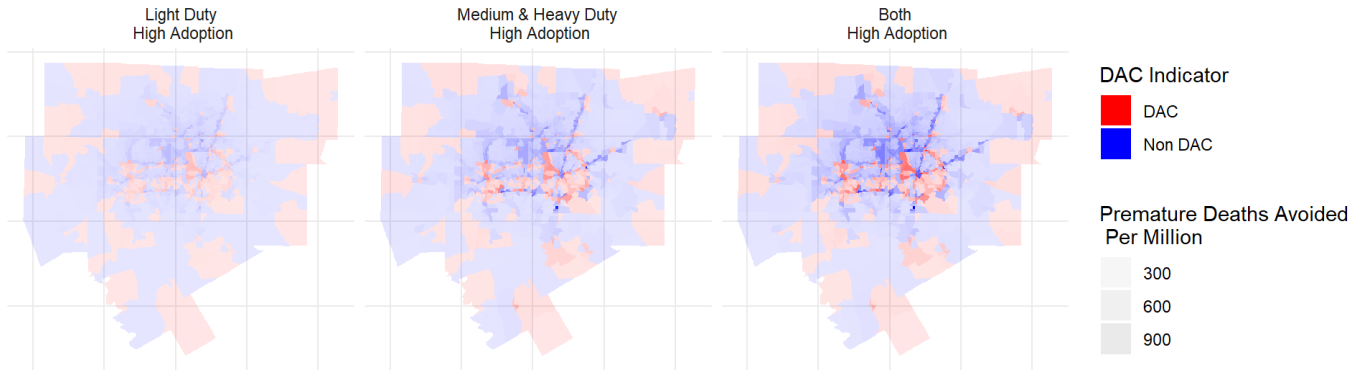# DETERMINING THE IMPACT OF ZERO EMISSIONS VEHICLES ON TRAFFIC-RELATED AIR POLLUTION EXPOSURE IN DISADVANTAGED COMMUNITIES

Light Duty
High Adoption

Medium & Heavy Duty
High Adoption

Both
High Adoption

DAC Indicator

■ DAC

■ Non DAC

Premature Deaths Avoided
Per Million

300

600

900

4/1/2024

Center for Advancing Research in
Transportation Emissions, Energy, and Health
A USDOT University Transportation Center

Disclaimer

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.		
4. Title and Subtitle Determining the Impact of Zero Emissions Vehicles on Traffic-Related Air Pollution Exposure in Disadvantaged Communities		5. Report Date August, 2023		
		6. Performing Organization Code		
7. Author(s) Rohit Jaikumar, Georges Bou-Saab, Minjie Xu, Elizabeth Rhinehart, Ben Ettelman		8. Performing Organization Report No. 06-59-TTI		
9. Performing Organization Name and Address: CARTEEH UTC Texas A&M Transportation Institute 3135 TAMU, College Station, TX 77843		10. Work Unit No.		
		11. Contract or Grant No. 69A3551747128		
12. Sponsoring Agency Name and Address Office of the Secretary of Transportation (OST) U.S. Department of Transportation (USDOT)		13. Type of Report and Period Final September 2022–August 2023		
		14. Sponsoring Agency Code		

16. Abstract
Traffic-related air pollution is an environmental and public health concern that disproportionately impacts populations in disadvantaged communities (DACs). Accelerating the adoption of zero (tailpipe) emissions vehicles has great potential to reduce these harmful emissions and improve health outcomes. This study evaluated whether electric vehicle (EV) adoption in DACs will result in significant emission and exposure reductions along with the associated health benefits when compared to non-DAC communities. The study utilized the Climate and Economic Justice Screening Tool and the United States Department of Transportation's Equitable Transportation Community Explorer tool to identify DACs. Vehicle-induced $PM_{2.5}$ emissions were estimated under varying levels of EV adoption rates for light-duty vehicles (LDVs), medium-duty vehicles (MDVs), and heavy-duty vehicles (HDVs). DACs identified through both classification methods typically experienced higher traffic densities, thereby amplifying their exposure to $PM_{2.5}$ emissions. Results indicated that each EV adoption scenario reduced $PM_{2.5}$ emissions, with the most significant declines observed in scenarios involving high adoption for medium- and heavy-duty EVs. The largest improvements were also observed within urban centers and along major roads within the identified DACs. The findings illuminate the necessity for targeted EV adoption strategies within these communities, which extend beyond LDVs to include MDVs and HDVs. Further research should delve deeper into the socio-demographic intricacies of these communities and the potential health benefits of lowered $PM_{2.5}$ concentrations.

17. Key Words Traffic-Related Air Pollution (TRAP), PM2.5, Zero Emissions Vehicles, Electric Vehicle Adoption, Environmental Justice, Disadvantaged Communities, Emissions, Exposure, Health Impacts, Policy Recommendations		18. Distribution Statement No restrictions. This document is available to the public through the CARTEEH UTC website. http://carteeh.org		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified		21. No. of Pages 36	22. Price $0.00

Form DOT F 1700.7 (8-72)   Reproduction of completed page authorized

Executive Summary

Traffic-related air pollution is an environmental and public health concern that disproportionately impacts populations in disadvantaged communities (DACs). Accelerating the adoption of zero (tailpipe) emissions vehicles (ZEV) has great potential to reduce these harmful emissions and improve health outcomes. This study evaluated whether electric vehicle (EV) adoption in DACs will result in significant emission and exposure reductions along with the associated health benefits when compared to non-DAC communities. The study utilized the Climate and Economic Justice Screening Tool and the United States Department of Transportation's Equitable Transportation Community Explorer tool to identify DACs. Vehicle-induced $PM_{2.5}$ emissions were estimated under varying levels of EV adoption rates for light-duty vehicles (LDVs), medium-duty vehicles (MDVs), and heavy-duty vehicles (HDVs). DACs identified through both classification methods typically experienced higher traffic densities, thereby amplifying their exposure to $PM_{2.5}$ emissions. Results indicated that each EV adoption scenario reduced $PM_{2.5}$ emissions, with the most significant declines observed in scenarios involving high adoption for medium- and heavy-duty EVs. The largest improvements were also observed within urban centers and along major roads within the identified DACs. The findings illuminate the necessity for targeted EV adoption strategies within these communities that extend beyond LDVs to include MDVs and HDVs. Further research should delve deeper into the socio-demographic intricacies of these communities and the potential health benefits of lowered $PM_{2.5}$ concentrations.

Table of Contents

List of Figures

List of Tables

Introduction

Air pollution from traffic-related activities is a persistent environmental and public health issue that has severe consequences for society. Certain communities, particularly disadvantaged communities (DACs), are disproportionately impacted by traffic-related air pollution (TRAP). DACs are more likely to be exposed to higher levels of TRAP, resulting in environmental and health disparities. Socioeconomic factors, physical infrastructure, and land-use patterns have been shown to influence these communities' inequitable exposure to TRAP (Gold and Wright, 2005). Populations living in low-income neighborhoods, marginalized populations, and communities of color experience adverse health outcomes and environmental injustices.

Harmful pollutants emitted from various vehicle types, including nitrogen oxides (NO_x), particulate matter (PM), and volatile organic compounds (VOCs), are associated with poor air quality and health effects (Orban et al., 2016). Therefore, addressing and mitigating challenges posed by TRAP is important. This can be accomplished by decarbonizing the transportation sector (Orban et al., 2016; Khatri et al., 2021). One of the effective and prevalent strategies to reduce vehicular emissions involves the transition to cleaner vehicles, and vehicle electrification plays a significant role in achieving this goal (Orban et al., 2016; Khatri et al., 2021). Electric vehicles (EVs) have the potential to reduce emissions and consequently improve public health outcomes, especially in DACs since they are mostly located near major highways (Bowe et al., 2019; Gelfand et al., 2020).

To assess the benefits of EVs, it is essential to understand their current and future adoption trends (Bowe et al., 2019). Research has demonstrated that EVs are widely being accepted considering the increase in their sales globally, which is driven by factors such as government incentives, environmental awareness, and technological advancements (Helveston et al., 2015). On the other hand, barriers to EV adoption exist (Helveston et al., 2015; Bowe et al., 2019) since DACs may lack access to adequate charging infrastructure in their neighborhoods and EVs are still expensive. Therefore, challenges in EV adoption must be addressed to ensure equitable access to the benefits of EVs. Moreover, prioritizing the electrification of not only light-duty vehicles (LDVs) but also medium- and heavy-duty vehicles (MDVs and HDVs) is necessary for decarbonizing the transportation sector (Mohan et al. 2023). MDVs and HDVs are significant contributors to TRAP, and electrifying them will substantially benefit the environment and health in DACs.

As a result, this study aims to evaluate the impact of TRAP on communities in a metropolitan area by assessing whether different EV adoption scenarios can provide equitable benefits for all populations, especially DACs. The research is particularly relevant in the current setting of EV adoption, which shows a trend of higher adoption rates among higher-income urban dwellers. Hence, potentially leading to exposure disparities in local air pollution. The study aspires to provide new insights and guidance for policymakers, decision-makers, researchers, and stakeholders in their efforts to address environmental justice (EJ) issues and the broader goal of reducing air pollution. Through a comprehensive review of current practices, data collection, and thorough analysis, the study can contribute to the understanding of TRAP's impacts on DACs and explore the potential of EVs in mitigating these impacts.

Background

Ambient air pollution is a significant public health threat globally associated with a range of adverse health outcomes. Over 99 percent of the world's population in 2019 was living in areas that did not meet the World Health Organization (WHO) air quality guidelines levels (WHO, 2022). Besides adversely impacting the health of communities, these pollutants play a major role in climate change. The transportation sector, consisting of both on-road and non-road sources, is a major contributor to ambient air pollution. Long-term exposure to air pollution from traffic-related activities is associated with cardiovascular disease, decreased lung function, asthma, birth defects, and premature mortality, among many others (Boogaard et al., 2022; Environmental Protection Agency

[EPA], 2022a). A recent research study indicated that increases in PM concentrations can negatively impact performance and cognition (Massachusetts Institute of Technology, 2023). Moreover, exposure to TRAP may cause over 300,000 premature deaths globally each year (Anenberg et al., 2019).

The importance of equity in transportation has been increasingly recognized in recent years, encompassing not only access to transportation options but also disparities in exposure to TRAP. Incorporating equity in strategic plans will ensure that all communities, especially DACs, receive unbiased benefits from transportation improvement projects, such as the deployment of EVs (U.S. Department of Transportation [USDOT], 2022a). However, to effectively incorporate equity into transportation decision-making, it is important to understand the concept of environmental justice. EJ refers to the fair treatment and meaningful involvement of all people, regardless of race or socioeconomic status, with respect to the implementation of environmental policies, including those related to transportation (USDOT, 2019). EJ concerns have intensified over the past several years with the nation's renewed focus on equity. The most recent mandate introduced by the federal government is the Justice40 Initiative (USDOT, 2022b). The program is designed to help address inequities experienced by DACs through comprehensive investments in various categories to advance EJ and establish a commitment to equity. The goal is for 40 percent of overall benefits from certain federal investments to flow to DACs. The program defines DACs to include variables such as low income, high unemployment rates, racial and ethnic segregation, high housing and transportation cost burdens, low transportation access, disproportionate environmental stressors, and others (Young et al., 2021). Ultimately, Justice40 will allow USDOT to prioritize projects that benefit DACs, measure their impacts, and bring additional resources to communities most impacted by pollution and climate change.

Decarbonizing the transportation sector is crucial since the transportation sector plays a significant role in greenhouse gas and other air pollutant emissions. This can be achieved by implementing technological advancements, infrastructure improvements, and policy frameworks. Recent legislation, such as the Infrastructure Investment and Jobs Act (IIJA) and Inflation Reduction Act, offer new opportunities to meet the nation's decarbonization goals of net zero emissions by 2050. They focus on provisions that accelerate the deployment of clean technologies to reduce vehicle emissions and improve public health (Alternative Fuels Data Center [AFDC], 2023; Sherlock, 2023). Additionally, the new vehicle pollution standards proposed by the Biden-Harris administration aim to protect public health by avoiding nearly 10 billion tons of CO_2 emissions (White House, 2023). EPA reinforced the administration's goals by introducing the most ambitious pollution standards to date for all vehicle types (EPA, 2023a). These proposed regulations aim to accelerate the EV market and other clean vehicle technologies in the next decade. This study will focus on vehicle electrification as a decarbonization strategy since EVs are among the most widely available alternative fuel vehicles (AFVs) following the IIJA's provisions.

EV adoption can decrease overall TRAP levels and in return support the nation's decarbonization goals. Adopting EVs can lead to the reduction of harmful pollutants, including NO_x, PM, and VOCs, in urban areas, especially for shorter trips in congested regions (Hu et al., 2021; Rizza et al., 2021). A modeling case study in Houston, Texas, showed that moderate electrification has the potential to prevent hundreds of premature deaths, asthma exacerbation days, and school loss days while simultaneously generating economic benefits (Pan & Gao, 2019). In the context of DACs, vehicle electrification can reduce inequities in air pollution exposure (Reichmuth, 2019). A recent EV penetration modeling study by Chang et al. (2023) found that air quality benefits in DACs may be greater than in other communities. EVs can also increase mobility and accessibility to jobs and other local services for DACs. However, the use of EVs in urban areas can potentially shift pollutants from areas near power plant facilities to DACs and rural communities (Bai et al., 2021; Ji et al., 2015). Another study found that individuals below the median income level and some minority communities experience negative environmental benefits from EV adoption compared to other populations (Holland et al., 2019).

