how stakeholders are engaged. The most commonly used methods include a literature review, secondary data analysis, primary data collection via survey, focus group and interview, and participatory approaches for stakeholder engagement [6].

In the United States, from 2004–2013, 73 transportation projects using HIA were completed by various local and state transportation agencies, county and city councils and planning agencies, park departments, and other state agencies. The projects, policies, or interventions that were addressed include bridge replacements, new transit stations, bus rapid transit, bicycle and pedestrian facilities, corridor redevelopment, greenways and walking trails, port expansions, road pricing, speed limits, and complete streets. The health impacts assessed include physical activity, transportation-related injury, air and water quality, noise, social capital, mental health, social cohesion, crime, access to goods and services, affordable housing, discretionary time, etc. [8] A limited number of studies did evidence-based HIA associated with TRAP, and there is a lack of empirical studies that quantify TRAP-related HIA. This study specifically focuses on the two quantitative approaches to quantify the health impact of TRAP: QHIA and BoD.

QHIA and BoD Related to TRAP

The QHIA and BoD of TRAP studies have seen an increase recently, especially in academic literature.

QHIA: Is a systematic and analytical process used in public health and environmental science to assess and quantify the potential effects of various factors, such as environmental exposures, policies, interventions, or other determinants, on the health of a population. This assessment involves the use of quantitative methods, data analysis, and mathematical models to estimate the magnitude, distribution, and probability of health outcomes associated with specific exposures or interventions. QHIA aims to provide numerical estimates and measurements of health impacts, allowing policymakers, researchers, and public health professionals to make informed decisions and prioritize interventions to improve public health [9-13].

BoD: Is a comprehensive and systematic approach used in public health and epidemiology to assess the overall impact of diseases, injuries, and risk factors on a population's health. BoD involves quantifying and evaluating the morbidity (illness) and mortality (death) associated with specific health conditions and their associated risk factors within a defined population over a specific period [9–13].

In brief, within the context of the TRAP field, QHIA assesses changes of a policy, program, or project (e.g., transportation-related intervention) impact on the health of a population, while BoD assesses the contribution of a risk factor (e.g., levels of air pollution) to the fraction of disease or death in the population without an intervention or scenario design. The difference between QHIA and BoD is whether scenarios comparing different exposures (changes) are investigated. QHIA and BoD provide methods for quantifying the positive and/or negative health impacts of baseline conditions (i.e., burden of disease assessments) and public policies, projects, and programs (i.e., health impact assessments), and the distribution of these impacts [9–13].

Conducting a QHIA or BoD study can be combined into five steps [7, 14]:

- **Step 1: Exposure assessment:** Defining exposures of interest, exposure measurements, and ranges. Refer to Table 1 and Table 2 for details on exposure assessment steps, method comparisons, and study examples.
- **Step 2: Health outcome:** Defining health outcomes of interest associated with exposures and their frequency (incidence) among the exposed population. Refer to Table 3 for examples of health outcome categories/variables and exsiting studies.
- **Step 3: Exposure-response functions:** Selecting exposure-response functions (risk estimates) to quantify strength of association between selected exposures and selected health outcomes. Those are risk estimates reported by general epidemiological studies, including prevalence or incidence of disease, relative risk, odds ratios, or population attributable risks.

- **Step 4: Quantifying attributable cases:** Combining exposures data with population data and exposure-response functions to quantify attributable proportional health burden of the health outcome of interest. Results from study examples can be found in Table 3.
- **Step 5: Quantifying uncertainty:** Quantifying uncertainty (e.g. 95 percent confidence intervals [CIs]) in estimated health burden (range of potential effects).

The methodology of QHIAs and BoDs that look to quantify the impacts of TRAP varies from traditional HIA because TRAP requires specific assessment of traffic-related components of air pollution and therefore requires different methods such as a full chain HIA or source apportionment methods for exposure assessments. In addition, these specific methods require different input data sets and models, which would be more resourceful and time consuming. The following sections discuss the methodology and data required for evaluating a QHIA or BoD study for TRAP.

Methodology

Methods for QHIA and BoD

The following sections discuss the five steps to conduct a QHIA or BoD study, including methodologies, functions, data and data processing, and sources.

Exposure Assessment

Exposure assessment is the first step for conducting a QHIA or BoD study through defining exposure of TRAP, exposure measures, and ranges. The exposure is assessed at a level where population data can be obtained, allowing the exposure estimate to be attributed to the population residing in each geographical catchment area. Typically, an average exposure estimate at that geographical level is assigned to all individuals living in that area, often using available census data, such as the census block or tract in the United States [15]. Long-term, annual, average air pollution exposures (e.g., population weighted annual average $PM_{2.5}$ in census tract level) are commonly calculated for this purpose. Exposure assessment involves two steps:

- **Generating Spatial Profiles of TRAP**: different methodologies used for producing spatial profiles of air pollution.
- **Linking Pollutant Concentrations to Population**: techniques used to link these spatial concentration profiles with populations for the purpose of assessing health impacts.

Generating Spatial Profiles of TRAP

The initial phase of the exposure assessment process involves creating spatial concentration profiles of TRAP at the desired resolution. Various techniques are used to achieve this including air-monitoring, land-use regression models, exposure surrogates, exposure to traffic proxies, dispersion models, geostatistical interpolation models, and satellites/remote sensing [16].

Air-Monitoring

Air-monitoring is a direct measurement of TRAP exposure, including stationary, and mobile monitoring. In the United States, the State and Local Air Monitoring Stations network is designed to monitor ambient air pollution concentrations and provide air pollution data to the public in a timely manner. EPA and other regulatory agencies routinely monitor air quality, but only at a small number of locations. Mobile monitors often are small, portable, and battery-operated devices that can be carried on by a person to measure personal exposures and have potential to better capture local-scale TRAP than stationary air monitors. Studies found that exposure of TRAP taken on roadways revealed significantly higher concentrations compared to ambient levels measured at air-monitoring stations [17]. Air-monitoring of TRAP is critically important for validating emissions models.

Land-Use Regression (LUR) Models

LUR models treat the pollutant of interest as the dependent variable and the proximate land-use, traffic, and physical environmental variables as independent predictors. They predict pollution concentrations at a given site based on surrounding land use and traffic characteristics. Each characteristic is assumed to be linearly related to pollutant concentrations. Validation of these models has shown that they generally perform as well as dispersion models [18].