Electrification efforts have mostly focused on LDVs; however, it is necessary to extend these efforts to MDVs/HDVs to address the impacts of TRAP. This is primarily because emissions from MDVs/HDVs make up a rapidly growing component of total transportation sector emissions (Hao et al., 2019; EPA, 2022c). Freight volume is anticipated to increase as the U.S. population grows and demand for goods rises (National Environmental Justice Advisory Council, 2009). Shipments of goods in the United States are expected to grow another 45 percent by 2040, potentially leading freight emissions to exceed emissions from all other transportation sectors (EPA, 2022c). Additionally, the Federal Highway Administration (FHWA) predicts that travel by single-unit trucks and combination trucks will grow by 101 percent and 57 percent, respectively, over the next 30 years (FHWA, 2022). Therefore, electrifying MDVs/HDVs can substantially benefit air quality by eliminating harmful emissions. Moreover, pollution from MDVs/HDVs has been shown to disproportionately impact DACs in both urban and rural areas (Houston et al., 2008; Ross et al., 2015; Han et al., 2018). Populations from these communities tend to live, work, or go to school closer to HDV routes, industrial facilities, or ports. Consequently, truck-focused policies can help reduce pollutant exposure disparities and protect public health, especially for DACs located near major truck traffic (Chang et al. 2023).

There is still a knowledge gap in evaluating whether changes in TRAP emissions in the past three decades have led to a change in environmental justice over time (Clark et al., 2017). This is particularly true for exposure by race, ethnicity, and socioeconomic status. Minorities and low-income households are more likely to live near a major road with higher exposure to TRAP. Overall, there is still mixed evidence regarding whether the adoption of EVs will have equitable benefits for all segments of the population, including DACs. Studies, such as Chang et al. (2023) and Sharma et al. (2023), noted that although the air quality benefits associated with increased EV adoption are well-documented, the literature on the distribution of these benefits across all community members is still lacking. One reason for this research gap is that assessing the equity implications of EV adoption scenarios can be challenging since it influences emissions from the transportation, electricity, and manufacturing sectors (Sharma et al., 2023). While many studies have indicated that increased EV charging demand could strain the electricity sector and lead to more power plant emissions that would disproportionately impact DACs, other studies claimed that health benefits associated with fewer vehicle emissions would still be recognized by communities with low EV adoption rates. There is also considerable variation in the terminology used by different studies to define DACs. Some studies refer to these populations as "environmental justice communities," "low-income communities," or "minority communities," thus making it difficult to compare findings across studies. Although the Justice40 Initiative has provided a list of variables that are used to define DACs, not all studies consider each of these variables, especially if they were conducted prior to Justice40's introduction.

Methodology

The study area for this research was selected after DACs were identified at the census tract level using established tools. The next step involved determining the different EV penetration scenarios that will be evaluated in this study. The traffic demand model (TDM) of the study area was then obtained, and input data required to run the different scenarios were prepared. Collecting and processing traffic data is an essential element of any TDM. Following the TDM runs, the total running exhaust emissions were estimated for all scenarios. Subsequently, dispersion modeling was completed to assess the exposure to TRAP at the census tract level. Finally, a health assessment was incorporated into the analysis.

The North Central Texas Council of Governments (NCTCOG) region was selected as a case study for this research, and it consists of the following 16 counties: Collin, Dallas, Denton, Ellis, Erath, Hood, Hunt, Johnson, Kaufman, Navarro, Palo Pinto, Parker, Rockwall, Somervell, Tarrant, and Wise. The largest cities in the region are Dallas, with approximately 1.3 million people; Fort Worth, with more than 970,000 people; Arlington, with more than 400,000 people; and Plano, with almost 293,000 people.

The next step in this study involved the identification of DACs, which is a requirement for state agencies that receive federal funding, as per Executive Order 12898 (EPA, 2023b). Identifying DACs will address the disproportionate and adverse impacts experienced by these communities from implementing programs and policies. In addition, the recent Executive Order 14008 (EPA, 2023c), reiterates a commitment to turn DACs that are historically marginalized and overburdened into thriving communities by investing in a clean energy economy and securing equity. As a result, various national- and state-level classification models were developed to identify and measure the environmental impacts on DACs in the United States. Examples include EJScreen (EPA, 2023d), the Climate and Economic Justice Screening Tool (CEJST) (USDOT, 2023), USDOT's Transportation Disadvantaged Census Tracts, Equitable Transportation Community (ETC) Explorer tool (USDOT, 2023), and the state-level Texas Environmental Justice Explorer tool (Climate Cabinet Education, 2023). These tools were compared to select the optimal identification approaches that fit the purpose of this study. The CEJST and USDOT ETC Explorer classification methods were selected since the study utilizes the Justice40 Initiative definition of DACs. Figure 1 provides a visual diagram of the overall methodology implemented.
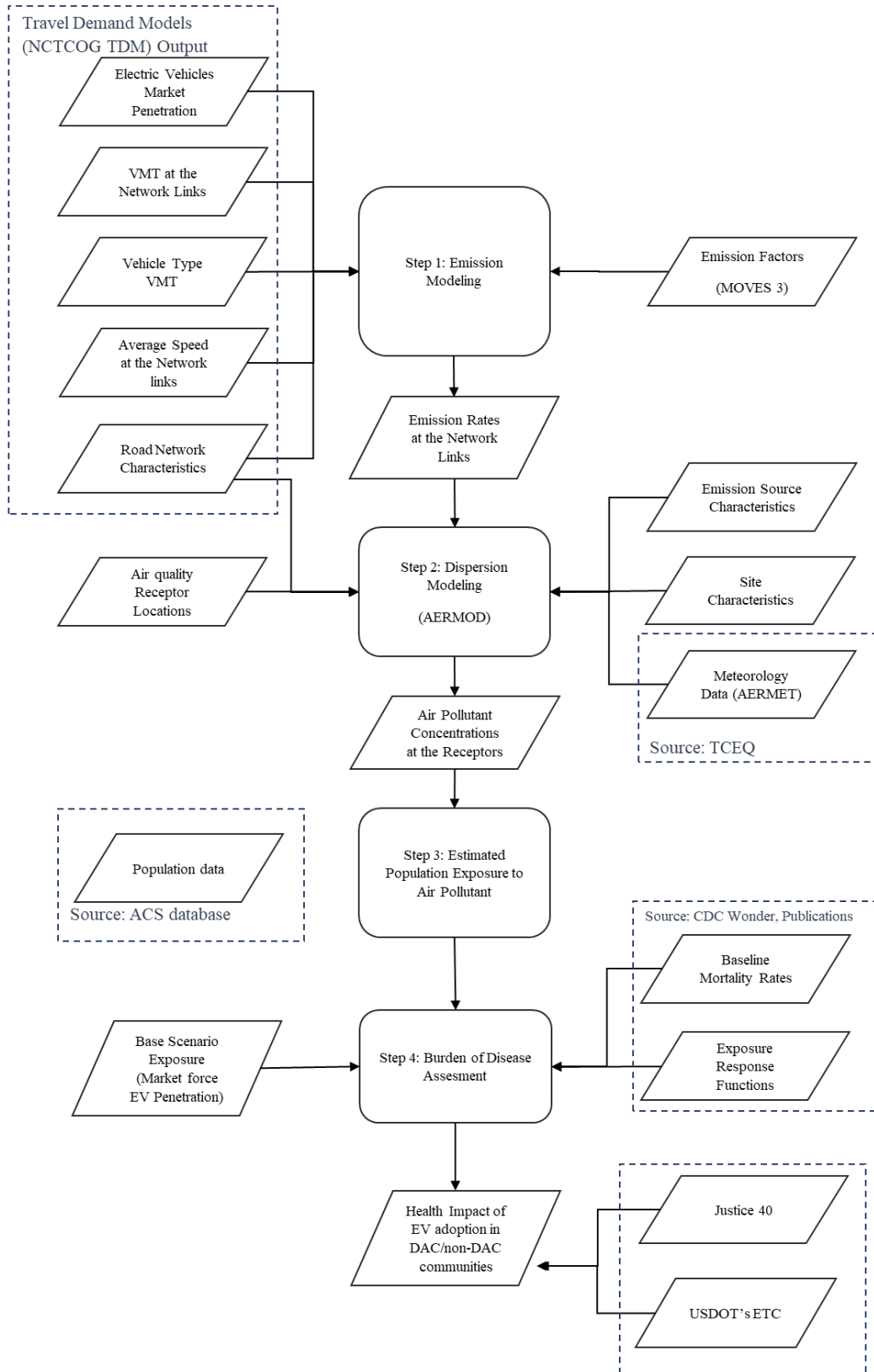
Figure 1. Research study methodology flowchart.

Climate and Economic Justice Screening Tool

The CEJST is a geospatial mapping tool that can be used to identify DACs across the United States and to support the goals of the Justice40 Initiative. The tool is intended to be used by federal agencies to help them comply with requirements under the Justice40 Initiative and ensure they are reaching DACs in their investments. CEJST identifies over 27,000 communities across the United States as being "disadvantaged" or "partially disadvantaged" if the census tract meets the threshold for one or more environmental or climate indicators and is above the threshold for socioeconomic indicators (White House CEQ, 2022). The indicators of burden include low income, poverty, climate risks, $PM_{2.5}$ levels, transportation barriers, traffic proximity and volume, housing cost, etc. A beta version of the tool was launched in February 2022, applying lessons learned from EJScreen before launching version 1.0 in November 2022. Table 1 provides a list of indicators that are used in the DAC identification process in the CEJST. These indicators are summarized into eight distinct categories, as shown in the table. For a census tract to be identified as disadvantaged, the following thresholds for at least one of the eight categories must be met (USDOT, 2023):

- At or above the 90th percentile for one or more of the indicators in a category,
- At the same time, the income level must be at or above the 65th percentile.

Census tracts are also considered disadvantaged if they are surrounded by DACs and meet at least the 50th percentile for income level. In addition, if a census tract contains land within the boundaries of Federally Recognized Tribes, then these communities will be displayed in the tool as partially disadvantaged.

Table 1. CEJST Categories and Indicators of Burden.

Categories	Indicators
Climate change	Expected agriculture loss rate
	Expected building loss rate
	Expected population loss rate
	Projected flood risk
	Projected wildfire risk
Energy	Energy cost
	$PM_{2.5}$ in the air
Health	Asthma
	Diabetes
	Heart disease
	Low life expectancy
Housing	Historic underinvestment
	Housing cost
	Lack of green space
	Lack of indoor plumbing
	Lead paint
Legacy pollution	At least one abandoned mine land
	At least one formerly used defense site
	Proximity to hazardous waste facilities
	Proximity to superfund sites
	Proximity to risk management plan facilities
Transportation	Diesel PM exposure
	Transportation barriers
	Traffic proximity and volume
Waste and wastewater	Underground storage tanks and releases
	Wastewater discharge
Workforce development	Linguistic isolation
	Low median income
	Poverty
	Unemployment

Equitable Transportation Community Explorer Tool

The ETC Explorer tool is an equity screening and mapping tool that was developed to explore the burdens experienced by DACs due to an underinvestment in transportation. It was designed to complement the CEJST by specifically highlighting transportation-related components of disadvantage. A score for each of the following components—transportation insecurity, climate and disaster risk burden, environmental burden, health vulnerability, and social vulnerability—is calculated from a combination of indicators and datasets. Then, these individual scores are incorporated to create an overall index score. This tool can be used by state departments of transportation and metropolitan planning organizations (MPOs) when applying for USDOT grant programs to ensure they are meeting the needs of identified DACs. USDOT released the finalized version of the ETC Explorer in May 2023 to support the agency's commitment to the Justice40 Initiative.

The indicators used in the ETC Explorer DAC identification method are divided into five categories, as summarized in Table 2. The tool calculates the cumulative impacts of disadvantage across all census tracts and does not require a category to exceed a certain number of set thresholds as in the CEJST. The following is a summary of how the tool calculates the cumulative scores (USDOT, 2023):

- Indicators' data are normalized and transformed to a standard range between 0 and 1 using min-max scaling. Normalization will enable a simple comparison considering the indicators have different units of measurement.
- The normalized indicators are then ranked and summed for each component, hence creating a composite score for each component. The component scores of each census tract are compared to all other census tracts nationally using percentile ranking.
- Census tracts in the 0 percentile are the least disadvantaged and those in the 100th percentile are the most disadvantaged.
- The next step involves calculating an overall score by summing the ranked component scores across all components and then ranking the overall score using percentile ranking to generate the final index score rank.
- A census tract is designated as DAC if the overall index score places it in the 65 percent (or higher) of all U.S. census tracts.

Table 2. ETC Explorer Tool Categories and Indicators of Burden.