The formula of LUR is shown in **Equation 1**, where Z is the pollution concentration of monitoring locations as the response variable, and X is the proximate land-use, traffic, and physical environmental variables as the predictor variables [18].

$$Z_j = \beta_o + \sum_{i=1}^{n} \beta_i X_{i,j} + \varepsilon_j \qquad (1)$$

The major limitation of LUR models is that they typically reflect only the predictors used in the model. Though the models include traffic-related variables, they cannot comprehensively model the traffic exposures and often miss important confounding factors due to study limitation and/or data unavailability, resulting in misleading bias and/or misinterpretation of the results [19].

Exposure Surrogates

A widely used approach to characterize traffic pollution is to utilize individual pollutants as surrogates to represent exposure to all TRAP. The most used traffic-pollutant surrogates include CO, NO_2, elemental carbon (EC) or black carbon (BC), PM, benzene, and ultrafine particles. EC has been used as a surrogate for diesel exhaust. A surrogate for traffic emissions should (a) have traffic as the dominant source of atmospheric emissions, (b) vary with other constituents of motor-vehicle exhaust over time, (c) be measurable at ambient concentrations using reasonably inexpensive and accurate methods, and (d) not have independently adverse health effects associated with it at concentrations encountered in various environments. In addition, the goal in most epidemiologic studies is to relate individual exposures to some health-related outcome, so a surrogate measure should reasonably approximate personal exposure to traffic emissions [2].

Exposure to Traffic Proxies

Rather than directly measuring the concentration of pollutants, a number of studies assessed exposure levels using direct measures of traffic proxies. Traffic proxies include vehicle mix (e.g., diesel and gasoline-fueled vehicle volumes), traffic density or volume (e.g., the daily number of vehicles), traffic density within buffers, distance to roadways, street segments, and self-reported traffic exposures. The most basic exposure assessment methods are proximity-based models, which assume that the distance to roadways (or traffic) from place of residence serves as a surrogate for exposure to TRAP. While these models could prove useful, they overlook the compounded influence on residences that might be affected by multiple roadways with varying traffic levels. Additionally, they fail to account for potential meteorological influences [18].

Moreover, several other studies established connections between traffic density and TRAP concentrations near roadways or homes. These studies suggested that variations in total traffic and traffic composition (i.e., the mix of cars and trucks) can influence the levels of TRAP in near roadways. However, each study was conducted in a unique area and may not be easily applicable to other geographic regions. This discrepancy arises because these studies utilized different measures of traffic density or vehicle volume; varied in traffic composition, specific vehicle conditions, and characteristics; collected data at different distances from roadways under varying meteorological conditions in diverse geographical areas; and often did not account for background concentrations. Additionally, they employed variable sampling periods and averaging times, further adding to the complexity of comparing and generalizing the findings [20–25].

Dispersion Models

Air pollution dispersion models have been used for decades to estimate ambient concentrations from emission sources. They are a mathematical simulation of how air pollutants disperse in the ambient atmosphere. The Gaussian dispersion approach is the most applicable one and derives models such as AERMOD, CALINE, and ADMS. The Gaussian dispersion approach considers emissions coming from a point in space (source) that is adding additional pollutants above a fixed background concentration. If the emissions continue over time, a series of air parcels containing these emissions will be produced (plume). If these polluted air parcels are warmer than the surrounding air (e.g., a smokestack or tailpipe), then the air parcel will be buoyant and tend to rise until it is in equilibrium with the background air (plume rise). The plume will also move downstream with the wind flow resulting in dilution and will begin to disperse due to the presence of turbulence. The degree of turbulence dictates the rate of spread of the plume and the mixing of pollutants both vertically and cross-wind, although the degree of spreading will normally be different in each direction, and vertical spread is partially constrained by contact with the surface of the Earth [26].

Dispersion models combine motor vehicle emissions and air-quality data and incorporate meteorological data and population data. This combination has allowed information from empirical monitoring systems and data on population distribution in the study area to be analyzed together, but they must be calibrated correctly to realize their advantages [18].

Chemical Transport Models

Chemical transport models (CTMs) are computational tools used in atmospheric science and environmental research to simulate and study the transport, dispersion, and chemical reactions of various pollutants in the Earth's atmosphere. These models help researchers and policymakers understand how pollutants, such as gases, aerosols, and particulate matter, move and interact in the atmosphere, which is crucial for assessing air quality, pollutant sources, and the impact of emissions on human health and the environment. CTMs incorporate data on atmospheric conditions, emissions, chemical reactions, and other relevant factors to provide insights into air pollution, climate change, and related phenomena. Some of the commonly used chemical transport models include CMAQ, CAMx, EMEP, Chimere, and Lotos-Euros [27, 28].

Geostatistical Interpolation Models

Geostatistical interpolation models utilize geostatistical properties to create pollution "surface," an attribute that varies continuously over space within a specific study domain. These models estimate pollution levels at unsampled locations based on spatial correlations and relationships with known sample points [2]. There are four commonly used interpolation models for air-pollution exposure assessments: (1) spatial averaging, (2) nearest monitor, (3) inverse distance weighting, and (4) kriging. The most advanced form of spatial interpolation is kriging, which produces the best linear unbiased estimate and allows for mapping of error variances [29]. Geostatistical interpolation models for air pollution are best implemented in conjunction with dense, well-distributed monitoring networks. However, the size of the network and the number of measurements is needed over time to estimate the spatial distribution of pollution surrogates accurately [18].

Remote Sensing

Remote sensing has emerged as an important resource for air pollution exposure assessment. Remote sensing involves the capture, retrieval, analysis, and display of information on surface and atmospheric conditions. These data are gathered using satellite, aircraft, or other specialized technologies capable of sensing energy, light, or optical properties from a distance. The potential applications of remote sensing in studying exposures to TRAP can be grouped into three categories: (1) Estimating pollutant concentrations—remote sensing can be utilized to estimate the concentrations of specific pollutants; (2) Direct data input for pollution prediction models—remote sensing data can serve as direct inputs for models used to predict air pollution based on land use, traffic patterns, or other ground-level information; and (3) Cross-validation of ground or atmospheric data—remote sensing can be used to cross-validate data captured by ground-based or traditional meteorological devices, enhancing the accuracy and reliability of the information gathered. The emergence of satellite imagery-based remote sensing technologies improved refinement of the data inputs. However, direct estimates of ground-level pollution from remote sensing data typically have coarser scales compared to near-source impacts. Further research is required to integrate the rich data available from remote sensing into ground-based estimates [2].

Summary Table of Methods for Generating Spatial Profiles of TRAP

Table 1 summarizes the comparison among methods for generating spatial profiles of TRAP as the first step of exposure assessment. Samples of studies employing each method for generating spatial profiles of TRAP are cited in the method column.

Table 1. Comparison of Methods for Generating Spatial Profiles of TRAP

Method	Description	Strengths	Limitations	Data/Computational Requirements
Air Monitoring [30, 31]	Direct measurement of TRAP exposures	Accurate when using regulatory grade sensors; can validate emission models	Limited locations; does not capture local-scale TRAP well	Needs air quality monitoring equipment; moderate computational requirements
Land-Use Regression (LUR) Models [32-35]	Predicts pollutant concentrations based on surrounding land use and traffic characteristics	Accurate and validated against dispersion models	Cannot quantify specific contribution of traffic to exposure	Requires geographical, land use, and traffic data; high computational requirements
Exposure Surrogates [32-36]	Uses individual pollutants as surrogates to represent exposures to all TRAPs	Practical for characterizing traffic pollution	Difficult to capture full range of TRAPs	Requires data on surrogate pollutants; moderate computational requirements
Exposure to Traffic Proxies [37-39]	Uses direct measures of traffic proxies to assess exposure levels	Simple and direct	Overlooks compounded influence from multiple roadways	Requires traffic data; low to moderate computational requirements
Dispersion Models [40-42]	Estimates ambient concentrations from emission sources	Incorporates emissions, air-quality, meteorological, and population data	Must be accurately calibrated	Requires emissions, meteorological, and population data; high computational requirements
Chemical Transport Models [43, 44]	Simulates the transport, dispersion, and chemical reactions of pollutants in the Earth's atmosphere	Capable of dealing with chemical reactions	Requires large and high-resolution data inputs and computational resources; chemical complexity and interaction	Requires large emissions and meteorological data; high computational requirements
Geostatistical Interpolation	Uses spatial correlations to	Allows for mapping of error variances	Needs well-distributed monitoring networks	Requires monitoring network data; high

Models [36, 45]	estimate pollution levels at unsampled locations			computational requirements
Remote Sensing [46]	Uses satellite or aircraft technologies to capture information on surface and atmospheric conditions	Allows estimation of specific pollutant concentrations; useful for cross-validation	Direct estimates have coarser scales than near-source impacts	Requires remote sensing data and equipment; high computational requirements

Linking Pollutant Concentrations to Population

Once spatial concentration profiles are generated, the subsequent step in exposure assessment is to assign pollutant concentrations to a population. The assignment process should be performed at a scale where health effects can be examined and understood. Techniques including population-weighted average concentration and dynamic exposure assessment can be utilized.

Population-Weighted Average Method

The population-weighted average (PWA) method is a valuable approach to estimate exposure concentrations in a study area. It considers both the spatial distribution of air pollution and the population distribution. This method provides an estimate of the average exposure of the population to a certain pollutant. The basic principle behind the PWA method is to assign more weight to the air pollution concentrations in areas where more people live, thus reflecting the fact that a higher population in a polluted area would lead to a higher collective exposure [47].

To calculate a population-weighted average concentration, typically the grid is overlaid on the study area, then for each grid cell, the concentration of the pollutant in that cell is multiplied by the number of people living in that cell. The sum of these products is then divided by the total population of the study area. In mathematical terms, if C_i is the pollutant concentration and P_i is the population in grid cell *I*, the population-weighted average concentration (C_{pwa}) can be calculated as Equation 2 [47]:

$$C_{pwa} = \Sigma\,((C_i\, *\, P_i))/\,\Sigma\, P_i \qquad (2)$$

The PWA method is advantageous because it takes into account both where people live and the levels of pollution they are exposed to. It is a particularly useful tool when investigating health impacts at a population level since it aligns the exposure estimation more closely with where people reside. However, like other methods, it also has its limitations. The PWA method relies on the availability and accuracy of population and pollutant distribution data. Also, it does not account for individual behavior patterns (e.g., time spent indoors vs. outdoors, use of air conditioning), individual susceptibility, or variations in exposure within a day or between different days. In conclusion, while the PWA method offers a useful tool for estimating population-level exposure, it is also valuable to complement this method with other exposure assessment methods to account for individual-level variability and other influencing factors [47].

Dynamic Exposure Assessment Methods

Dynamic exposure assessment methods are a set of innovative approaches to evaluate individuals’ exposure to air pollution. These methods consider people’s movements, behaviors, and specific microenvironments they encounter during their daily activities. These methods are designed to capture the temporal and spatial variability of pollutant exposure, recognizing that people are not stationary and that their exposure levels can significantly change based on where they are, what they’re doing, and the time of day [48].

There are several types of dynamic exposure assessment methods, including [48]:

- **Personal Monitoring:** As previously discussed, personal monitoring involves the use of portable devices carried by individuals to measure their exposure levels in real time. This method captures the dynamic nature of an individual's exposure to air pollution as they move across different environments.
- **GPS Tracking Combined with Modeling:** This approach involves tracking an individual's location over time using GPS and then using these data to estimate their exposure levels by combining it with air pollution concentration data from models or monitoring stations. The integration of individual mobility data and air pollution data provides a more detailed and accurate picture of a person's exposure over time and space.
- **Time-Activity Diaries:** Time-activity diaries are self-reported records where individuals log their activities and locations throughout the day. These data can then be used in combination with pollutant concentration data from models or monitoring stations to estimate exposure.
- **Wearable Sensors:** Wearable sensors are increasingly being used in exposure assessment studies. These devices can monitor both environmental parameters (e.g., air pollution levels) and physiological parameters (e.g., heart rate), providing a dynamic assessment of both exposure and health response.