Components	Indicators
Transportation insecurity	Transportation access
	Transportation cost burden
	Transportation safety
Environmental burden	Ozone level
	PM$_{2.5}$ level
	Diesel PM level
	Air toxics cancer risk
	Hazardous sites proximity
	Toxics release sites proximity
	Hazardous waste treatment, storage, and disposal facilities proximity
	Risk management sites proximity
	Coal mines proximity
	Lead mines proximity
	Pre-1980's housing
	High-volume road proximity
	Railways proximity
	Airport proximity
	Ports proximity

	Impaired surface proximity
	200% poverty line
	No high school diploma
	Unemployment
	House tenure
	Housing cost burden
Social vulnerability	Uninsured
	Lack of internet access
	Endemic inequality
	65 or older
	17 or younger
	Disability
	Limited English proficiency
	Mobile homes
	Asthma prevalence
	Cancer prevalence
Health vulnerability	High blood pressure prevalence
	Diabetes prevalence
	Low mental health prevalence
	Anticipated changes in extreme weather
Climate and disaster risk burden	Annualized disaster losses
	Impervious surfaces

Outputs from the CEJST and ETC Explorer were compared in terms of census tracts that met the requirements of the methodologies applied in the tools to identify DACs in the NCTCOG region. A summary of the descriptive statistics are presented in Table 3. The table also compares the data sources for some of the key and common parameters used in the tools. Moreover, the maps in **Error! Reference source not found.** exhibit a visual representation of DACs classified using (a) CEJST and (b) the ETC Explorer tool.

Table 3. DAC and Data Source Comparison between CEJST and ETC Explorer Tool for NCTCOG Region.

Parameters	CEJST	USDOT ETC Explorer Tool
Total Number of Census Tracts	1,330	1,730
Number of Census Tracts: DACs	450	494
Number of Census Tracts: Non-DACs	880	1,236
Percent of DACs	34.49%	28.55%
Total Population	7,507,217	7,641,334
Percent of Population in DACs	30.74%	28.18%
Percent of Population in Non-DACs	69.26%	71.82%
Census Data Source	ACS 2015–2019	ACS 2016–2020
Geography Boundaries Data Source	Census tract boundaries from 2010	Census tract boundaries from 2020
Health Data Source	CDC Places 2016–2019	CDC Places 2020
$PM_{2.5}$ Data Source	Model and monitor data from 2017	EPA's EJScreen 2022

(b) CEJST
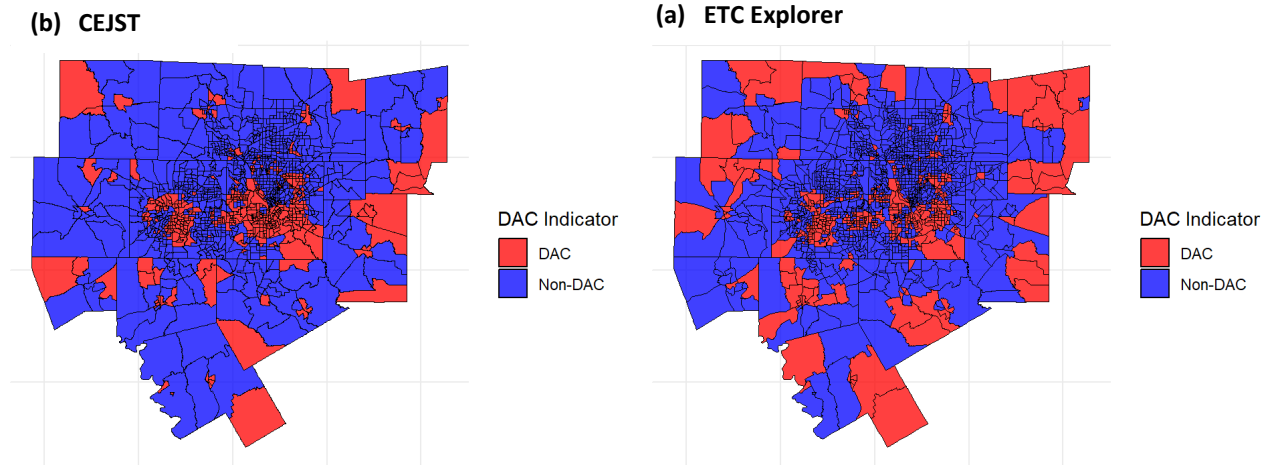
(a) ETC Explorer

Figure 2. Census tracts identified as DACs in NCTCOG using (a) CEJST and (b) ETC Explorer tool.

Electric Vehicle Penetration Scenarios

The scenarios developed for this study were based on the following Texas-based EV penetration rates:

- Existing share of EVs by vehicle class in 2019.

    - 0.6 percent for LDVs—obtained from projection tool developed by Texas A&M Transportation Institute (TTI) researchers.
    - 0.0 percent for MDVs—obtained from ERCOT EV allocation study (Sergici et al., 2022).
    - 0.0 percent for HDVs—obtained from ERCOT EV allocation study (Sergici et al., 2022).

- Market force projection of EVs by vehicle class in 2026.

    - 3.9 percent for LDVs—obtained from projection tool developed by TTI researchers.
    - 1.4 percent for MDVs—obtained from ERCOT EV allocation study (Sergici et al., 2022).
    - 0.9 percent for HDVs—obtained from ERCOT EV allocation study (Sergici et al., 2022).

- Hypothetical high projection of EVs by vehicle class in 2026.

    - 25.0 percent for LDVs.
    - 25.0 percent for MDVs.
    - 25.0 percent for HDVs.

When comparing scenarios, hypothetical projections will allow researchers to explore potential outcomes based on different assumptions. Therefore, the potential impacts of the various EV scenarios can be simulated and analyzed using hypothetical high projections in this study. Hypothetical projections are not meant to predict the future with certainty, rather they serve to inform decision-making processes based on data-driven analysis.

Based on these projection rates, the following four scenarios were developed:

1. **Baseline:** This scenario uses the market force projections for both light-duty and medium/heavy-duty EV penetration rates. The model year for this scenario is set to the future year of 2026.

2. **Light-Duty High Adoption:** This scenario assumes a higher adoption rate for light-duty EVs as indicated by the hypothetical high projection. The penetration rate for medium/heavy-duty EVs remains the same as the market force projection. The model year for this scenario is also set to 2026.

3. **Medium- and Heavy-Duty High Adoption:** This scenario assumes a higher adoption rate for medium/heavy-duty EVs as indicated by the hypothetical high projection. The penetration rate for light-duty EVs remains the same as the market forces projection. The model year for this scenario is also set to 2026.

4. **Both High Adoption:** This scenario assumes a higher adoption rate for both light-duty and medium/heavy-duty EVs, as indicated by the hypothetical high projection. The model year for this scenario is set to 2026.

These scenarios will explore the impacts of varying levels of EV adoption on emissions, exposure, and health outcomes, particularly in DACs. The use of different penetration rates for the multiple vehicle classes can capture a range of possible future conditions and their implications for environmental justice and public health.

Air Quality Modeling

The process of air quality modeling comprises several steps, including traffic modeling, emissions estimation, and dispersion modeling. Table 4 provides an overview of the set of considerations/assumptions used in each step of air quality modeling.

Table 4. Air Quality Modeling Parameters.

Modeling and Analysis Parameters	Description
Traffic Modeling	
Study Area	NCTCOG region
Model Year	2026
Traffic Data	NCTCOG travel demand model—calibrated and validated
Number of Links	43,087
Traffic Data by Time Period	Morning peak, evening peak, and off-peak hours
Traffic Data by Vehicle Class	LDVs, MDVs, and HDVs
Time Period Split into Hours	By hourly activity factors
Model Output	Vehicle miles traveled, speed, and traffic density at the link level
Emission Modeling	
Modeling Tool	Motor vehicle emission simulator third version (MOVES3)
Modeled Pollutant	$PM_{2.5}$ due to its significant health implications
Emission Rates (g/mile)	MOVES3 emission rate lookup tables at the district level (Dallas and Fort Worth regions)
Model Output	Total emissions at the link level
Dispersion Modeling	
Modeling Tool	AERMOD
Meteorological Data	Texas Commission on Environmental Quality preprocessed 2019 data for all 365 days
Receptor Placement	50, 150, and 300 meters from the highway centerline, and mesh of gridded receptors at 500 meters and 1-kilometer distance
Total Number of Receptors	88,783
Model Output	Pollutant concentration in $\mu g/m^3$

Exposure Assessment

It is important to estimate the exposure of the population residing within each census tract to $PM_{2.5}$. In the absence of specific residential location data within each census tract or a detailed population grid, it was assumed

that the population was evenly distributed within each census tract. Therefore, the population exposed to PM$_{2.5}$ can be estimated by determining the area within a census tract that corresponds to each exposure level.

Figure 3 provides an example of a census tract (C_i,) that is divided into various exposure zones. The area A_{grid} represents a grid where the population is exposed to the PM$_{2.5}$ concentration level measured at M_{grid} (as shown in the purple area). Similarly, the population residing within the area $A_{150-300}$ is exposed to the concentration level measured at $M_{150-300}$ (as shown in the beige area). Spatial analysis tools were used to determine these exposure levels and corresponding areas.
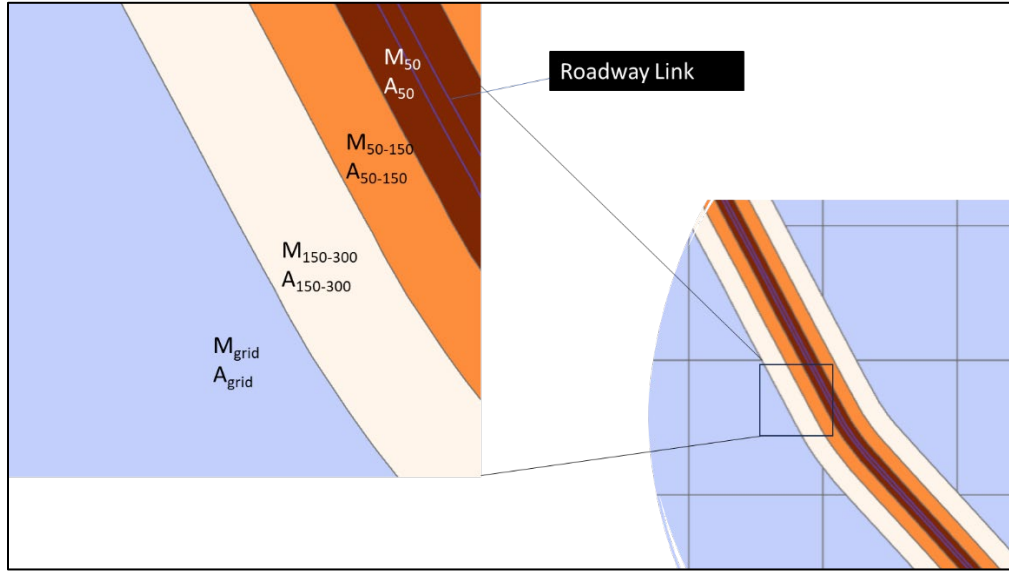
Figure 3. Exposure levels in each census tract (C$_i$).

Health Impact Assessment

The exposure levels between the baseline scenario and the other EV adoption scenarios were compared. The health impacts of EV implementation were estimated using a standard Burden of Disease (BoD) assessment framework, which has been utilized previously in related literature (Mueller et al., 2016).

Inputs to the BoD model include the concentrations of PM$_{2.5}$ and the baseline all-cause mortality rate in the study area. Subsequently, the difference in relative risk (RR_{diff}) of all-cause mortality between the baseline and various EV adoption scenarios can be estimated using Equation 1.

$$RR_{diff} = RR \times \frac{(E_{Baseline} - E_{EV\ Adoption\ Scenario})}{RR_{unit}} \tag{1}$$

Where *RR* is the relative risk obtained from the exposure-response function (ERF) derived from a systematic review and meta-analysis conducted by Chen and Hoek (2020). *RR* is equivalent to 1.08. This value applies to ambient PM$_{2.5}$ from all sources and not specifically to traffic-related PM$_{2.5}$. This is a common limitation in TRAP health impact assessment studies. *E$_{Baseline}$* and *E$_{EV\ Adoption\ Scenario}$* represent the PM$_{2.5}$ concentration levels under the baseline and other EV adoption scenarios, respectively. *RR$_{unit}$* is the exposure unit of the relative risk derived from the original ERF for all-cause mortality.

Next, the population attributable fraction (PAF) can be calculated using Equation 2. PAF represents the proportion of premature deaths attributable to PM$_{2.5}$, based on the difference in PM$_{2.5}$ concentration levels between the baseline and other EV adoption scenarios.

$$PAF = \frac{RR_{diff} - 1}{RR_{diff}} \qquad (2)$$

Finally, the number of premature deaths prevented per million people (i.e., potential health benefits) in each census tract can be estimated using Equation 3.

$$Premature\ Deaths\ Prevented\ Per\ Million = PAF \times Million\ People \qquad (3)$$

Results and Discussion

This section will compare traffic characteristics, estimated emissions, exposure levels, and health benefits between DACs and non-DACs that were identified using the two classification methods and across all EV adoption scenarios.