Dynamic exposure assessment methods are more complex and data-intensive than traditional static methods. However, they offer a more realistic assessment of exposure by capturing the complexity of real-world situations. These methods have been enabled by advances in technology, including improvements in portable monitoring devices, the widespread use of smartphones with built-in GPS, and the growth of machine learning techniques for data analysis. Despite the complexity and potential challenges in data collection and analysis, dynamic exposure assessment methods are increasingly being recognized as a critical tool in the field of environmental health [48].

Summary Table of Methods for Linking Pollutant Concentrations to Population

Table 2 compares the two methods for linking pollutant concentrations to population. Samples of studies employing each method for linking pollutant concentrations to population are cited in the method column.

Table 2. Comparison of Methods for Linking Pollutant Concentrations to Population

Method	Description	Strengths	Limitations	Data/Computational Requirements
Population Weighted Average [47, 49, 50]	Allocates pollutant concentrations based on population density	Simple to implement; provides a single representative concentration for entire population	Might not reflect high-exposure hotspots	Requires population density data and pollution concentration data; moderate computational requirements
Dynamic Exposure Assessment [48]	Incorporates temporal and spatial variability in both pollution concentrations and population activities	Reflects real-world variability; can capture high-exposure events	More data-intensive; requires detailed data on population movement and activity patterns	Requires detailed temporal and spatial data on population and pollution; high computational requirements

Defining Health Outcomes

This step involves establishing health outcomes linked to the exposures and their frequency (incidence) within the exposed population. In this context, the exposures are air pollution and specifically TRAP, and the health outcomes can be any that have been associated with TRAP in epidemiological studies.

Health outcomes from air pollution epidemiology can be grouped into three categories [1, 51]:

- **Accumulated indicators:** In air pollution epidemiology, the widely used accumulated indicators are premature mortality, all-cause mortality, and life expectancy. Refer to Table 3 for examples of studies using accumulated indicators as health outcomes.
- **Category of diseases:** This term refers to the practice of grouping or categorizing diseases based on certain common characteristics, symptoms, or related factors. In the field of air pollution epidemiology, common disease categories include respiratory diseases, cardiovascular and heart diseases, cancer, and obesity. Refer to Table 5 for the CDC PLACE dataset and specific studies associated with each disease category.
- **Specific diseases:** Specific diseases refer to well-defined and distinct illnesses or health conditions that have specific sets of symptoms, causes, and treatments. These diseases are characterized by their unique features and diagnostic criteria, such as childhood asthma, lung cancer, and stroke. Refer to Table 3 and Table 5 for a collection of specific diseases linked to the field of air pollution epidemiology.

Conceptually, QHIA studies assess the changes of TRAP on health outcomes of interest among the exposed population, therefore QHIA studies require longitudinal health outcomes (e.g., baseline and follow-up phases). BoD studies evaluate the contribution of a risk factor to the fraction of disease or death within the exposed population, hence health outcomes are often accumulated indicators and could be either cross-sectional or longitudinal. However, there is no distinct usage of health outcomes between QHIA and BoD in current studies, and they often overlap.

Studies found that TRAP impacts many health outcomes, including all-cause mortality, cardiovascular morbidity, stroke risk, respiratory disease, deteriorated symptoms among adults, increased prevalence of asthma in children, changes in lung function among asthmatic children, cardiovascular and cardiopulmonary mortality, cancer, stress, and more [51]. Table 3 shows a list of selected QHIA or BoD studies quantifying impacts of TRAP on various health outcomes.

Table 3. Selected QHIA and BoD Studies Quantifying Health Impacts of TRAP

Method	Exposure Source	Exposure Assessment	Health Outcomes	Findings
QHIA	Traffic-related NO_2 and NO_x	Dispersion model	All asthma cases	Found that 128 (7%) and 219 (12%) of all asthma cases may be attributable to traffic related NO_2 and NO_x, respectively, in Bradford, England [40].
QHIA	Traffic-related NO_2	Geostatistical interpolation model	Premature deaths	Found that NO_2 can be reduced from 47.18 µg/m³ to 35.72 µg/m³, resulting in 291 preventable premature deaths in Barcelona, Spain [45].
QHIA	Traffic-related $PM_{2.5}$	Geostatistical interpolation model, exposure surrogate	All-cause mortality	Found that the annual average urban $PM_{2.5}$ concentration would decline by 0.1 µg/m³ and mortality would decrease by 608 deaths per year in the Midwestern United States [36].
QHIA	Traffic-related $PM_{2.5}$	Land-use regression model, exposure surrogate	Premature deaths	A larger number of deaths (i.e., 253 and 145, respectively) could be prevented by reducing air and noise pollution levels well below the guidelines in Bradford, United Kingdom [32].
QHIA	Traffic-related NO_2, NO, and BC	Remote sensing	Cardiovascular events	Found a one standard deviation increase in NO_2, NO, and BC was associated with a change in risk of a cardiovascular event of 3%, 3%, and −1%, respectively. Among the elderly (≥ 65 years), an increased risk of a cardiovascular event of 12% for

				NO_2, 12% for NO, and 7% for BC per one SD increase [46].
QHIA	Traffic-related NO_x	Land-use regression model, exposure surrogate	Cancer incidence	Found a 10-ppb increase in mean NO_x exposure was associated with hazard ratios of 1.07 for all-site cancer and 1.16 for cancers previously linked to TRAP (i.e., lung, breast, prostate, kidney, and bladder). A stronger association was observed for breast cancer [33].
BoD	Traffic-related $PM_{2.5}$ and ozone	Chemical transport modeling	Premature deaths	Found that traffic-related $PM_{2.5}$ and ozone were associated with 361,000 deaths in 2010 and 385,000 deaths in 2015, which translated into 11.7% of total global ambient $PM_{2.5}$ and ozone deaths in 2010 and 11.4% in 2015 [43].
BoD	Long-term exposure to TRAP	Exposure to traffic proxies	Arterial blood pressure (BP)	Traffic load on major roads within 100 m of the residence was associated with increased systolic and diastolic BP in nonmedicated participants (0.35 mmHg and 0.22 mmHg per 4,000,000 vehicles × m/day, respectively) [37].
BoD	Traffic-related $PM_{2.5}$	Land-use regression model, exposure surrogate	Annual preventable morbidity and disability-adjusted life-years (DALYs)	Found air pollution, noise, heat, and access to green spaces was estimated to generate a large morbidity burden and resulted in 52,001 DALYs in Barcelona each year (13% of all annual DALYs) [34].
BoD	Traffic-related NO_2	Land-use regression model, exposure surrogate	Childhood asthma	Using the state-specific incidence rates, researchers estimated a total of 134,166 childhood asthma incident cases attributable to NO_2, accounting for 17.6% of all childhood asthma incident cases. Using the national-level incidence rate, researchers estimated a total of 141,931 incident cases attributable to NO_2, accounting for 17.9% of all childhood asthma incident cases [35].