Traffic Characteristics

For a fair comparison, baseline traffic density per square mile was calculated and assessed. Vehicle miles travelled (VMT) for each hour of the day on all links was aggregated within a census tract and then divided by the area of the census tract. Figure 4 (a) and (b) depict the traffic density of LDVs across different hours of the day and DAC indicators, as classified by both the CEJST and ETC Explorer tool. Both DAC classification tools show that DAC regions have higher vehicle densities throughout the day, indicating a higher potential exposure to TRAP.

Similarly, the traffic density of MDVs/HDVs across different hours of the day and DAC indicators are illustrated in Figure 5 (a) and Figure 5(b). Mirroring the LDV patterns, both DAC classification tools consistently show that DAC regions have higher MDV/HDV densities, implying a potentially higher TRAP exposure risk for these communities. Moreover, the traffic density mean values between the DACs and non-DACs were compared for each hour using a t-test. Significance figures for each hour are indicated on top of the box plots. The convention for statistical significance shown on the plots is as follows:

- ns: not significant.
- One asterisk (*): p-value less than 0.05.
- Two asterisks (**): p-value less than 0.01.
- Three asterisks (***): p-value less than 0.001.
- Four asterisks (****): p-value less than 0.0001.

Overall, findings suggest a consistent trend of higher traffic densities in DAC regions, regardless of vehicle type or the classification method used to identify DACs. This pattern holds true across different times of the day, indicating a higher exposure to traffic for DAC residents. In addition, the difference in traffic densities between DACs and non-DACs was greater during the morning peak hours compared to the afternoon peak hours. The percent change in traffic densities between DACs and non-DACs for LDVs for every hour varied between 29 percent and 38 percent. This difference was greater for MDVs and HDVs since it varied between 37 percent and 44 percent. This shows that DACs tend to have higher MDV and HDV traffic when compared to non-DACs. The t-test confirmed these results, showing significant change for MDVs and HDVs for all hours of the day when compared to LDVs. The traffic densities of LDVs and MDVs/HDVs were further assessed to determine which vehicle type had more impact on DACs. As a result, an overall percent difference in traffic density between DACs and non-DACs was computed across the entire day for all vehicle types and both DACs classification tools, as represented in Figure 6. Notably, MDVs and HDVs demonstrated a higher percent change in traffic density than LDVs. The t-test confirmed that the difference between the vehicle types is statistically significant.
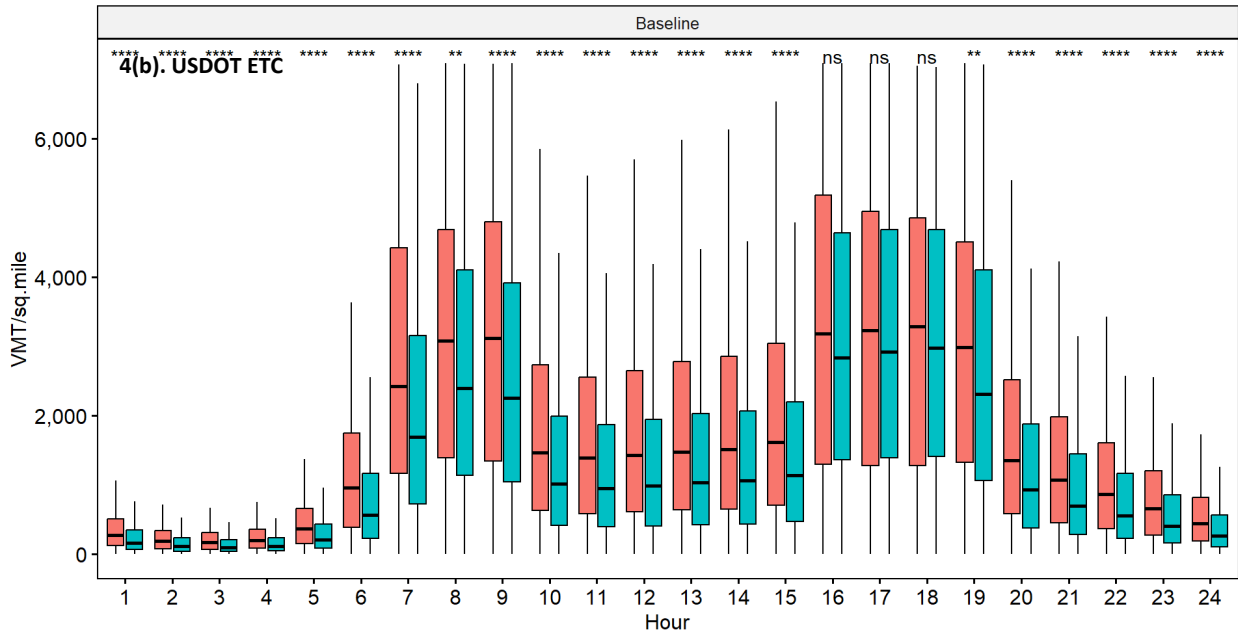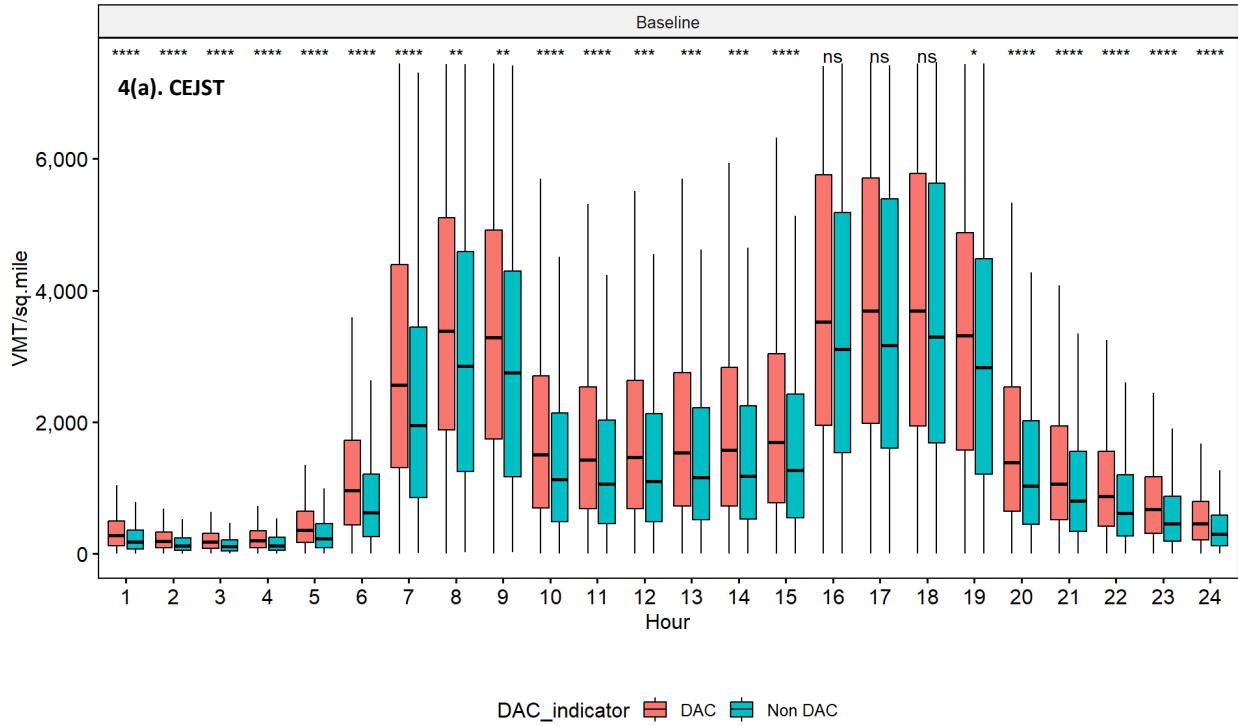
Figure 4. LDV traffic density across different hours for DACs and non-DACs as classified by (a) CEJST and (b) ETC Explorer tool.
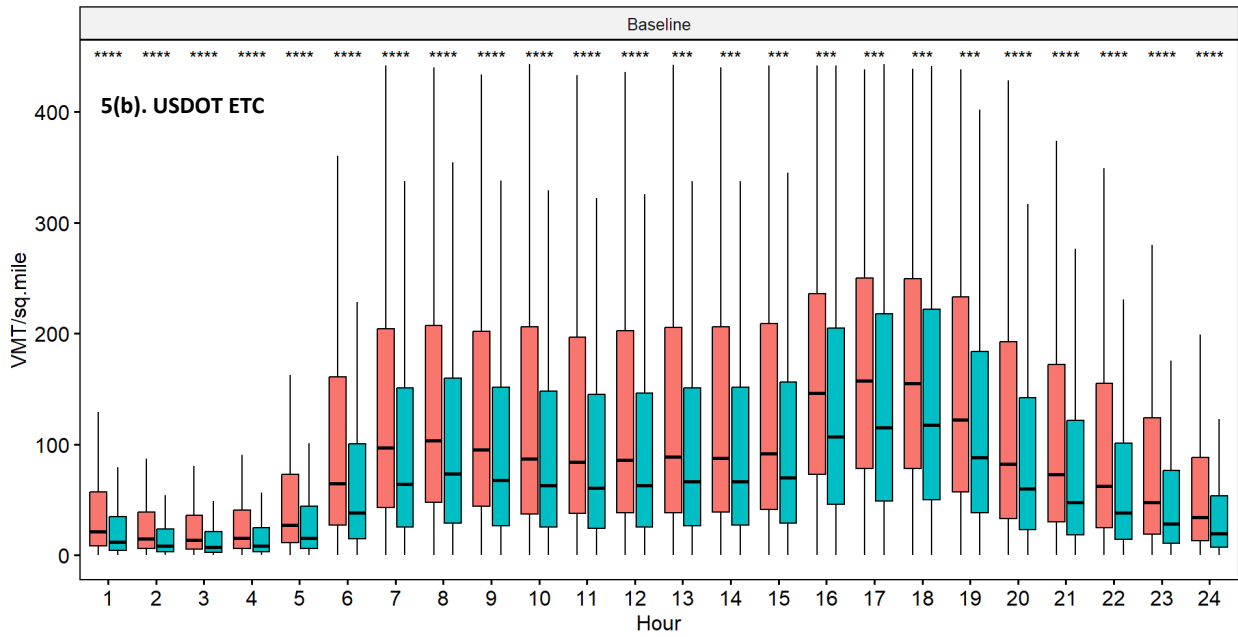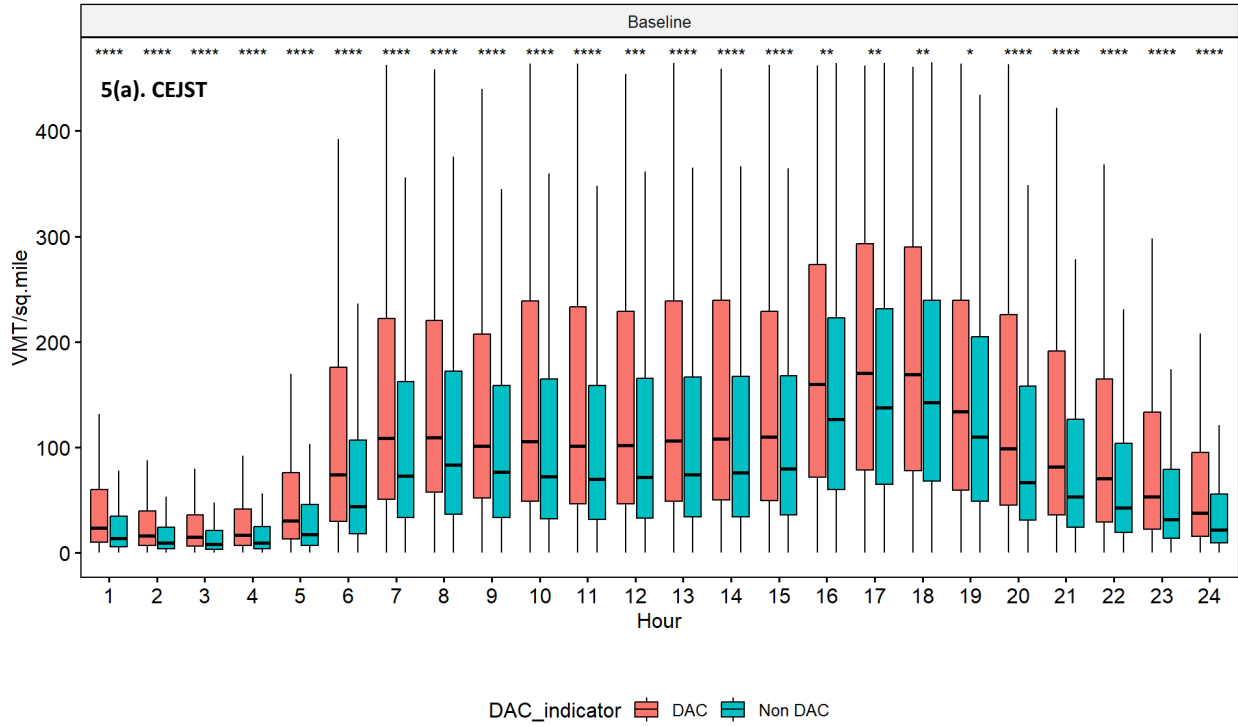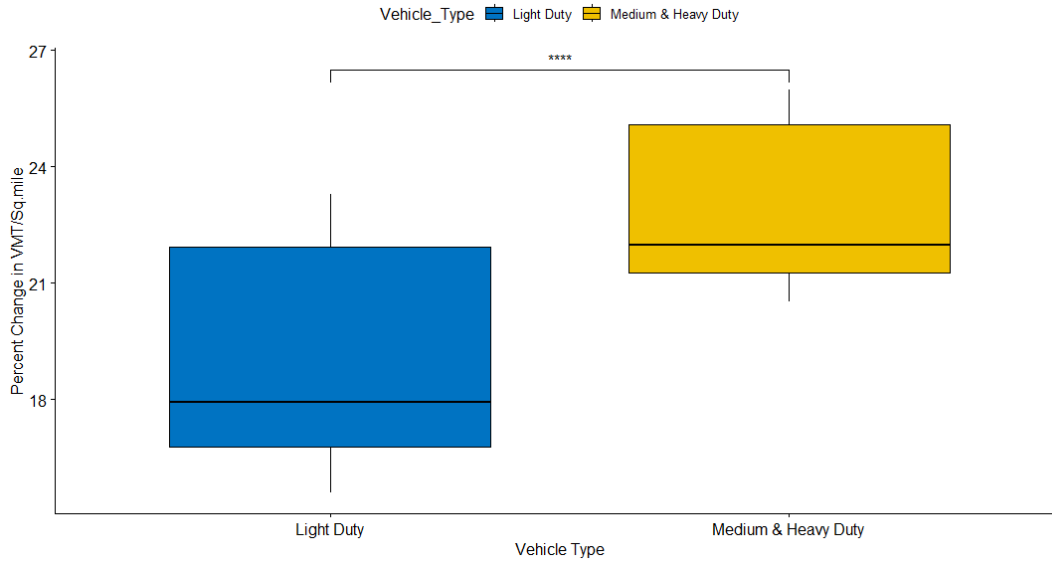
Figure 5. MDV and HDV traffic density across different hours for DACs and non-DACs as classified by (a) CEJST and (b) ETC Explorer tool.