Exposure-Response Functions

The third step is to select exposure-response functions (i.e., risk estimates) to measure the degree of association between the exposure and health outcome of interest. Ideally, using exposure-response functions derived from the specific population under study are preferred. This would more accurately reflect the level of risk studies, the population characteristics, and their particular response to exposure. The selection of the pollutant for analysis is also important to consider and should be based on the available epidemiological evidence. However, such localized data or epidemiological evidence may often be unavailable or based on limited sample sizes, leading to imprecise estimates with wide confidence intervals [52, 53].

In the absence of specific local exposure-response functions, using pooled exposure-response functions from meta-analyses is a preferable alternative. This approach is more generalizable and offers more statistical power due to the pooling of larger human population data. Nonetheless, they may introduce higher and unexplained heterogeneity due to the variation in methodologies and underlaying populations across the studies included in the meta-analysis, thereby causing bias and poor estimates [13].

Risk estimates from the exposure-response functions reported by most epidemiological studies are prevalence or incidence of disease, relative risk, odds ratios, or population attributable risks. The following step introduces a general protocol of exposure-response function calculation for quantifying attributable cases.

Quantifying Attributable Cases

The fourth step is to combine exposures data with population data and exposure-response functions to quantify the attributable proportional health burden of the health outcomes. The selected exposure-response function needs to be scaled to represent the difference in exposure levels between the baseline exposure and the counterfactual exposure, which is commonly conducted at the geographical level of analysis. **Equation** 3 shows the calculation for the relative risk (*RR*) of the health outcome of interest [13, 54].

$$RR_i = e^{\left(\frac{\ln(RR_E)}{E} \times ED_i\right)} \qquad (3)$$

Where *i* is an element of the set *i* ∈ {1,…,n}, *n* is the number of exposures at the geographical level of analysis (e.g., census tracts/block groups, neighborhoods, districts), RR_E is the relative risk obtained from the exposure-response function, E is the exposure unit that corresponds to the RR_E obtained from the exposure-response function, and ED_i is the exposure level difference, which is the difference in the exposure level resulting from the comparison of the baseline exposure level with the counterfactual exposure level [13, 54].

The next step is to calculate the population attributable fraction (PAF). PAF defines the proportional health burden of the health outcome that is attributable to the difference in exposure level ED_i and is calculated as shown in **Equation 4**, where P_i is the proportion of exposed population, and RR_i is the previously scaled relative risk [13, 54]:

$$PAF_i = \frac{P_i \times RR_i - 1}{P_i \times RR_i} \qquad (4)$$

Finally, the total attributable burden (AB) is calculated. The attributable burden describes the total burden of the health outcome that is attributable to the difference in exposure level ED_i and is calculated as shown in **Equation 5**, where TB_i is the total burden of the health outcome, and PAF_i is the previously calculated proportional health burden of the health outcome that is attributable to the difference in exposure level ED_i [13]:

$$AB = \sum_{i=1}^{n} TB_i \ \times \ PAF_i \qquad (5)$$

Furthermore, with RR, health impact function can also be evaluated. Health impact function is widely used in air pollution epidemiology studies to assess the impacts of air pollution exposure on health outcome of interest. It is the core function that BenMAP applied to model health impacts of air pollution-related outcomes. The function explores a log-linear relationship between exposure and RR, as shown in **Equation 6**, where ΔY is the change in the health outcome of interest, Y_0 is the baseline disease incidence rate, RR is relative risk associated with a change in exposure, ED is the difference (change) in exposure level, and *Pop* is the exposed population [54–57].

$$\Delta Y = Y_0\,(1 - e^{-RR\,*\,ED}) * Pop \qquad (6)$$

Quantifying Uncertainty

The final step is to quantify the uncertainty from the estimated health burden. This could be achieved through various methods that consider the ranges of input data used in the assessments, including: (1) incorporating the ranges of the exposure estimates, (2) considering the ranges of incidence rate for the health outcome of interest, (3) using the ranges for the exposure-assessment functions, and (4) using a combination of the above. The uncertainty is often presented as 95 percent CIs [13].

Currently, there is a lack of specific guidance, standards, and best practices on how to quantify and present uncertainty in BoD and QHIA. One approach for presenting the range of uncertainty is using the most conservative estimate obtained from all the lower ranges of the input data as the lower 95 percent CI and using the most extreme estimate from all the upper ranges of the input data as the upper 95 percent CI. This way results in the widest possible 95 percent CI around the central estimate, but it requires running the analysis for multiple combinations of data, making it impractical and often not performed in practice [15].

Programs

There are programs that aim to automate part or full chain modeling processes of health impacts caused by air pollution, including the Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE), Intervention Model for Air Pollution (InMAP), AirQ+, and Airviro. None of these programs can offer one-step solutions, and each requires specific data input and preprocessing. Among these programs, InMAP excels in modeling the full chain, encompassing pollutant emissions, dispersion, exposure, and health impact assessments. In contrast, BenMAP-CE and AirQ+ are primarily focused on modeling exposure to health impacts, with AirQ+ having fewer capabilities for modeling concentration-response relationships and health impact outcomes. Lastly, Airviro is specialized for emission-dispersion modeling, with a more limited scope compared to the others. Table 4 summarizes the comparison among these programs for modeling health impacts of air pollution.

BenMAP-CE

BenMAP is an EPA open-source computer program that calculates the number and economic value of air pollution-related deaths and illnesses. The software incorporates a database that includes many of the concentration-response relationships, population files, and health and economic data needed to quantify these impacts. The program can enable users to load their own data or use pre-loaded datasets for the United States and China, including air quality data, demographic data, economic values, and concentration-response relationships. BenMAP-CE estimates health impacts using health impact functions that are constructed using information from the published epidemiology literature. Most of the functions have been discussed in the previous sections. BenMAP-CE is available for downloading from https://www.epa.gov/benmap [58].

InMAP

InMAP is a recently developed model that offers a new approach to estimate the human health impacts caused by air pollutant emissions and how those impacts are distributed among different groups of people. InMAP offers an alternative to comprehensive air quality models for estimating the air pollution health impacts of emission reductions and other potential interventions. InMAP estimates annual-average changes in primary and secondary $PM_{2.5}$ concentrations. InMAP leverages pre-processed physical and chemical information from the output of a state-of-the-science chemical transport model and a variable spatial resolution computational grid to perform simulations that are several orders of magnitude less computationally intensive than comprehensive model simulations. Potential uses of InMAP include studying exposure, health, and environmental justice impacts of potential shifts in emissions for annual-average $PM_{2.5}$ [59]. InMap is available for downloading from http://spatialmodel.com/inmap [59].

AirQ+

AirQ+ is a software tool for quantifying the health burden and impact of air pollution. It estimates the effects of short-term changes in air pollution (based on risk estimates from time-series studies) and long-term exposures (using life-tables approach and based on risk estimates from cohort studies). It is developed by the World Health Organization (WHO) and is mainly used in Europe. AirQ+ is available from https://www.who.int/tools/airq [60].

Airviro

Airviro is a web-based system for air quality management co-developed by the Swedish Meteorological and Hydrological Institute and Apertum IT AB. It serves as an integrated platform for managing time series data, emission inventories, and dispersion modeling. With its inception in 1990, Airviro has been under continuous development and has garnered a global user base. Airviro has been co-developed in collaboration with regional authorities and air quality consultants. Engagements have been noted with entities like SLB Analys in Stockholm, EERC in Estonia, Sweco and IVL in Gothenburg, and the Ministerio de Medio Ambiente in Santiago, Chile. Airviro is a more complicated setup, which can be set up based on the application with availability of different emission and dispersion models. Once deployed, it can be set up as a web-based application with ease of use for the end user. Airviro is available from http://www.airviro.com [61].

Table 4. Comparison of Programs for Quantifying the Impacts of Air Pollution

Method	Modeling Pathway	Strengths	Limitations	Data/Computational Requirements
BenMAP-CE [58, 62]	Air pollution exposure (air quality changes) to health effects	Can also calculate the economic value of air quality change using both "cost of illness" and "willingness to pay" metrics	Cannot be used to conduct source specific analyses without inputs from other modeling programs; expertise required to conduct an analysis	Source-specific input data for air quality changes in integer, text, and csv. format
InMAP [59]	Full chain modeling: emissions, concentrations, exposure, health impacts, economic damage, environmental justice	The only full chain modeling program researchers could find; better performance for population-weighted metrics	The performance for area-weighted metrics is lower; prediction/accuracy for certain pollutant concentrations are low; does not predict concentrations of ground-level ozone	User-specified input required is a shapefile or set of shapefiles containing locations of changes in annual total emissions of VOCs, SO_X, NO_X, NH_3, and $PM_{2.5}$ (e.g., polygon, line, or point entities)
AirQ+ [60, 63]	Air pollution exposure to health effects	Quantify both short-term and long-term health burden and impact of air pollution	Preprocessing air pollution and health data are required; only annual results are generatable; pollutants limited to PM_{10} and $PM_{2.5}$, the interaction between pollutants cannot be studied	Air pollution concentration input data, mortality incidence rate, and other health outcome data in csv. format
Airviro [61, 64]	Monitoring, emission inventories, and dispersion modelling	State-of-the-art and most extensive air quality management system on the international market; easy to access and use with exceptional performance and stability; offer hosting of servers	No health impact function; Not free.	Local topography, emissions, and meteorological data

Other Statistical Modeling

There are other studies that have attempted to model the association between traffic-related environmental factors (i.e., exposure to traffic proxies such as traffic density, noise, perceived air pollution) and health outcomes (e.g., obesity, depression, traffic-related mortality) using statistical modeling such as multiple linear regression, logistic regression, mixed regression, cox hazard model, and negative binomial models [65, 66]. These studies usually are survey-based or community-based studies using localized data. The findings are mixed and often have generalizable problems. There is a growing trend to use machine learning and data mining in air pollution epidemiology for prediction of exposure impacts, generation of hypotheses, and source appointment. The potential to support air pollution epidemiology continues to growth with advancements in data mining and deep learning technologies related to geo-spatial and temporal data mining as well as wealth and better quality of data [67].

Data

Health data are an essential element in quantifying health impacts of TRAP. However, obtaining local health data is often challenging due to issues like data unavailability or the prohibitive cost and time required for data collection within the study area. As a result, many studies end up utilizing disease incidence rates data from larger geographical regions, such as counties, regions, or national levels, and then scaling down these estimates to match the local study population based on population counts. Very few studies investigated the localized health impacts on QHIA or BoD estimates. There is evidence found that using local versus national incidence rates for evaluating childhood asthma in BoD assessment made a difference to the final estimates between city and state health data, especially when variations of interest among cities and states are large [35, 68].

The section aimed to compile and inventory health data and sources that could be linked with air pollution epidemiology, especially for local scale (e.g., neighborhood level), to strengthen the linkage between air pollution epidemiology and the health impact of TRAP. This section discusses the available health data that can be measured as health outcomes in QHIA and BoD studies for quantifying health impacts of TRAP. It focuses on introducing health data related to TRAP in the CDC PLACES database and providing additional health data sources.

CDC PLACES

PLACES is a collaboration between CDC, the Robert Wood Johnson Foundation, and the CDC Foundation. PLACES provides health data for small areas across the country. This allows local health departments and jurisdictions, regardless of population size and rurality, to better understand the burden and geographic distribution of health measures in their areas and assist them in planning public health interventions. PLACES provides model-based, population-level analysis and community estimates of health measures to all counties, places (incorporated and census designated places), census tracts, and ZIP Code Tabulation Areas (ZCTAs) across the United States.

Table 5 shows a list of selected health outcomes from CDC PLACES local data for better health in the census tract data 2023 release. Based on previous literature and authors' knowledge, 16 out of 30 health indicators related to TRAP were selected and grouped into five categories: respiratory disease (two health outcomes), cardiovascular and heart disease (five health outcomes), cancer (one health outcome), physical activity and obesity (two health outcomes), and other health conditions (six health outcomes), with corresponding health outcome indicators [51]. All health outcome indicators were normalized by sampling in population percentage, and health impact findings were summarized with citations.