Figure 6. Comparison of overall percent change in traffic density between DACs and non-DACs by vehicle type.

The impact of baseline traffic density on various levels of income within DACs was also investigated in this section. The income levels were defined by the percentage of population living below 200 percent of the poverty threshold. Census tracts classified as disadvantaged using the CEJST and ETC Explorer were categorized into three groups: Low (65th percentile and above), Lower (between 80th and 90th percentile), and Lowest (90th percentile and above). Figure 7 (a) and (b) represent the traffic density of LDVs by hour of the day and income level, categorized by the CEJST and ETC Explorer classification methods, respectively. Traffic densities varied by time of day but did not significantly differ across the different income levels for both DAC classification methods. A similar trend was observed for MDVs and HDVs, as shown in Figure 8 (a) and (b). Therefore, these findings suggest that the impact of traffic was uniformly distributed across different income levels within DACs. Since income level did not show significant disparity in traffic density between DACs and non-DACs, it was excluded as a parameter to compare further results.
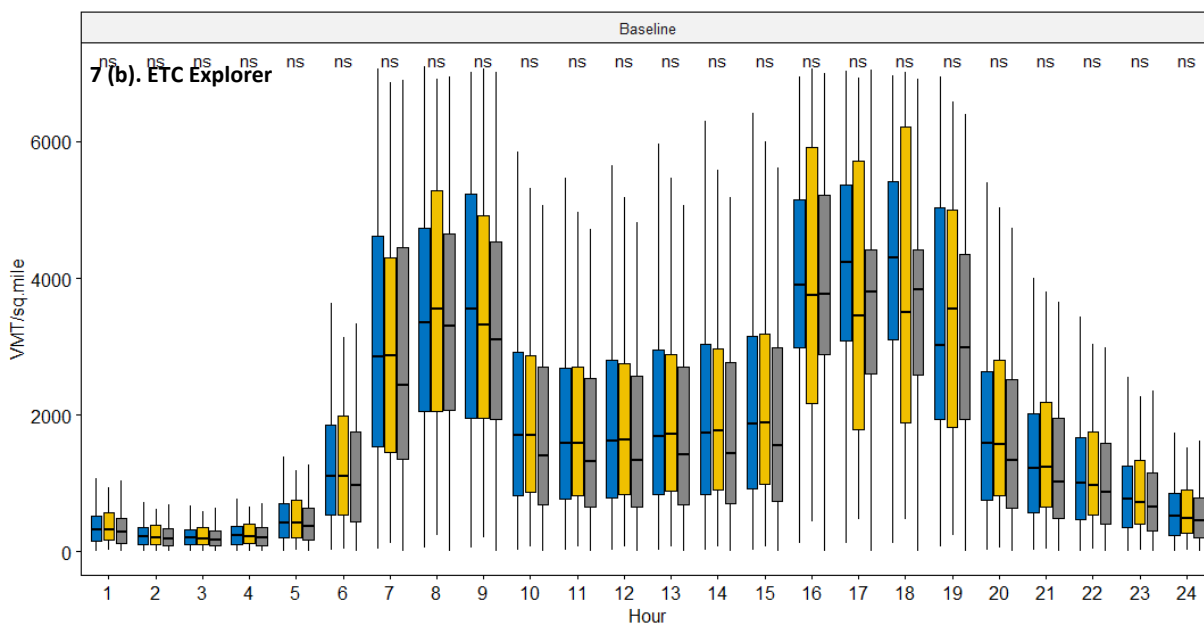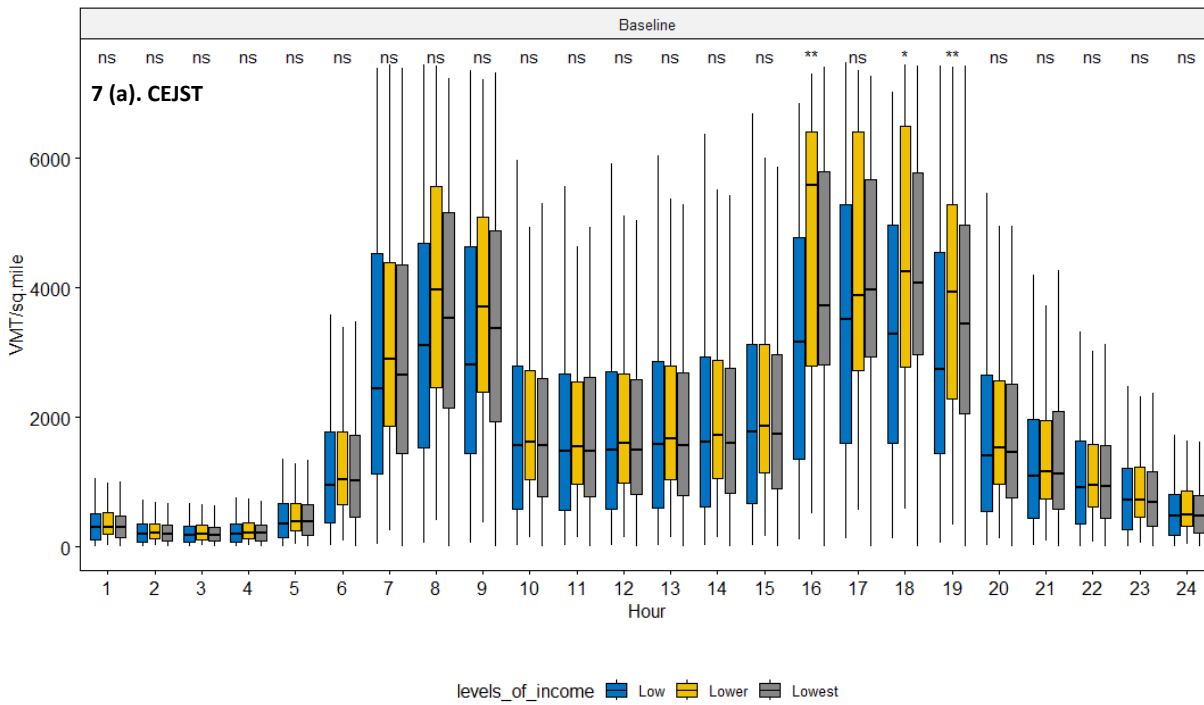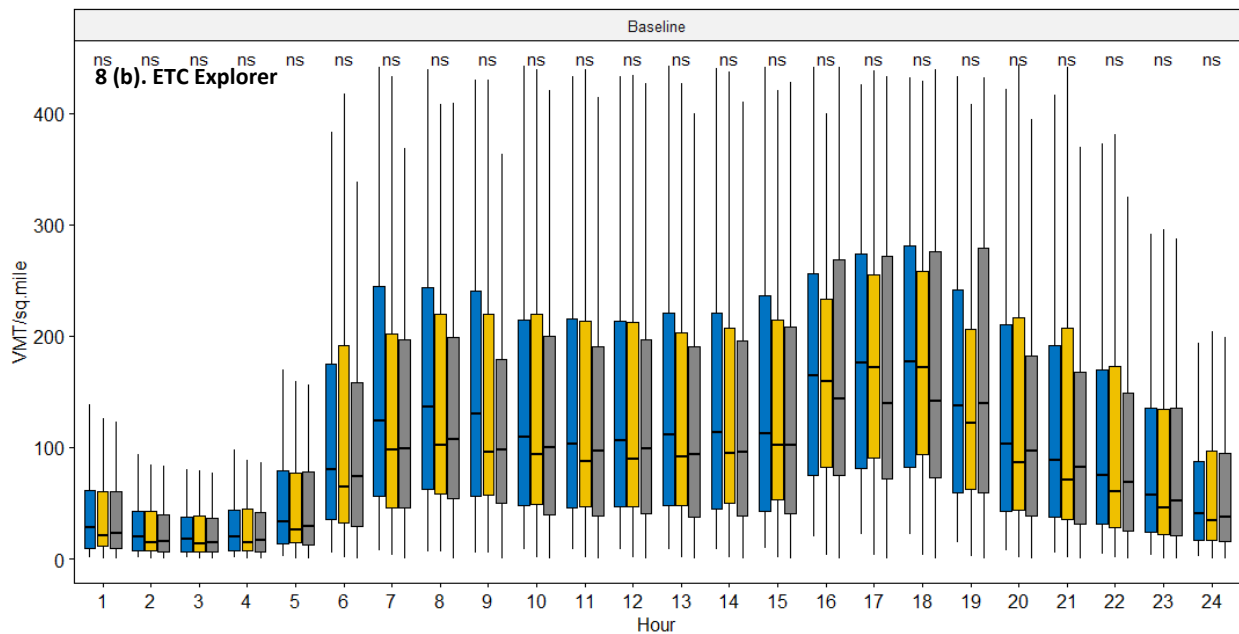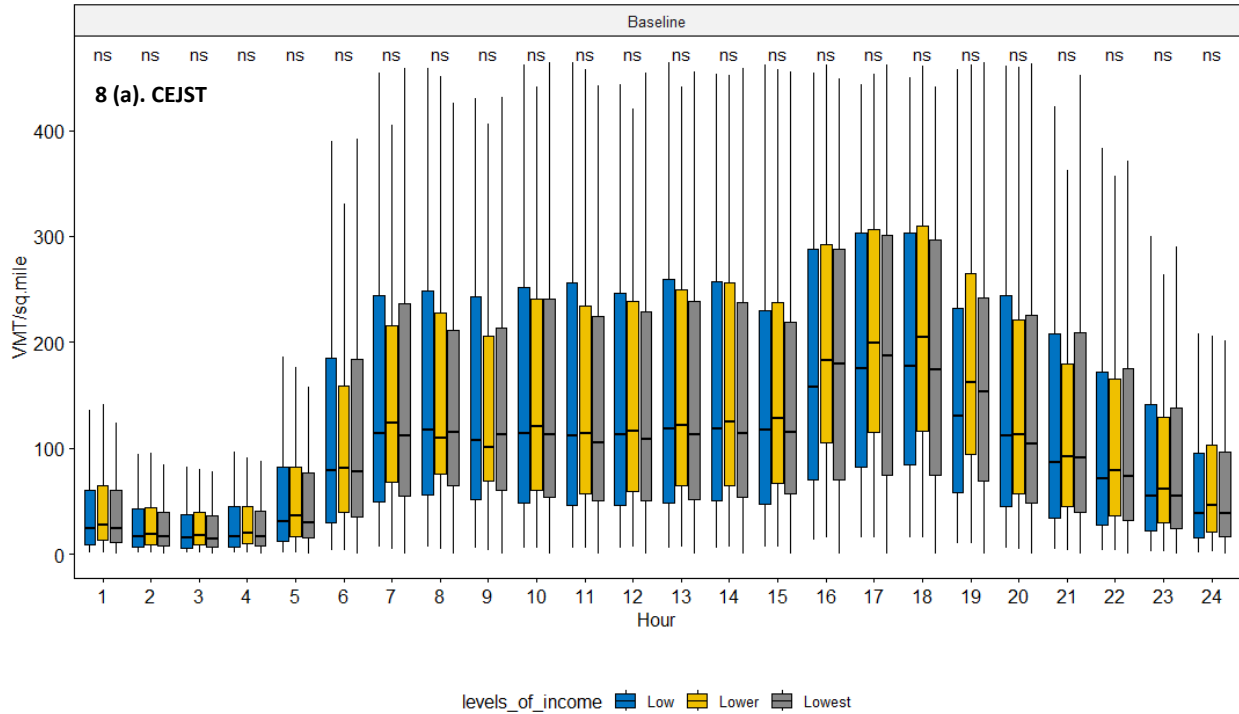
Figure 7. LDV traffic density across different hours of the day and income levels within DACs as classified by (a) CEJST and (b) ETC Explorer tool.