Table 5. Health Outcomes Related to TRAP from CDC PLACES

Category	Variable Name	Variable Description & Measurement (Sampling in population %)	Related Studies
Respiratory Disease	casthma_cr	Current asthma among adults aged ≥ 18 years	[51, 69, 70]
	copd_crude	Chronic obstructive pulmonary disease among adults aged ≥ 18 years	[38, 51, 71]
Cardiovascular and Heart Disease	bphigh_cru	High blood pressure among adults aged ≥ 18 years	[37, 51, 72]
	chd_crudep	Coronary heart disease among adults aged ≥ 18 years	[51, 73, 74]
	highchol_c	High cholesterol among adults aged ≥ 18 years	[51, 75, 76]

	kidney_cru	Chronic kidney disease among adults aged ≥ 18 years	[51, 77, 78]
	stroke_cru	Stroke among adults aged ≥ 18 years	[51, 79, 80]
Cancer	cancer_cru	Cancer (excluding skin cancer) among adults aged ≥ 18 years	[33, 51, 81]
Physical Activity and Obesity	obesity_cr	Obesity among adults aged ≥ 18 years	[82]
	lpa_crudep	No leisure-time physical activity among adults aged ≥ 18 years	[83]
Other Health Conditions	depression	Depression among adults aged ≥ 18 years	[51, 84, 85]
	diabetes_c	Diagnosed diabetes among adults aged ≥ 18 years	[51, 86, 87]
	ghlth_crud	Fair or poor self-rated health status among adults aged ≥ 18 years	[88, 89]
	mhlth_crud	Mental health not good for ≥ 14 days among adults aged ≥ 18 years	[51, 90, 91]
	phlth_crud	Physical health not good for ≥ 14 days among adults aged ≥ 18 years	[88, 89]
	checkup_cr	Visits to doctor for routine checkup within the past year among adults aged ≥ 18 years	[92]

Data Source

Table 6 lists a collection of available data sources for health outcomes and cohort (epidemiological) studies in the Unites States, United Kingdom, and worldwide. This is not a full list, and more publicly available sources can be found online on researchers' expertise and study areas.

Table 6. Data Source of Health Outcomes and Cohort Studies

Sources	Area	Description	Link
CDC PLACE	U.S.	PLACES provides health data for small areas across the country.	https://www.cdc.gov/places/index.html
CDC EPHT	U.S.	The National Environmental Public Health Tracking Network brings together health data and environmental data from national, state, and city sources.	https://ephtracking.cdc.gov/
Environmental Justice Index	U.S.	The Environmental Justice Index ranks each census tract on 36 environmental, social, and health factors and groups them into 3 overarching modules and 10 different domains.	https://www.atsdr.cdc.gov/placeandhealth/eji/index.html
CDC WONDER	U.S.	WONDER online databases utilize a rich ad-hoc query system for the analysis of public health data.	https://wonder.cdc.gov/
CDC Behavioral Risk Factor Surveillance System (BRFSS)	U.S.	BRFSS is the nation's premier system of health-related telephone surveys that collect state data about U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services.	https://www.cdc.gov/brfss/index.html
CDC Asthma Call-back Survey (ACBS)	U.S.	The ACBS is conducted approximately two weeks after BRFSS. BRFSS respondents who report ever being diagnosed with asthma are eligible for the asthma call-back.	https://www.cdc.gov/asthma/acbs.htm
CDC U.S. Small-Area Life Expectancy Estimates Project (USALEEP)	U.S.	USALEEP produced estimates of life expectancy at birth—the average number of years a person can expect to live—for most of the census tracts in the United States for the period 2010–2015.	https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html
The Cohort Directory	UK	The Cohort Directory is a collection of UK population cohorts.	https://www.ukri.org/councils/mrc/facilities-and-resources/find-an-mrc-facility-or-resource/cohort-directory/
Dementias Platform	UK	Dementias Platform provides a list of cohorts representing a wide range of studies from across the United Kingdom.	https://portal.dementiasplatform.uk/CohortDirectory

Global Burden of Disease (GBD) database	World	GBD database provides sources of national data on the incidence of various health outcomes.	http://ghdx.healthdata.org/gbd-results-tool
Birthcohorts.net	World	Birthcohorts.net provides inventory of birth cohorts.	https://www.birthcohorts.net/
Epidemiology Resources web tool	World	The Epidemiology Resources web tool was created to organize and share information about National Institute of Environmental Health Sciences–funded environmental epidemiology studies.	https://tools.niehs.nih.gov/cohorts/
Global Cohort Portal	World	The EU Join Programme—Neurodegenerative Disease Research Global Cohort Portal is a searchable catalogue of cohort studies that covers both disease-focused and general population studies.	https://www.neurodegenerationresearch.eu/jpnd-global-cohort-portal/
Gateway to Global Aging Data	World	Gateway to Global Aging Data is a platform for population survey data on aging around the world	https://g2aging.org/

Discussion

QHIA and BoD are important tools to integrate health evidence into policy decision-making processes and introduce and implement Health in All Policies. The findings from these assessments offer valuable guidance to policymakers, emphasizing the significance of prioritizing outcomes that can be quantified and measured. Moreover, the outcomes can raise public awareness and advocacy regarding the health consequences and implications of existing and proposed public policy scenarios and influence decision-making processes [13].

Furthermore, QHIA and BoD are tools that can be implemented proactively to provide outlooks for expected health consequences and forecasting, and therefore plan appropriate mitigation strategies accordingly—before health problems occur. The tools allow the comparison of alternative counterfactual or policy scenarios and provide insights for evaluating proposed interventions, policies, or programs (e.g., TRAP mitigation) from a health perspective or beyond (e.g., health economics). They can directly or indirectly inform associated health benefits and risks and cost-benefit analyses as well as appraisal schemes for proposed transportation projects or investments [13]. In addition, these tools are context specific and sensitive to contextual variables, health parameters, and underlying population. Hence, they can help identify the sub-population that would disproportionally be affected or disadvantaged by the interventions, policies, or programs, which could be utilized to evaluate health disparity in disadvantaged communities and environmental justice research.