Figure 8. MDV and HDV traffic density across different hours of the day and income levels within DACs as classified by (a) CEJST and (b) ETC Explorer tool.

Effects of EV Adoption on Emissions, Exposure, and Health

This section provides an analysis of the impacts of EV adoption scenarios on the reduction in emissions and exposure to $PM_{2.5}$ exhaust emissions as well as the consequent health outcomes in terms of premature deaths avoided. The analysis considers the comparisons across different EV penetration scenarios, the two distinct DAC classification methods, and DAC indicators.
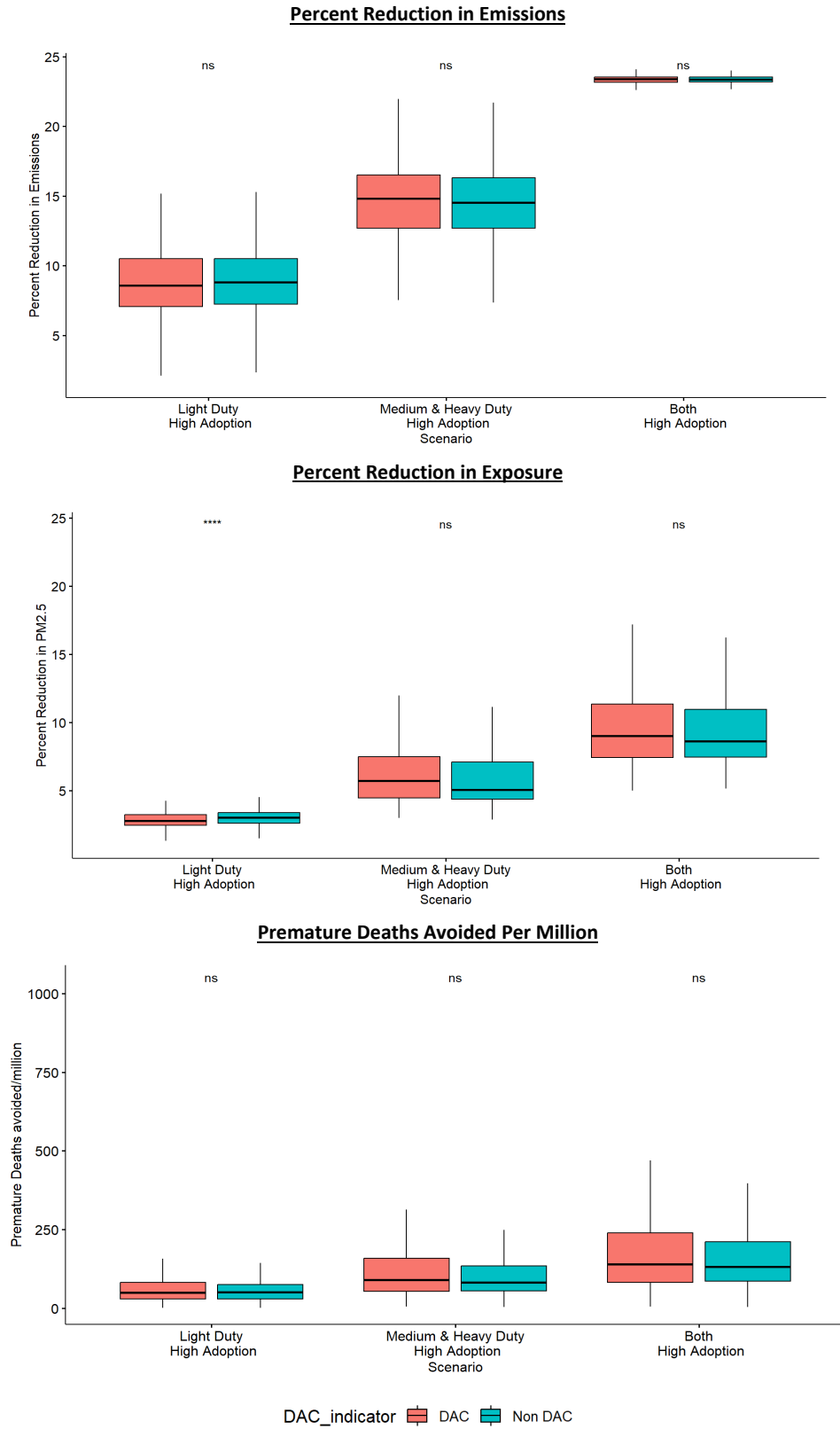
The comparisons were made by applying the following steps:

- Calculate total emissions per square mile: Emissions from each link were aggregated within a census tract for all hours of the day and then divided by the area of the census tract.
- Calculate exposure per square mile: Population-weighted $PM_{2.5}$ exposure concentrations from the AERMOD dispersion modeling results were divided by the area of the census tract.
- Calculate the percent reduction in emissions by comparing the total emissions per square mile of the different EV adoption scenarios to the baseline.
- Calculate the percent reduction in $PM_{2.5}$ exposure by comparing the exposure per square mile of the different EV adoption scenarios to the baseline.
- All the above steps were accomplished for the DAC indicators identified using the two tools and across the different EV penetration scenarios.
- Finally, the health outcomes were assessed in terms of avoided premature deaths per million people for each scenario relative to the baseline.

For the CEJST DAC classification method, as shown in Figure 9, the results were as expected for the hypothetical high adoption rates for all vehicle types. This scenario generated the highest benefits in terms of emission and exposure reductions along with associated health benefits. Another observation was the impact of the medium- and heavy-duty high adoption scenario, which offered substantial benefits across all parameters—emissions, exposure, and health—when compared to the light-duty high adoption scenario. This is an essential finding given the current policy and technology focus on light-duty EVs. Therefore, these findings highlight the importance of focusing electrification efforts on MDVs and HDVs.

The impact of EV adoption scenarios on emission, exposure, and health across DAC indicators using the ETC Explorer classification method showed similar trends as the CEJST, as presented in Figure 10. Results also emphasized the importance of medium- and heavy-duty high adoption. All scenarios indicated a higher reduction in emissions and $PM_{2.5}$ exposure in DACs. This reaffirms that the benefits of EV adoption can be enhanced through a greater focus on MDVs and HDVs. Health benefits under the ETC Explorer classification method highlight the advantages of the medium- and high-duty high adoption scenario, which were notably higher than the light-duty high adoption scenario.

In summary, findings from this study underscore the importance of medium- and heavy-duty EV adoption in reducing emissions, improving air quality, and enhancing health outcomes, especially in DACs. While light-duty EVs have been the focus of policy and technological advancements, the substantial benefits of medium- and heavy-duty EV adoption should not be overlooked. These outcomes have significant implications for policymaking, featuring the need for a balanced approach that considers all vehicle classes in the transition towards a net zero emission transportation sector.

Percent Reduction in Emissions

Percent Reduction in Exposure

## Premature Deaths Avoided Per Million

Figure 9. Effects of EV adoption scenarios on emission, exposure, and health for DACs vs. non-DACs as classified by CEJST.
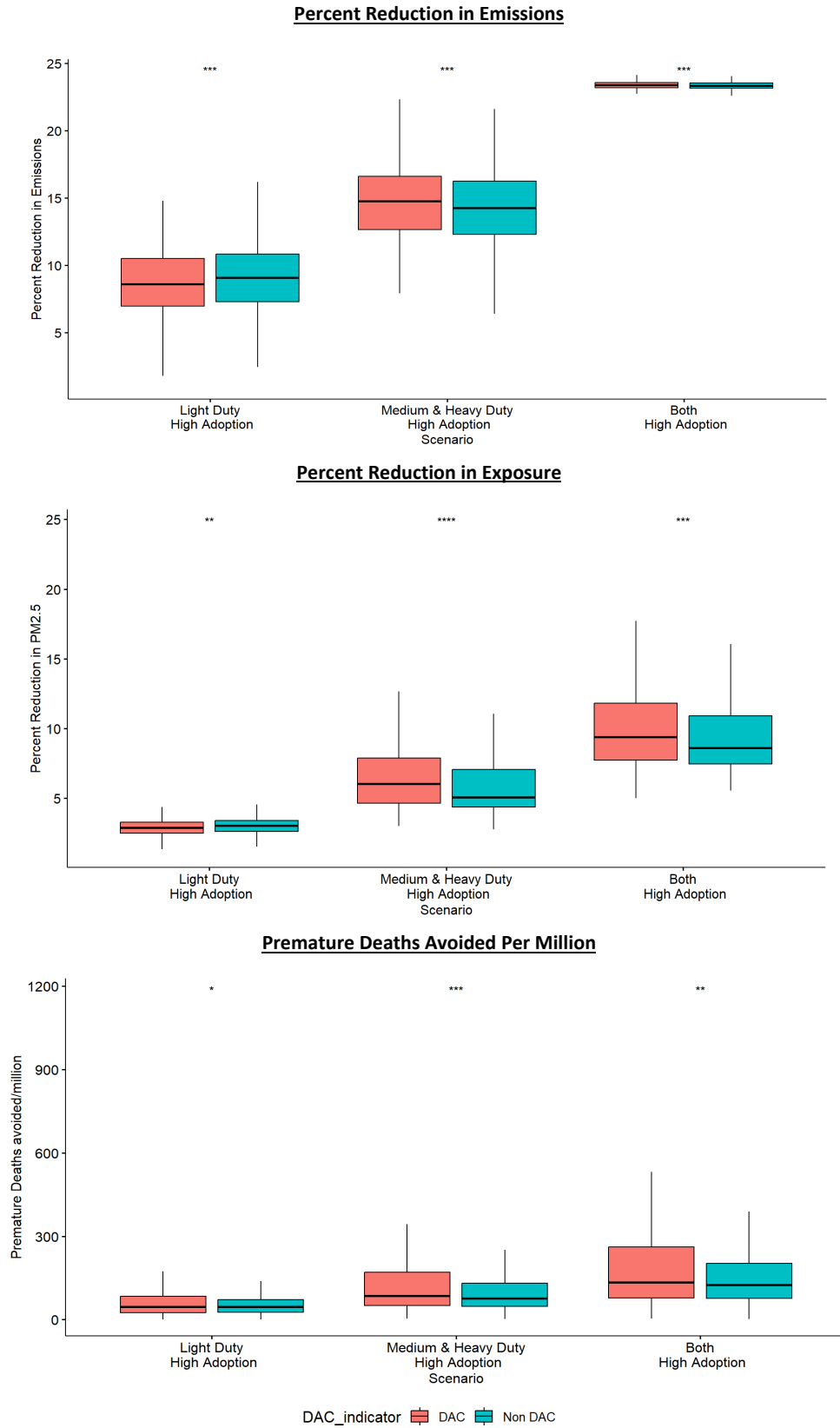
Figure 10. Effects of EV adoption scenarios on emission, exposure, and health for DACs vs. non-DACs as classified by ETC Explorer tool.

Finally, spatial visualization was used to provide geographical context for the impacts of EV adoption scenarios across all census tracts in the NCTCOG region. Three sets of maps were generated for each classification method, Figure 11 for CEJST and Figure 12 for ETC Explorer tool, each depicting the impacts in terms of emissions reduction, reduction in exposure to PM$_{2.5}$, and health benefits, respectively. Census tracts were color coded to distinguish between DACs (coded in red) and non-DACs (coded in blue). The intensity of the colors represent the magnitude of emissions, exposure, and health benefits. Areas with darker shades indicate greater reductions in emissions and exposure, as well as greater number of premature deaths avoided due to EV adoption.
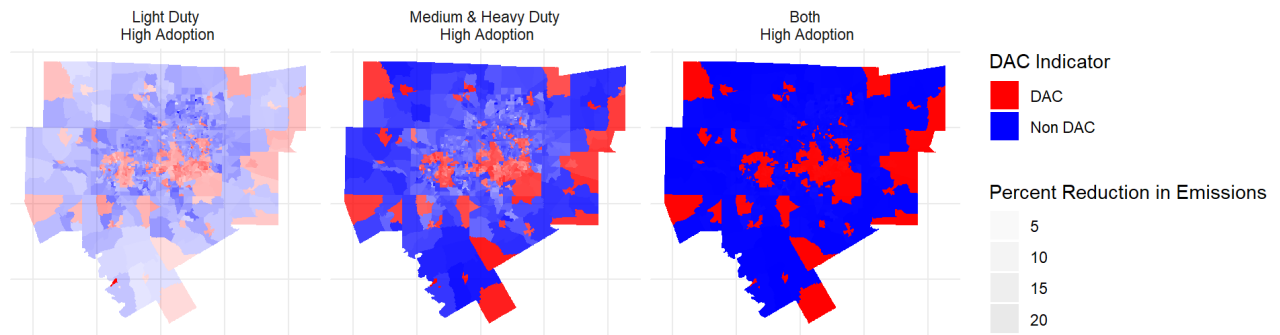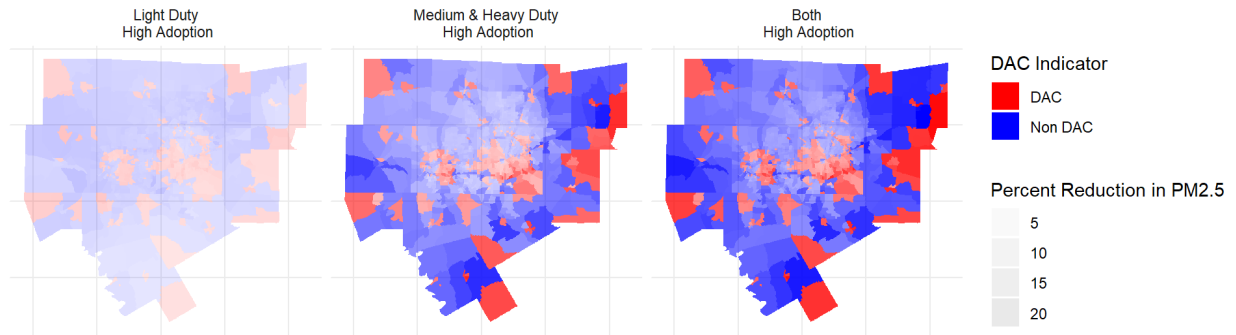
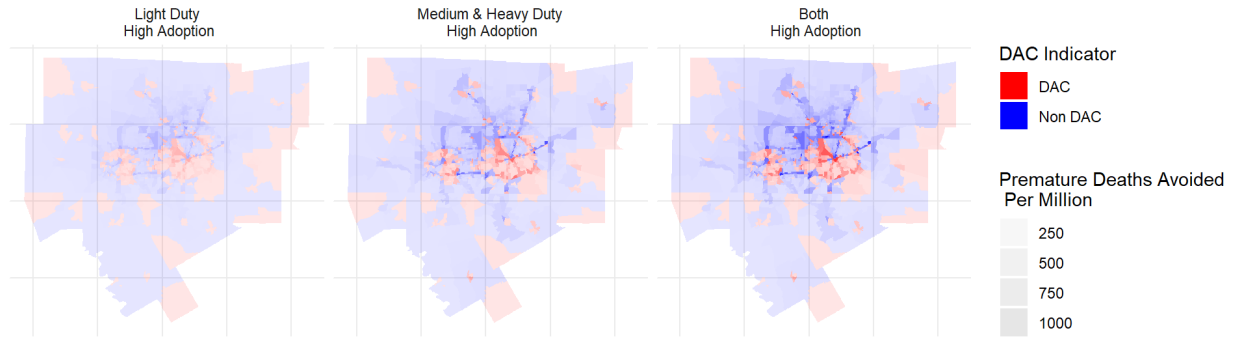**Figure 11.** Spatial distribution of emissions reduction, exposure reduction, and health benefits for different EV adoption scenarios and DAC indicators identified according to CEJST classification.
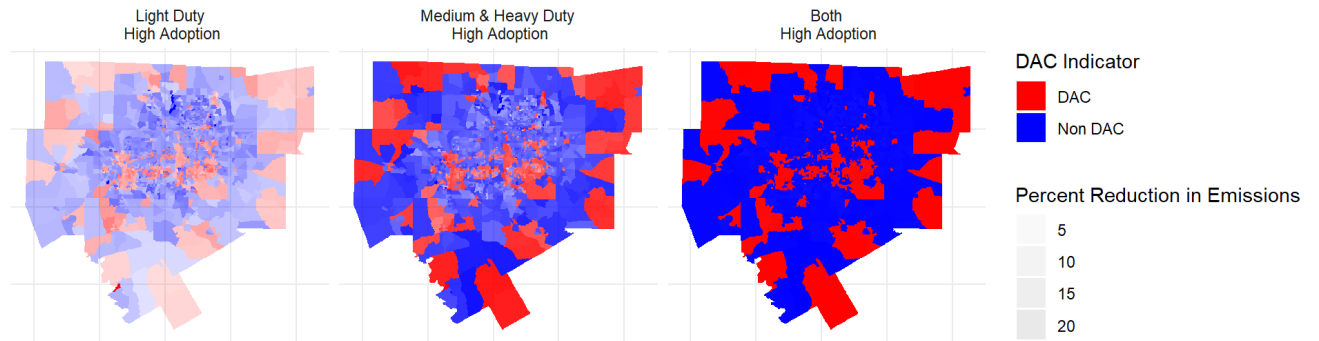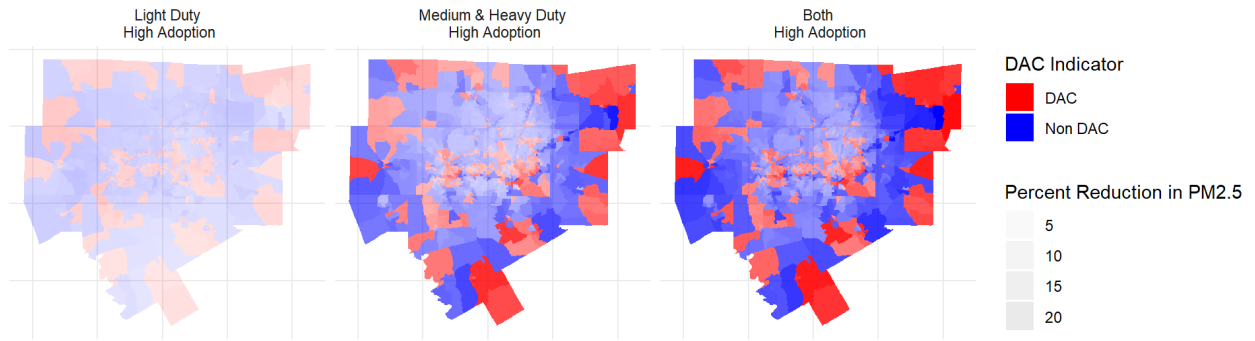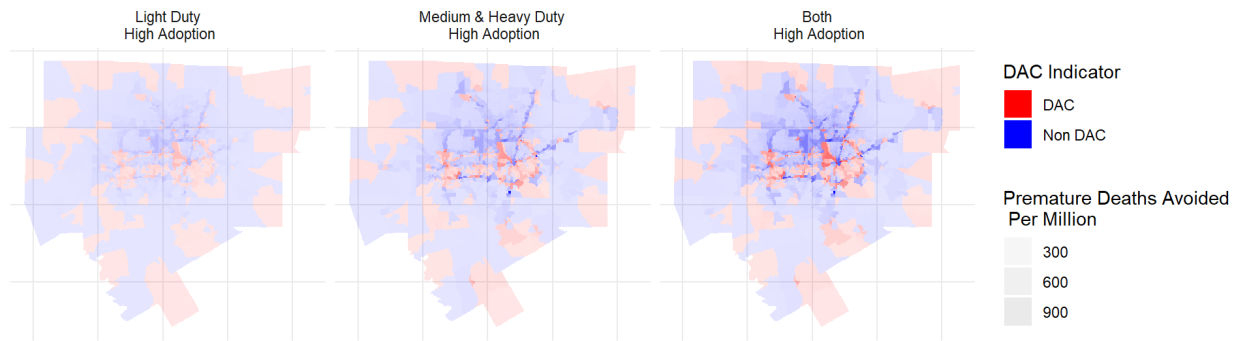
Health

**Emissions**

Exposure

Health

Figure 12. Spatial distribution of emission reduction, exposure reduction, and health benefits for different EV adoption scenarios and DAC indicators identified according to ETC Explorer classification.

Figure 13 can be used as a reference to better explain trends and/or patterns in the spatial distribution maps. The figure consists of NCTCOG region maps that show (a) urban vs. rural designation for census tracts, (b) roadway density in each tract measured in miles per square mile, and (c) population density in each tract measured in population per square mile.

In terms of emissions reduction, the light-duty high adoption scenario appeared to be the least impactful across all census tracts. In contrast, the hypothetical high EV adoption rate for all vehicle types resulted in substantial emissions reduction. Spatially, DACs, which are primarily located in dense urban centers as well as in in rural areas, benefited from EV adoption, particularly under the medium- and heavy-duty high adoption and both high adoption scenarios. This underlines the potential of these scenarios to address environmental justice issues by reducing emissions in the most affected communities. The exposure reduction maps revealed a similar pattern to the emissions reduction maps. However, it illustrates a more pronounced reduction in $PM_{2.5}$ exposure near major roadways, underscoring the direct health benefits of EV adoption in areas with high traffic density.

In terms of health impacts, the benefits of EV adoption, represented by the number of premature deaths avoided per million people, were most evident in high-population urban centers and near roadways. Hence, aligning with the findings from the exposure maps. This further emphasizes the necessity of targeting these areas for EV adoption (or more broadly, zero-tailpipe emissions vehicle adoption). On the contrary, the health benefits were less pronounced in rural DACs, despite these areas also experiencing significant reductions in emissions and exposure. This observation suggests that while rural areas might benefit from EV adoption in terms of improved air quality, the direct health impacts might be less significant due to lower population densities.
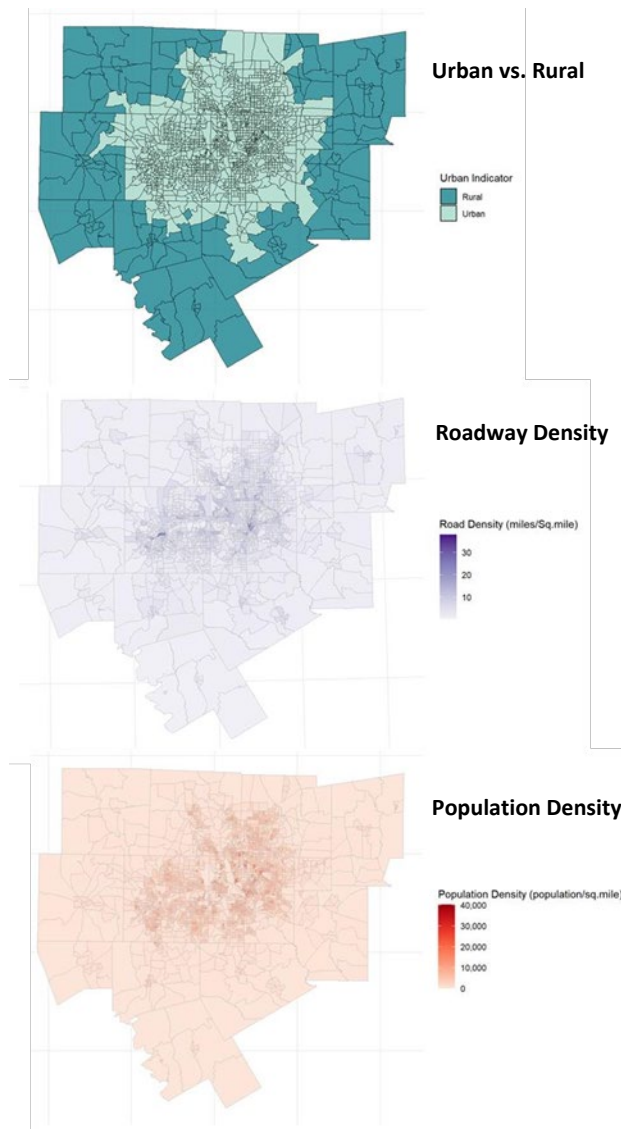
Figure 13. NCTCOG region maps for (a) urban vs. rural area designation, (b) roadway density, and (c) population density.

Conclusions, Limitations, and Future Research

This study explored the implications of EV adoption, with an emphasis on environmental justice, particularly for DACs. The research encompassed four distinct EV adoption scenarios, focusing on LDVs, MDVs, and HDVs. The scenarios highlighted potential impacts on emissions, exposure, and health outcomes across communities, with DACs and non-DACs differentiated using the CEJST and ETC Explorer classification methods.

Results indicated that DACs, as classified by both CEJST and the ETC Explorer, experienced higher vehicle densities, suggesting higher exposure to TRAP. This underscores the need for policy interventions targeted towards reducing the pollution burden in these communities. Analysis from this study also revealed that varying income levels within DACs did not significantly alter the benefits derived from EV adoption. This indicates that income level should not be a primary focus when classifying DACs in policy interventions. Another finding from this study is the potential benefits of EV adoption, with a noteworthy impact observed from medium- and heavy-duty EVs, particularly in DACs. These findings suggest that policy and technological advancements should extend beyond LDVs to

MDVs/HDVs for more substantial emissions reductions and health benefits. Spatially, urban centers and major roadways showed the most pronounced benefits of EV adoption, emphasizing location-specific policies. However, rural DACs showed less pronounced health benefits despite substantial reductions in emissions and exposure, highlighting the need for nuanced, location-specific policies.