The QHIA and BoD studies mentioned above relied on modeling methods and tools primarily limited to research, but they have potential to be more widely applied in practice if further developed and improved. Due to a communication gap between different sectors, while researchers possess the expertise to develop and apply QHIA models, they often lack practical background and experience to determine whether their counterfactual scenarios are realistic and plausible for practice. Additionally, the developed models and tools are often not user-friendly. On the other hand, practitioners, policy, and decision-makers lack the motivation, knowledge, methods, and resources to routinely conduct health impact modeling projects to inform their decision-making process [3, 13, 93].

Several limitations exist in the modeling processes of QHIA and BoD that need to be acknowledged. Firstly, QHIA and BoD differ fundamentally from evaluation studies or pre-post intervention studies. They rely on assumptions and extrapolations, and there remains uncertainty regarding whether health impacts will truly occur as estimated. Consequently, the outputs can only be interpreted as an indication of the expected magnitude of health impacts under the counterfactual scenario. Second, the scope and impact of QHIA and BoD approaches are constrained by the lack of epidemiological evidence (dose- or exposure-response functions). Only those relationships that are supported by existing causal epidemiology can be quantified. As a result, these approaches are applicable only to exposure-response functions that have been validated through high-quality cohort studies, time-series analyses, or meta-analyses. Thirdly, uncertainties and errors arise when incorporating input data with varying quality and scale during the modeling processes. Any step involving the assessment of exposure proxies, exposure-response functions, resolution of exposure estimates, baseline health conditions, accuracy of population parameters, or risk estimates for that population can introduce errors and uncertainties in the estimation of health impacts. Fourthly, while there is robust epidemiological evidence linking TRAP to specific health outcomes, this evidence (e.g., RR, PAF) often applies only to certain populations, such as adults or children. Therefore, when applying this epidemiological evidence in QHIA and BoD, the health impacts captured will be limited to those specific populations for which the evidence is applicable. Lastly, in most cases, QHIA and BoD utilize counterfactual scenarios that describe ideal situations. However, these ideal scenarios tend to be overly optimistic, leading to a partial quantification of reality. As a result, the outcomes from QHIA and BoD may not fully reflect the complexities and challenges present in real-world conditions [3, 13, 94].

Conclusion

Currently, there is a lack of standards and best practices of assessing health impacts of TRAP and selecting input data from diverse data sources. Additionally, there is a lack of comprehensive syntheses on available datasets for these assessments. Future studies should address the aforementioned research gaps and limitations by focusing on the following areas [3, 13, 94]:

1. Develop participatory integrated full chain BoD and QHIA models in collaboration with stakeholders to assess plausible real-world scenarios or counterfactual exposures relevant to cities and local authorities.

2. Account for multiple exposures, interdependencies, and uncertainties present in the real world to create more comprehensive and robust assessments.

3. Establish and synthesize models alongside high-quality datasets tailored for policy purposes, including developing a comprehensive strategy for searching for quality input data and validating the models.

4. Develop sub-population exposure-response functions based on ethnicity, sex, socioeconomic class, etc. These functions should reflect baseline health conditions at a smaller geographical level, such as the neighborhood level, to improve model accuracy of health impact estimates for local-scale assessments, thus providing more nuanced insights for decision-makers.

This study comprehensively reviews and investigates approaches, methods, data, tools, and models for assessing health impacts of transportation emissions, focusing on QHIA and BoD. It discusses the practicalities of conducting such research, including the exact methods and calculations, data requirements, and data sources, in the context of the health impacts of TRAP. Specifically, this study emphasizes compiling a comprehensive inventory of methods, functions, and sources, comparing their strengths, limitations, and data requirements, and offering an elaborate step-by-step procedure for integrating health outcomes into modeling processes of the full chain pathway from exposure assessment to health impact assessment. Additionally, it explores existing health outcome data and sources that can be overlaid to provide a more comprehensive perspective on the relationship between TRAP and health. This work serves as an exploratory effort, setting the stage for future research and modeling endeavors. The aims are to strengthen the linkage between air pollution epidemiology and the health impact of TRAP, leading to more robust QHIA or BoD studies for assessing the full chain of TRAP's impacts on health.

Here are the key takeaways and actionable improvements:

- **Significance of QHIA and BoD**: These tools are instrumental in integrating health evidence into policy-making. Their outcomes not only guide policymakers but also elevate public awareness about the health implications of policy scenarios.

- **Proactive Implementation**: QHIA and BoD can be used to forecast health consequences, allowing for the planning of mitigation strategies in advance. They facilitate the comparison of alternative scenarios and provide insights for evaluating interventions.
- **Context-Specific Tools**: These tools are sensitive to specific contexts and populations. They can identify sub-populations that might be disproportionately affected by certain policies.
- **Potential for Wider Application**: While QHIA and BoD studies have been primarily research-focused, there's potential for broader practical application. Bridging the communication gap between researchers and practitioners can lead to more realistic and actionable models.

The following are improvements for the modeling pipeline:

- **Integration with Full Chain Modeling**: The findings from this study can be directly incorporated into the full chain modeling work. This includes refining exposure-response functions, leveraging extensive health data, and integrating feedback from real-world applications.
- **Enhanced Collaboration**: Engaging stakeholders, including policymakers, public health experts, and communities, can lead to more holistic and relevant models. This collaborative approach ensures that models are both scientifically rigorous and practically applicable.
- **Refining Models with Real-World Data**: The study highlights the importance of using real-world data, such as the CDC PLACE data, to enhance model accuracy. Future modeling efforts should prioritize the integration of such datasets.
- **Addressing Identified Limitations**: The study outlines several limitations in current QHIA and BoD approaches. Addressing these, especially in terms of assumptions, extrapolations, and the scope of epidemiological evidence, will significantly improve the modeling pipeline.
- **Incorporating Advanced Technologies**: Leveraging advancements in data science, artificial intelligence, and machine learning can enhance the accuracy and efficiency of health impact assessments.

In essence, the findings of this study offer a roadmap for refining the modeling pipeline. By addressing the identified challenges and leveraging the insights provided, there's a significant opportunity to enhance the full chain modeling work and ensure its relevance and effectiveness in real-world applications.

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