The study's methodology has several limitations, including the use of simulated traffic parameters for scenarios beyond the baseline, the exclusive focus on vehicle density without considering other factors influencing TRAP levels, and the assumption of uniform population distribution within a census tract for exposure areas. Potential emissions from power plants due to increased electricity demand from EVs were also not considered in this study.

Despite these limitations, the study provided valuable insights into the spatial variability of EV adoption impacts. DACs, especially those in urban areas and near major roadways, stand to gain significant benefits from EV adoption. However, rural and suburban areas might not see equally pronounced health impacts due to lower population densities.

Future research can build on this study by incorporating additional factors influencing TRAP, such as using more detailed population distribution data like EPA's Dasymetric data and exploring potential challenges and solutions related to large-scale EV adoption. Additionally, research could explore the potential challenges and solutions related to large-scale EV adoption, such as infrastructure and energy needs. This would inform effective and sustainable policy interventions. Furthermore, future studies can delve deeper into DACs' socio-demographic characteristics and compare different classifications for DACs. Lastly, employing geospatial analysis techniques can help identify specific locations that would benefit most from EV adoption, aiding the development of targeted emissions reduction and health improvement policies.

References

Alternative Fuels Data Center (AFDC). (2023). *Bipartisan Infrastructure Law (Infrastructure Investment and Jobs Act of 2021)*. U.S. Department of Energy. https://afdc.energy.gov/laws/infrastructure-investment-jobs-act

Anenberg, S. C., Miller, J., Henze, D. K., Minjares, R., & Achakulwisut, P. (2019). The global burden of transportation tailpipe emissions on air pollution-related mortality in 2010 and 2015. *Environ. Res. Lett., 14*(9). https://doi.org/10.1088/1748-9326/ab35fc

Bai, B., Wang, Y., Xiong, S., & Ma, X. (2021). Electric vehicle-attributed environmental injustice: Pollutant transfer into regions with poor traffic accessibility. *Science of the Total Environment*, 756. https://doi.org/10.1016/j.scitotenv.2020.143853

Boogaard, H., et al. (2022). Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. *Environment International*, 164. https://doi.org/10.1016/j.envint.2022.107262

Bowe, B., Xie, Y., Yan, Y., & Al-Aly, Z. (2019). Burden Of Cause-Specific Mortality Associated with PM2.5 Air Pollution in the United States. *JAMA Network Open*, 11(2), e1915834. https://doi.org/10.1001/jamanetworkopen.2019.15834

Chang, S. Y., et al. (2023). Electric vehicle fleet penetration helps address inequalities in air quality and improves environmental justice. *Commun Earth Environ*, 4(135). https://doi.org/10.1038/s43247-023-00799-1

Chen, J., and G. Hoek. (2020). Long-Term Exposure to PM and All-Cause and Cause-Specific Mortality: A Systematic Review and Meta-Analysis. Environment international, Vol. 143. https://doi.org/10.1016/J.ENVINT.2020.105974

Clark, L. P., Millet, D. B., & Marshall, J. D. (2017). Changes in Transportation-Related Air Pollution Exposures by Race-Ethnicity and Socioeconomic Status: Outdoor Nitrogen Dioxide in the United States in 2000 and 2010. *Environmental Health Perspectives*, 125(9). https://doi.org/10.1289/EHP959

Climate Cabinet Education. (2023). *The Texas Environmental Justice Explorer*. https://ej.txrising.org/

Environmental Protection Agency (EPA). (2022a). *How Mobile Source Air Pollution Affects Your Health*. https://www.epa.gov/mobile-source-pollution/how-mobile-source-pollution-affects-your-health

EPA. (2022b). *Research on Near Roadway and Other Near Source Air Pollution*. https://www.epa.gov/air-research/research-near-roadway-and-other-near-source-air-pollution

EPA. (2022c). *Why Freight Matters to Supply Chain Sustainability*. https://www.epa.gov/smartway/why-freight-matters-supply-chain-sustainability

EPA. (2023a). *Biden-Harris Administration Proposes Strongest-Ever Pollution Standards for Cars and Trucks to Accelerate Transition to a Clean-Transportation Future*. https://www.epa.gov/newsreleases/biden-harris-administration-proposes-strongest-ever-pollution-standards-cars-and

EPA. (2023b). *Summary of Executive Order 12898 - Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations*. https://www.epa.gov/laws-regulations/summary-executive-order-12898-federal-actions-address-environmental-justice

EPA. (2023c). *EO 14008: Tackling the Climate Crisis at Home and Abroad*. https://www.epa.gov/greeningepa/eo-14008-tackling-climate-crisis-home-and-abroad

EPA. (2023d). *EJScreen: Environmental Justice Screening and Mapping Tool*. https://www.epa.gov/ejscreen

Federal Highway Administration (2022). *Special Tabulations: 2022 FHWA Forecasts of Vehicle Miles Traveled (VMT)*. https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.cfm

Gold, D. R., & Wright, R. J. (2005). Population Disparities in Asthma. *Annual Review of Public Health*, 1(26), 89–113. https://doi.org/10.1146/annurev.publhealth.26.021304.144528

Hajat, A., Hsia, C., & O'Neill M.S. (2015). Socioeconomic Disparities and Air Pollution Exposure: a Global Review. *Current Environmental Health Reports*, *2*, 440–450. https://doi.org/10.1007/s40572-015-0069-5

Han, I., Samarneh, L., Stock, T. H., Symanski, E. (2018). Impact of transient truck and train traffic on ambient air and noise levels in underserved communities. *Transportation Research Part D: Transport and Environment, 63*, 706-717. https://doi.org/10.1016/j.trd.2018.07.010

Hao, H., et al. (2019). Impact of Transport Electrification on Critical Metal Sustainability with a Focus on the Heavy-duty Segment. *Nat Commun*, 1(10). https://doi.org/10.1038/s41467-019-13400-1

Helveston, J. P., et al. (2015). Will Subsidies Drive Electric Vehicle Adoption? Measuring Consumer Preferences in the U.S. and China. *Transportation Research Part A: Policy and Practice*, (73), 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2019). Distributional Effects of Air Pollution from Electric Vehicle Adoption. *Journal of the Association of Environmental and Resource Economists, 6*(S1). https://doi.org/10.1086/701188

Houston, D., Krudysz, M., & Winer, A. (2008). Diesel Truck Traffic in Low-Income and Minority Communities Adjacent to Ports: Environmental Justice Implications of Near-Roadway Land Use Conflicts. *Transportation Research Record, 2067*(1), 38–46. https://doi.org/10.3141/2067-05

Hu, X., Chen, N., Wu, N., & Yin, B. (2021). The Potential Impacts of Electric Vehicles on Urban Air Quality in Shanghai City. *Sustainability,* 13(2), 496. https://doi.org/10.3390/su13020496

Ji, S., et al. (2015). Environmental Justice Aspects of Exposure to $PM_{2.5}$ Emissions from Electric Vehicle Use in China. *Environ. Sci. Technol., 49*(24), 13912–13920. https://doi.org/10.1021/acs.est.5b04927

Khatri, M., Dahiya, P., & Chaturvedi, A. (2021). Performance Enhancement of Suspension System of an Electric Vehicle Using Nature Inspired Meta-Heuristic Optimization Algorithm. Smart Innovation, *Systems and Technologies*, 157–170. https://doi.org/10.1007/978-981-16-3675-2_11

Massachusetts Institute of Technology. (2023). Chess players face a tough foe: Air pollution: Study: Even chess experts perform worse when air quality is lower, suggesting a negative effect on cognition. *ScienceDaily*. www.sciencedaily.com/releases/2023/02/230201134204.htm

Mohan, A., Bruchon, M. B., Michalek, J. J., & Vaishnav, P. (2023). Life Cycle Air Pollution, Greenhouse Gas, and Traffic Externality Benefits and Costs of Electrifying Uber and Lyft. *Environmental Science and Technology*, 23(57), 8524–8535. https://doi.org/10.1021/acs.est.2c07030

Mueller, N., et al. (2017), Health impacts related to urban and transport planning: A burden of disease assessment, Environment International, Volume 107, 2017, Pages 243-257, ISSN 0160-4120, https://doi.org/10.1016/j.envint.2017.07.020

National Environmental Justice Advisory Council. (2009). *Reducing Air Emissions Associated With Goods Movement: Working Towards Environmental Justice*. https://www.epa.gov/sites/default/files/2015-02/documents/2009-goods-movement.pdf

Orban, E., et al. (2016). Residential Road Traffic Noise and High Depressive Symptoms After Five Years of Follow-up: Results from the Heinz Nixdorf Recall Study. *Environ Health Perspectives*, 5(124), 578–585. https://doi.org/10.1289/ehp.1409400

Pan, S., & Gao, H. O. (2019). *Potential impacts of electric vehicles on air quality and health endpoints in the Greater Houston Area in 2040*. Center for Transportation, Environment, and Community Health. https://cpb-us-w2.wpmucdn.com/sites.coecis.cornell.edu/dist/6/132/files/2020/12/CU_YR3_GAO_FINAL_POTENTIAL-IMPACTS.pdf

Pratt, G. C., Vadali, M. L., Kvale, D. L., & Ellickson, K. M. (2015). Traffic, Air Pollution, Minority and Socio-Economic Status: Addressing Inequities in Exposure and Risk. *Int. J. Environ. Res. Public Health, 12*(5), 5355–5372. https://doi.org/10.3390/ijerph120505355

Reichmuth, D. (2019). *Inequitable Exposure to Air Pollution from Vehicles in California*. Union of Concerned Scientists. https://www.ucsusa.org/sites/default/files/attach/2019/02/cv-air-pollution-CA-web.pdf

Rizza, V., Torre, et al. (2021). Effects of deployment of electric vehicles on air quality in the urban area of Turin (Italy). *Journal of Environmental Management,* 297. https://doi.org/10.1016/j.jenvman.2021.113416

Ross, C. L., Amekudzi, A., Guhathakurta, S., & Welch, T. F. (2015). Freight Impacts on Small Urban and Rural Areas. *National Center for Transportation Systems Productivity and Management*. https://rosap.ntl.bts.gov/view/dot/35818

Sergici, S. et al. (2022). ERCOT EV Allocation Study: Methodology for Determining EV Load Impact at Substation Level. *Brattle*. https://www.brattle.com/wp-content/uploads/2023/01/ERCOT-EV-Allocation-Study.pdf

Sharma, A., Shiwang, J., Lee, A., & Peng, W. (2023). Equity implications of electric vehicles: A systematic review on the spatial distribution of emissions, air pollution, and health impacts. *Environ Res Lett*, 18(5). https://doi.org/10.1088/1748-9326/acc87c

Sherlock, M. F. (2022). Clean Vehicle Tax Credits in the Inflation Reduction Act of 2022. *Congressional Research Service*. https://crsreports.congress.gov/product/pdf/IN/IN11996

Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., & Marshall, J. D. (2021). PM2.5 polluters disproportionately and systematically affect people of color in the United States. *Science Advances, 7*(18). https://doi.org/10.1126/sciadv.abf4491

The White House Council on Environmental Quality (CEQ). (2022). *Climate and Economic Justice Screening Tool: Frequently Asked Questions*. https://www.whitehouse.gov/wp-content/uploads/2022/02/CEQ-CEJST-QandA.pdf

The White House. (2023). *FACT SHEET: Biden-Harris Administration Proposes New Standards to Protect Public Health that Will Save Consumers Money, and Increase Energy Security*. https://www.whitehouse.gov/briefing-room/statements-releases/2023/04/12/fact-sheet-biden-harris-administration-proposes-new-standards-to-protect-public-health-that-will-save-consumers-money-and-increase-energy-security/

United States Department of Transportation (USDOT). (2019). *Environmental Justice*. https://www.transportation.gov/transportation-policy/environmental-justice

USDOT. (2022a). *Equity Action Plan*. https://www.transportation.gov/sites/dot.gov/files/2022-04/Equity_Action_Plan.pdf

USDOT. (2022b). *Justice40 Initiative*. https://www.transportation.gov/equity-Justice40

USDOT. (2023). *Federal Tools to Determine Disadvantaged Community Status*. https://www.transportation.gov/grants/dot-navigator/federal-tools-determine-disadvantaged-community-status

Wodtke, G. T., Ard, K., Bullock, C., White, K., & Priem, B. (2022). Concentrated poverty, ambient air pollution, and child cognitive development. *Science Advances, 8*(48). https://doi.org/10.1126/sciadv.add0285

World Health Organization. (2022). *Ambient (outdoor) air pollution*. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

Young, S. D., Mallory, B., & McCarthy, G. (2021). Memorandum for the Heads of Departments and Agencies: Interim Implementation Guidance for the Justice40 Initiative. *The White House Executive Office of the President: Office of Management and Budget*. https://www.whitehouse.gov/wp-content/uploads/2021/07/M-21-28.pdf